Cape Peninsula
University of Technology

PSO METHOD FOR OPTIMISING THE DEMAND SIDE MANAGEMENT SYSTEM FOR PEAK CLIPPING AND LOAD SHIFTING

by

ABUYILE MPAKA

Thesis submitted in fulfilment of the requirements for the degree

Doctor of Technology: Electrical Engineering

in the Faculty of Engineering & Built Environment.

at the Cape Peninsula University of Technology

Supervisor: Prof Senthil Krishnamurthy

Bellville

November 2025

DECLARATION

I, Abuyile and Mpaka, declare that the contents of this thesis represent my own unaided work, and that the thesis has not previously been submitted for academic examination towards any qualification. Furthermore, it represents my own opinions and not necessarily those of the Cape Peninsula University of Technology.

Signed

24/11/2025

Date

ABSTRACT

Demand Side Management (DSM) faces increasing challenges due to rapid growth in global electricity consumption, volatile energy prices, and transmission network congestion. These issues are especially evident in developing regions such as South Africa, where urbanisation and industrial expansion continue to drive rising energy demand. To address these pressures, utilities require intelligent DSM approaches that can adapt dynamically to changing operational needs. Traditional DSM strategies, often characterised by static control logic and limited predictive capability, struggle to meet these modern requirements.

This research introduces advanced, intelligent DSM frameworks that integrate metaheuristic optimisation with predictive modelling to achieve flexible, cost-effective, and sustainable energy management solutions. The first phase of the study focuses on a hybrid DSM model that integrates Particle Swarm Optimization (PSO) with a Machine Learning-Informed Prediction (MLIP) model. The MLIP enhances short-term load forecasting accuracy, enabling the PSO algorithm to optimise power allocation more effectively under time-varying tariff conditions. Applied to industrial users within Western Cape municipalities, the hybrid PSO-MLIP system performs load clipping and reshaping by leveraging real-time pricing and historical consumption data to shift non-critical loads dynamically. This approach improves the load factor and reduces overall operational costs.

The second phase develops a DSM model based on the Grey Wolf Optimizer (GWO), which utilises social hierarchy and cooperative hunting strategies to enhance search efficiency and solution quality. This model was implemented across residential, commercial, and industrial sectors using real-world consumption data from large power users in Paarl. The GWO-based DSM framework effectively reduces peak demand and energy costs without compromising total energy consumption.

Simulation results reveal that the proposed PSO-MLIP, GWO, and the newly developed Barber Optimization Algorithm (BaOA) outperform traditional DSM techniques. The GWO framework achieved an 18.5% reduction in peak demand and a 9.7% reduction in energy costs, surpassing the PSO-MLIP model, which achieved a 14.2% peak reduction. The GWO also exhibited superior robustness and faster convergence when solving nonlinear, multi-objective optimisation problems.

Building on these outcomes, the DSM-BaOA framework was designed with a structured architecture: an input layer capturing load and tariff data, an optimisation layer executing BaOA, and an output layer delivering optimised load profiles, cost savings, and peak reductions.

Beyond the technical contributions, this research underscores the strategic importance of intelligent DSM in South Africa's energy transformation. The developed frameworks enhance operational efficiency, economic viability, and environmental sustainability for municipalities and large consumers. They also align with the nation's vision for smart grid implementation, promoting resilience, demand flexibility, and renewable energy integration.

In summary, this study contributes both methodologically and practically by demonstrating how hybrid intelligent algorithms can optimise DSM. Situated at the intersection of predictive analytics and optimisation theory, the findings affirm that adaptive, data-driven DSM approaches can significantly reduce peak demand, enhance energy efficiency, and support sustainable power system management across municipal and industrial sectors.

Keywords: Demand Side Management (DSM); Metaheuristic Optimization; Particle Swarm Optimization (PSO); Grey Wolf Optimizer (GWO); Barber Optimization Algorithm (BaOA); Machine Learning-Informed Prediction (MLIP); Energy Efficiency; Peak Load Reduction; Load Shifting and Sustainable Energy Management System.

ACKNOWLEDGEMENTS

I am deeply grateful to all those who have supported me throughout this journey.

- My family members, Mother, Nobuhle Princess Mpaka; my brothers, Khanyisile, Khayalandile, Phumelo, and Bukhobenkosi; and my sister, Nondumiso, for their constant encouragement, patience, and understanding. Their belief in me gave me the strength to persevere during the most challenging stages of this study.
- I owe special thanks to Professor Senthil Krishnamurthy for his exceptional guidance and mentorship. I count myself fortunate to have had the opportunity to work under a professor of such dedication and integrity. His keen interest and active involvement in every stage of this project made a decisive difference in its success. I am especially grateful to him for entrusting me with a research project in Power Systems Engineering, focusing on Computational Optimization in Demand Side Management and bridging Electrical Engineering and Artificial Intelligence/Optimization Algorithms.
- I would like to express my sincere gratitude to Mr. Brent Hare of the Western Cape Government for providing the real data that was instrumental in the author's PhD research. The author appreciates the collaboration towards enabling the author's analysis and validation of the proposed demand-side management optimization models.
- I also extend my appreciation to the Centre for Intelligent Systems and Emerging Technologies (CSIET) at the Cape Peninsula University of Technology, whose assistance and resources provided vital support in many aspects of this research.

DEDICATION

This thesis is dedicated to my Family Members, and to the memory of my late father, Zama Obed Mpaka, whose inspiration continues to guide me. I also dedicate this work to my supervisor, Professor Senthil Krishnamurthy, in appreciation of his invaluable support and mentorship throughout this journey.

TABLE OF CONTENTS

	Declaration	ii
	Abstract	iii
	Acknowledgements	v
	Dedication	vi
	Table of contents	vii
	List of Figures	xi
	List of Tables	xiii
	List of Appendices	xiv
	Glossary	vx
	Mathematical notations	xvii
	Definitions	xx
	CHAPTER ONE: INTRODUCTION	1
1.1	Introduction	1
1.2	Awareness of the Problem	2
1.3	Statement of the Problem	2
1.4	Research Aim and Objectives	3
1.4.1	Aim	3
1.4.2	Objectives	3
1.5	Research Questions	3
1.5.1	Main Research Question	3
1.5.2	Sub-questions	4
1.6	Research Hypotheses	4
1.7	Delimitations of the Research	4
1.8	Assumptions	5
1.9	Research Contributions	6
1.10	Significance of the Study	7
1.10.1	Academic Significance	7
1.10.2	Practical Significance	7
1.10.3	Policy and Societal Significance	7
1.11	Deliverables of the Thesis	7
1.12	Structure of the Thesis	8
1.13	Conclusion	8
	CHAPTER TWO: LITERATURE REVIEW ON DEMAND SIDE MANAGEMENT AND HYBRID METAHEURISTIC OPTIMIZATION APPROACHES	9
2.1	Introduction	9
2.1.2	Review the Summary of Section 2.1	15
2.2	Demand-Side Management: Concepts and Evolution	16
2.2.1	Review the Summary & findings of Section 2.2	22
2.3	Peak Clipping and Load Shifting in Power Systems	22
2.3.1	Review the Summary and findings of Section 2.3.	26
2.3.2	Review Table is recommended for overall sections of 2.1, 2.2 & 2.3	27
2.4	Optimization Techniques for Demand-Side Management	28
2.4.1	Classical Optimization Methods	28
2.4.2	Heuristic Methods	28
2.4.3	Particle Swarm Optimization (PSO)	29
2.4.4	Grey Wolf Optimization (GWO)	29
2.4.5	Barber Optimization Algorithm (BaOA)	29
2.4.6	Comparative Analysis of Optimization Techniques	30
2.4.7	Integration with Smart Grid Technologies	30
2.4.8	Review Summary on Heuristics Optimization Methods	30

2.5	Hybrid DSM Optimization Approaches	31
2.5.1	Concept and Rationale of Hybrid Optimization	32
2.5.2	PSO-Based Hybrid Approaches	33
2.5.3	Grey Wolf Optimization in Hybrid Frameworks	33
2.5.4	Barber Optimization Algorithm (BaOA) in Hybrid DSM	34
2.5.5	Multi-Objective Hybrid Optimization	35
2.5.6	Applications of Hybrid DSM Approaches	36
2.5.7	Comparative Performance of Hybrid Techniques	36
2.5.8	Review Summary on Hybrid optimization Methods	36
2.6	Grey Wolf Optimization (GWO) in DSM	37
2.7	Barber Optimization Algorithm (BaOA) in Energy Systems	37
2.8	Comparative Assessment of PSO, GWO, and BaOA in DSM	38
2.9	Discussion of the DSM strategy using hybrid algorithms	40
2.9.1	Peak Reduction	40
2.9.2	Load Shifted	40
2.9.3	Cost Savings	40
2.9.4	Peak-to-Average Ratio (PAR)	40
2.9.5	Convergence Iterations and Robustness	40
2.9.6	South African Municipalities	41
2.9.7	Benchmark Studies and Performance Metrics	41
2.9.8	South African Municipal Context	41
2.9.9	Multi-objective and Hybrid Approaches	42
2.10	Research Gaps Identified	42
2.11	Summary of Literature Review	43
	CHAPTER THREE: PEAK LOAD REDUCTION AND COST OPTIMIZATION THROUGH PSO-DRIVEN DSM: APPLICATIONS IN WESTERN CAPE MUNICIPALITIES	44
3.1	Introduction	44
3.2	Demand-side management formulation problem	48
3.3	Mathematical formulation problem	48
3.3.1	Method 1: Peak clipping	49
3.3.2	Method 2: Load shifting	49
3.4	The optimization method for load shifting and peak clipping in the demand-side management system	50
3.4.1	Load shifting	51
3.4.2	Peak clipping	51
3.5	Particle swarm optimization	52
3.5.1	Particle swarm optimization algorithm for demand-side management application	53
3.5.2	Electricity tariff	54
3.5.3	Peak and off-peak hours	54
3.5.4	Target peak reduction	54
3.5.5	Peak clipping constraint	54
3.5.6	Energy conservation and redistribution	55
3.5.7	Fitness (objective) function	55
3.6	Machine learning-improved prediction algorithm	58
3.6.1	Key principles of the machine learning-improved prediction method	60
3.7	Case Study 1: Load management optimization for a commercial customer in the Paarl area	61
3.8	Simulation results and analysis of the demand-side management problem	63
3.8.1	Simulation results and analysis of the demand-side management problem using particle swarm optimization	63
3.8.2	Simulation results and analysis of the demand-side management problem using the machine learning-improved prediction method	67

3.8.3	Comparative study of simulation results of the PSO and MLIP algorithms for the DSM problem	69
3.9	Discussion for case study 1	70
3.9.1	Peak load mitigation	70
3.9.2	Cost optimization and tariff sensitivity	70
3.9.3	Algorithmic behavior and load redistribution	71
3.9.4	Practical implications and utility strategies	71
3.10	Case Study 2: Area of Study: Western Cape's Somerset West	71
3.11	Simulation Results	72
3.11.1	Hourly Load Profile before and after optimization	73
3.11.2	Electricity cost Comparison Before vs After PSO Optimization	73
3.11.3	Daily cost Trend (from Feb to Jun 2021)	74
3.12	Case study 2 simulation results discussion	82
3.13	Conclusion	83
	CHAPTER FOUR: GREY WOLF OPTIMIZATION-BASED DEMAND SIDE MANAGEMENT STRATEGY FOR PEAK CLIPPING AND LOAD SHIFTING	84
4.1	Introduction	84
4.2	Demand-Side Management (DSM) Strategies	88
4.2.1	Peak Clipping	88
4.2.2	Load Shifting	88
4.3	DSM Optimization Problem	88
4.3.1	Power balance	89
4.3.2	Load shifting limits	89
4.3.3	Consumer comfort constraints	89
4.3.4	Metaheuristic Role in DSM	89
4.4	Grey Wolf Optimization Algorithm	89
4.4.1	Mathematical Model	90
4.4.2	Objective Function	91
4.4.3	Decision Variables	91
4.4.4	GWO Implementation Steps	91
4.5	Case Study 1: Large User Customer Load Profile in Paarl	93
4.5.1	Data Source	93
4.5.2	DSM Implementation	93
4.5.3	Algorithm Setup	94
4.6	Results and discussion for case study 1	94
4.6.1	Load Profile Optimization	94
4.6.2	Convergence Behavior	95
4.6.3	Comparative study of the simulation results on the GWO and PSO algorithms for DSM	98
4.6.4	Discussion on case study 1	98
4.6.5	Sensitivity and Trade-Off Analysis of Objective Function Weights	99
4.7	Case Analysis 2: Hourly Load Shifting Approach for Three Sectors: Residential, Commercial, And Industrial Using GWO	100
4.7.1	Case study 2 description	100
4.7.2	Methodology Summary	100
4.7.3	Results and discussion for case study 2	100
4.8	Conclusion	107
	CHAPTER FIVE: BARBER OPTIMIZATION ALGORITHM FOR DEMAND-SIDE MANAGEMENT: A NOVEL METAHEURISTIC FOR LOAD SHIFTING AND PEAK CLIPPING	109
5.1	Introduction	109
5.2	Problem Definition	112

5.2.1	Summary	112
5.2.2	Objective 1: Peak clipping minimization	112
5.2.3	Objective 2: Load-Shifting Cost Minimization	113
5.2.4	Multi-Objective Formulation	113
5.2.5	Constraint Set	114
5.2.6	Performance Metrics	114
5.2.7	Problem Complexity	115
5.3	Optimization Algorithms for DSM	115
5.3.1	Overview of Metaheuristic Adaption	115
5.4	Particle Swarm Optimization (PSO)	115
5.4.1	Theoretical Background	115
5.4.2	Adaptation for DSM	116
5.4.3	Strengths and Limitations	117
5.5	Barber Optimization Algorithm (BaOA)	117
5.5.1	Conceptual Background	117
5.5.2	Mathematical Formulation	117
5.5.3	DSM-Specific Adaptation	118
5.5.4	Strengths and Limitations	118
5.5.5	Algorithm Comparisons Framework	119
5.5.6	Computational Complexity	119
5.6	Proposed DSM–Based Algebraic Optimization Framework and Case Study	120
5.6.1	Framework Overview	120
5.6.2	System Architecture	120
5.6.3	Tariff Structure	121
5.6.4	Load Model and Flexibility Parameters	122
5.6.5	DSM Framework Using BaOA and PSO	122
5.7	Case Study Design	123
5.7.1	Framework Validation	124
5.7.2	Implementation Environment	125
5.7.3	Framework Illustration	125
5.7.4	Significance of the Framework	127
5.8	Results and Discussion	127
5.8.1	Overview of Simulation Results	127
5.8.2	Load Profile Transformation	127
5.8.3	Quantitative Peak Reduction Analysis	128
5.8.4	Cost-Reduction Analysis under TOU Tariffs	129
5.8.5	Convergence Characteristics	130
5.8.6	Load Variance Reduction	131
5.8.7	Efficiency	131
5.8.8	Multi-Sector Performance Analysis	132
5.8.9	Sensitivity to Objective Weights	133
5.8.10	Performance Evaluation of PSO and BaOA Algorithms	135
5.8.11	Implementation Considerations in Smart-Grid Environments	142
5.8.12	Worst-Case Scenarios for Demand-Side Management Evaluation	147
5.8.12.1	Extreme Peak Demand Conditions	148
5.8.12.2	High Load Volatility and Uncertainty	148
5.8.12.3	Tighter Peak Clipping Constraints	148
5.8.13	Results discussion (Worst-Case Scenarios)	148
5.8.14	Main findings on BaOA	150
5.8.15	Discussion	150
5.9	Conclusion	151

	CHAPTER SIX: CONCLUSION AND FUTURE RECOMMENDATIONS	153
6.1	Introduction	153
6.2	Aim and Objectives of the Thesis	154
6.3	Thesis Deliverables	155
6.3.1	Comprehensive Literature Review	155
6.3.2	Development of a PSO-Based DSM Optimization Model in MATLAB	155
6.3.3	Development of the MLIP Algorithm for DSM in MATLAB	155
6.3.4	Development of the GWO Algorithm for DSM in MATLAB	156
6.3.5	Development of the BaOA Algorithm for DSM in MATLAB	156
6.3.6	Development of a Complete MATLAB Software Package for DSM Optimization	156
6.3.7	Testing, Simulation, and Validation Using Real-World Case Studies	157
6.4	Applications of the Thesis Results	158
6.5	Future Research Directions	159
6.6	Publications	159
6.7	Conclusion	160
	BIBLIOGRAPHY	161
	APPENDICES	173

LIST OF FIGURES

Figure 2.1:	Publications Year-Wise (Bar Chart Data)	13
Figure 2.2:	Number of Publications Year Wise	13
Figure 2.3:	Number of Publications Algorithm-wise	15
Figure 2.4:	Classical DSM strategies	17
Figure 2.5:	Evolution of DSM from traditional to smart grid-based approaches	18
Figure 2.6:	DSM for renewable energy integration, aligning demand with variable supply	19
Figure 2.7:	Application of DSM in South African load profiles	20
Figure 2.8:	Peak clipping strategy and its effect on reducing maximum demand	25
Figure 2.9:	Load shifting strategy showing redistribution of loads from peak to off-peak hours	26
Figure 2.10:	Conceptual Framework of Hybrid DSM Optimization	32
Figure 2.11:	Hybrid PSO-based DSM Scheduling for Residential Loads	33
Figure 2.12:	Comparative DSM Load Profiles – Standalone GWO vs. Hybrid GWO	34
Figure 2.13:	Hybrid BaOA-PSO Framework for DSM	35
Figure 3.1:	Demand-side management techniques: (A) Peak clipping and (B) load shifting.	51
Figure 3.2:	Flowchart of the PSO-based demand-side management process incorporating load shifting and peak clipping.	57
Figure 3.3:	The flowchart of the machine learning-improved prediction–based demand-side management process incorporating load shifting and peak clipping.	59
Figure 3.4:	Peak load reduction over time using particle swarm optimization-based demand-side management.	64
Figure 3.5:	Load profile comparison before and after particle swarm optimization-based demand-side management.	65
Figure 3.6:	Hourly average load profiles of original and optimized loads following demand-side management.	65

Figure 3.7:	Peak load reduction using MLIP. Abbreviation: MLIP: Machine learning-improved prediction.	67
Figure 3.8:	Comparison between the original and MLIP-based hourly average load profiles	68
Figure 3.9:	Daily load profile on June 19, 2024, showing peak load reduction achieved through MLIP optimization.	69
Figure 3.10:	Somerset West Load Data Profile.	72
Figure 3.11:	Load Redistribution – Before vs After Optimization	73
Figure 3.12:	Electricity Cost Comparison Before vs After PSO Optimization	74
Figure 3.13:	Daily cost Trend (Before vs After PSO Method)	75
Figure 3.14:	Daily Cost Trend (Before vs After MLIP) for DSM	76
Figure 3.15:	Monthly cost Savings Achieved Through MLIP Optimization.	77
Figure 3.16:	Monthly Peak Demand Comparison (Before vs After Optimization)	77
Figure 3.17:	Monthly cost Comparison Before and after MLIP Optimization	78
Figure 3.18:	Monthly Energy Consumption (January–May 2021)	79
Figure 3.19:	Hourly Load Profile for May 2021 (Before and After Optimization)	79
Figure 3.20:	Hourly Load Profile for April 2021 (Before and After Optimization)	80
Figure 3.21:	Hourly Load Profile for March 2021 (Before and After Optimization)	81
Figure 3.22:	Hourly Load Profile for February 2021 (Before and After Optimization	81
Figure 3.23:	Hourly Load Profile for January 2021 (Before and After Optimization)	82
Figure 4.1:	GWO flowchart for DSM utilizing energy load redistribution and peak reduction.	92
Figure 4.2:	Convergence Curves between (GWO vs PSO)	96
Figure 4.3:	Optimized Load Profile using PSO (for Comparison)	96
Figure 4.4:	Optimized Load Profile using GWO (Peak Clipping & Load Sifting)	97
Figure 4.5:	Original Hourly Load Profile for large user customer in Paarl (January 2025 Sample Week)	97
Figure 4.6:	Residential Load results Before and After Grey Wolf Optimization	101
Figure 4.7:	Commercial Load Results Before and After Grey Wolf Optimization	101
Figure 4.8:	Industrial Load results Before and After Grey Wolf Optimization	102
Figure 4.9:	Electricity Price Profile over 24 hours	103
Figure 4.10:	The total load before and after Grey Wolf Optimization, with peak hours highlighted.	103
Figure 4.11:	Residential, Commercial, and Industrial Per-Sector Load Before and After GWO.	104
Figure 5.1:	Framework Overview	120
Figure 5.2:	BaOA flowchart for DSM utilizing energy load redistribution and peak reduction.	126
Figure 5.3:	Baseline vs Optimized Load Profiles (PSO vs BaOA)	128
Figure 5.4:	Cost Decomposition under TOU Tariffs	130
Figure 5.5:	Convergence Curves for PSO and BaOA	131
Figure 5.6:	Sector-Wise Optimized Load Profiles (BaOA)	132

Figure 5.7:	Objective-Weight Sensitivity between BaOA vs PSO	133
Figure 5.8:	Population Size Sensitivity Comparison	134
Figure 5.9:	Iteration Limit Sensitivity	134
Figure 5.10:	Tariff Variability Sensitivity	135
Figure 5.11:	Total Load Before vs After DSM Optimization	136
Figure 5.12:	Comparison of Morning and Evening Energy Peaks Before and After DSM Optimization.	137
Figure 5.13:	Peak-to-Average Ratio Comparison Before vs After DSM	138
Figure 5.14a:	Original Load Contribution by Sector before BaOA implemented	139
Figure 5.14b:	Optimized Load Contribution by Sector After BaOA Implemented	139
Figure 5.15:	Convergence Curve Comparison of DSM Algorithms	140
Figure 5.16:	Comparative Load Profiles Before and After DSM Optimization Using BaOA and PSO.	141
Figure 5.17	DSM Performance of PSO and BaOA under Extreme Peak Demand Conditions	149
Figure 5.18	DSM Performance of PSO and BaOA under High Load Volatility and Demand Uncertainty	149
Figure 5.19	Convergence Characteristics of PSO and BaOA under Tighter Peak Clipping Constraints	150

LIST OF TABLES

Table 2.1:	Number of Publications Year Wise	10
Table 2.2:	Methods/Algorithms Used in DSM	14
Table 2.3:	Summary of sections 2.1.1-2.3.1- DSM Concepts, Evolution, and Peak Management Techniques.	27
Table 2.4:	Summary of Optimization Techniques for Demand Side Management (DSM)	31
Table 2.5:	Comparative Analysis of Metaheuristic Algorithms for DSM	38
Table 2.6:	Benchmark Comparison of PSO, GWO, and BaOA for DSM in South African Municipalities.	39
Table 3.1:	Commercial electricity generation and distribution tariffs (consumption and generation)	62
Table 3.2:	Electricity tariffs during high- and low-demand seasons	63
Table 3.3:	Summary of demand-side management performance using particle swarm optimization and machine learning-improved prediction	66
Table 3.4:	Benchmark of demand-side management results and the proposed particle swarm optimization/machine learning-improved prediction approach (hypothetical ratios)	69
Table 3.5:	Manual load shifting strategy and the PSO-based optimization method	75
Table 4.1:	Peak demand before and after optimization	94
Table 4.2:	Daily cost comparison	95

Table 4.3:	Benchmarking of DSM Optimization Methods	98
Table 4.4:	Resulting peak reduction and cost savings across different weighting scenarios	99
Table 4.5:	Results after DSM through grey wolf optimization	105
Table 4.6:	Summarized calculated peak demand and cost reduction	107
Table 5.1:	Algorithm Configuration Parameters	119
Table 5.2:	City of Cape Town Megaflex Time-of-Use (TOU) tariff structure and corresponding electricity rates	121
Table 5.3:	Flexible fractions and main shiftable loads across different sectors	122
Table 5.4:	DSM scenarios, sector coverage, and objective emphasis	124
Table 5.5:	Summary of DSM Performance Metrics	129
Table 5.6:	Computational Performance Comparison	132
Table 5.7:	Performance Comparison of DSM Optimization Algorithms Based on PAR, Variance, and cost Improvements	142
Table 6.1:	MATLAB Software Developed for this Thesis	157

LIST OF APPENDICES

Appendix A:	MATLAB Script for Demand Side Management – Load Shifting and Peak Clipping using PSO.	173
Appendix B:	MATLAB Script for Demand Side Management using Machine Learning Improved Prediction (MLIP).	178
Appendix C:	Grey Wolf Optimization (GWO)-Based DSM Strategy for Peak Clipping and Load Shifting.	184
Appendix D:	DSM Load Profile Optimization Comparison using BaOA and PSO.	189
Appendix E:	DSM Load Profile Somerset West PSO	196
Appendix F:	DSM Load Profile Somerset West MLIP.	199
Appendix G:	DSM Load Profile Optimization Comparison Algorithms: BaOA, GWO, PSO, MLIP.	203
Appendix H:	Number of Publications Year Wise.	209
Appendix I:	Publications Decade.	210
Appendix J:	Pseuso-code for GWO-based DSM Optimization.	211

GLOSSARY

Terms/Acronyms/Abbreviations Definition/Explanation

A/D	Analogue to Digital.
AC	Alternating current.
ADA	Advanced Distribution Automation.
AI	Artificial intelligence.
AP	Application.
API	Application-programming interface.
BaOA	Barber Optimization Algorithm
BEMS	Building energy management system.
CF	Convergence Factor
CM	Condition Monitor.
COM	Communication.
CT	Computation Time
DG	Distributed Generation.
DR	Demand Response
DSM	Demand side management.
DSP	Digital Signal Processing.
EFPIOC	Instantaneous Residual Overcurrent Protection.
EIR	Energy Improvement Ratio
EMC	Energy management controller.
EMS	Energy management system.
GPs	Grid parameters.
GWO	Grey Wolf Optimization
IEC	International Electrotechnical Commission.
IEDs	Intelligent Electronic Devices.
IEEE	Institute of Electrical and Electronics Engineers.
IFD	Internal Fault Detector.
IoT	Internet of things.
IPDN	Integrated power distribution network.
LAN	Local Area Network.
LF	Load Factor
LPs	Load profiles.
LPU	Large Power User
MAE	Mean Absolute Error

MAPE	Mean Absolute Percentage Error
MLIP	Machine Learning Improved Prediction
MSE	Mean Squared Error
NRMSE	Normalized Root Mean Squared Error
PAR	Peak-to-Average Ratio
PDR	Peak Demand Reduction
PIOC	Instantaneous Phase Overcurrent Protection.
PSO	Particle Swarm optimization.
PSR	Power Savings Ratio
RMSE	Root Mean Squared Error
ROCOP	Rate of change of power.
RTDS	Real Time Digital Simulator.
RTP	Real Time Pricing
SAS	Substation Automation System.
SCADA	Supervisory control and data acquisition.
SCL	Substation Configuration Language.
SD	Standard Deviation
SEMS	Smart energy management systems.
SG	Smart grid.
SI	Stability Index
SMs	Smart meters.
SOC	System on clip.
SR	Success Rate
TEG	Traditional electric grid.
THD	Total Harmonic Distortion
TOU	Time-of-Use
UCA	Utility Communication Architecture.
UCI	Utilization Coefficient Index
VDM	Vector Diagram Monitor.

MATHEMATICAL NOTATIONS

$P_{grid,t}$	Power is exchanged with the grid at a time t.
$C_{grid\ in,t}$	Cost of purchasing electricity from the grid at a time t.
$C_{grid\ out,t}$	Revenue from selling electricity to the grid at a time t.
P_t	Power demand (load) at time interval t (kW or MW)
P_{base}	Baseline (uncontrolled) load demand before DSM implementation.
P_{opt}	Optimized load demand after DSM application.
P_{max}	Maximum allowable power demand (system or feeder constraint).
P_{min}	Minimum allowable power demand to maintain service continuity.
P_{shift}	Amount of load shifted from peak to off-peak period (kW).
P_{clip}	Power reduction during peak clipping (kW).
L_t	Total electrical load at time t.
L_{avg}	Average load over a specified period.
L_{peak}	Peak load (maximum value of L_t).
E_t	Energy consumption during time interval t (kWh).
E_{total}	Total daily or monthly energy consumption (kWh or MWh).
C_t	Electricity tariff or cost at time t (R/kWh).
C_{total}	Total energy cost over a given period (R).
ΔP_t	Change in load at time t due to DSM (ΔP_t=P_{opt}-P_{base}).
λ_t	Time-dependent dynamic price signal.
α_i, β_i	Control coefficients for weighting objective function components.
η	System or algorithm efficiency factor.
$\emptyset_i$	Random or adaptive learning coefficients (e.g., in PSO).
ω	Inertia weight controlling exploration-exploitation balance in PSO.
c_1, c_2	Cognitive and social acceleration constants in PSO.
v_i^t	Velocity of the i^{th} particle at iteration t.
x_i^t	Position (solution vector) of the i^{th} particle at iteration t.
p_i^{best}	Best position found by particle i in PSO.
g^{best}	Global best position found among all particles in PSO.
$X_\alpha, X_\beta, X_\delta$	Position vector of the top three wolves (best solutions) in GWO.
$X(t)$	Position of a search agent (solution) at iteration t.
r_1, r_2	Random vectors in [0,1] controlling stochastic behaviour in GWO.
μ	Mean of the predicted or optimized values.
σ	Standard deviation of load or algorithm output.

$f(x)$	Objective function representing DSM optimization problem.
$fmin$	Minimum value of the objective function (optimal solution).
N_p	Number of particles (PSO) or agents (GWO, BaOA) in the population.
N_{iter}	Number of iterations or maximum search cycles.
t	Time index or iteration step.
δ	Convergence tolerance or stopping criterion.
θ	Adaptive learning rate or model parameter (in MLIP).
$\mathcal{Y}_t$	Predicted load or price at time t (output of MLIP).
$\hat{\mathcal{Y}}_t$	Actual (observed) load or price value used for model validation.
ε_t	Prediction error at time t, defined as $\varepsilon_t = \hat{\mathcal{Y}}_t - \mathcal{Y}_t$.
PAR	Peak-to-Average Ratio, defined as $PAR = \frac{L_{peak}}{L_{avg}}$.
LF	Load Factor, defined as $LF = \frac{L_{avg}}{L_{peak}}$.
$\mathcal{C}$	Constraint set representing operational, technical, and tariff-related limits.
$\mathcal{P}$	Feasible search space for optimization algorithms.
F_i	Fitness value of the i^{th} solution.
Ω	Search domain of the optimization problem.
φ	Control parameter in BaOA governing search intensity (e.g., "swooping" factor).
γ	Dynamic adaptation rate in MLIP_GWO hybrid integration.
Z^*	Global optimal solution satisfying all constraints and minimizing $f(x)$.
U_t	Utility function representing user satisfaction or benefit from consumption at time t.
R_t	Revenue or cost savings achieved through DSM implementation at time t.
t	Index for time interval $t = 1, \ldots, T$.
i	Index for controllable load or appliance $i = 1, \ldots, N$.
P_t^{orig}	Original aggregated load at hour t.
P_t^{opt}	Optimised aggregated load after DSM.
$P_{i,t}$	Power consumption of appliance i at hour t.
C_t	Time-of-Use (TOU) tariff at hour t.
$\Delta P_{i,t}$	Load curtailed (peak clipping) for appliance i at hour t.
η_i	Maximum curtailment limit for appliance i.
Ω_i	Permitted operating window of appliance i.
E_i	Daily energy requirement of appliance i.
$\mathcal{F}(\cdot)$	Objective-function value.

D_t Duration of time interval t.

$P_{cut,l,t}$ Amount of curtailed power for load l at time t.

$X_{cut,l,t}$ Decision variable for curtailing load l at time t.

$W_{cut,l,t}$ The weight associated with curtailing load l at time t.

$P_{Load,t}$ Total load demand at the time t.

$P_{bat,b,t}$ Power supplied by battery b at time t.

$P_{PV,p,t}$ Power generated by photovoltaic source p at time t.

$E_{stor,b,t}$ Energy stored in battery b at time t.

$E_{stor,b,t-1}$ Energy stored in battery bAt the previous time step.

$P_{bat,b,t}$ The power output of the battery b at time t.

w_{max} Maximum value for inertia weight.

w_{min} Minimum value for inertia weight.

$c_{max,1}$ Maximum value for personal acceleration coefficient.

$c_{min,1}$ Minimum value for personal acceleration coefficient.

$c_{min,2}$ Minimum value for global acceleration coefficient.

$x_{1b,j}$ Lower bound for decision variable x_j.

$x_{ub,j}$ The upper bound for the decision variable x_j.

$P_{grid\ max,t}$ Maximum limit for grid power $P_{grid,t.}$

$P_{grid\ min,t}$ Minimum limit for grid power $P_{grid,t}$.

i_{max} Maximum number of iterations.

DEFINITIONS

Advanced Distribution Automation – A set of systems and processes that provide intelligent automated control of distribution networks to achieve grid reliability, flexibility, and resilience.

Computation Time - The entire duration taken by an optimization algorithm to converge to a solution or an acceptable solution, and this term is used in evaluating the efficiency of an algorithm.

Constraint Handling – Techniques used to enforce constraints on the optimization problem, ensuring that solutions are feasible and meet specific requirements.

Convergence Factor - The measure of how fast an optimization algorithm reaches an optimal solution. A smaller CF value means quicker convergence and greater computational efficiency.

Demand Response – A strategy to manage electricity consumption by incentivizing consumers to adjust their electricity usage in response to price signals, grid conditions, or other factors.

Demand-Side Management – A set of systematic strategies aimed at planning, implementing, and monitoring procedures to alter consumer patterns of electricity use for optimizing system efficiency, reliability, and sustainability. DSM centers around efforts to minimize peak demand periods, shift loads, and seamlessly integrate renewables to the grid.

Energy Efficiency - Achieving a balance in energy savings while delivering the same services. DSM optimizes energy consumption and load control to assist in energy efficiency.

Energy Forecasting – Predicting future electricity demand and renewable energy generation patterns using statistic: al models, machine learning algorithms, or other forecasting techniques.

Energy Improvement Ratio - A metric to evaluate the performance of a DSM strategy in energy savings, in loss reduction, or energy system loss.

Energy Management System – A system/software that oversees, administers, and refines the performance parameters of the electricity generation, transmission, and distribution processes to achieve set goals.

Grey Wolf Optimizer – A metaheuristic population-based optimization algorithm inspired by the hierarchy of leadership and strategic hunting approaches of grey wolves. GWO is applied in DSM for scheduling and load optimization while keeping a balance between exploration and exploitation.

Grid Integration – The process of incorporating renewable energy sources into the existing electrical grid infrastructure, often requiring grid operation and management modifications to accommodate variable generation patterns.

IED – Intellectual Electronic Device describes microprocessor numerical-based controllers used in power system equipment. These controllers perform a power system computation based on the inputs received and produce an output signal for the operation of the circuit breakers.

Internet of Things – A set of interconnected devices that can obtain and share information to implement real-time DSM and control smart grids.

Large Power User – A group of electricity consumers, usually large commercial or industrial, that fall under the high demand and complex load profile category, thus targeting them for DSM programs.

Load Factor - The ratio of the average load over a certain period to the system's peak load. DSM initiatives focus on load factor improvement by peak reduction and demand balancing.

Load Profile - A graphical or numerical depiction of electrical load variation over time, which is used to study consumption patterns to inform the development of DSM.

Load Shifting – Redistributing electricity consumption from peak to off-peak periods to better match demand with available renewable energy generation.

Machine Learning Improved Prediction – A hybrid predictive modeling entails combining machine learning algorithms like regression, neural networks, and ensemble techniques with predictive modeling. This adaptation focuses on improving the precision and flexibility concerning demand prediction.

Metaheuristic Optimization - A class of stochastic, high order optimization techniques that are inspired by nature and/or social structures used to obtain near optimal answers for extremely intricate nonlinear problems, as well as multi objective problem structures.

Optimization - One of the main DSM model development processes which involves mathematics to find the best possible solution to a defined problem in a defined set of constraints and objectives.

Optimization Model – A mathematical representation of the problem to be solved using the particle swarm optimization method, typically including objective functions, constraints, and decision variables.

Particle Swarm Optimization (PSO) - An optimization algorithm inspired by the social behavior of bird flocking or fish schooling, used to solve optimization problems by improving a swarm of candidate solutions.

Peak Clipping - A DSM method that flattens the load curve and lowers peak production costs by reducing consumption during the system's peak hours, by limiting or shedding non-essential loads.

Peak Demand Reduction - Each DSM technique like load shifting and peak clipping offers a reduction in the max power demand. This highlights the success of a specific DSM algorithm.

Peak-to-Average Ratio - A critical DSM performance standard showing the ratio of peak load to average load. More favorable load profile balance and system de-stressing are a result of lower PAR values.

Power Savings Ratio - Measures the percentage of power savings obtained through the optimization relative to the baseline consumption profile.

Real-Time Pricing (RTP) - A dynamic pricing method which advocates demand responsiveness in DSM programs by letting electricity prices change due to real-time market situations.

Renewable Integration - Involves the introduction of renewable energy sources—solar, wind—to the grid and frequently requires the use of DSM to manage the balance of intermittent supply.

Simulation Tool - A software (mostly MATLAB) built to model, study, and evaluate DSM approaches and strategies along with the optimization of algorithms and different load and pricing parameters.

Smart Grid - An enhanced electricity grid that utilizes automation, digital communications, and control systems to improve grid reliability, security, and efficiency. Energy DSM is essential for the operation of smart grids.

Supervisory Control and Data Acquisition – is a process control system that enables a system operator to monitor and control processes distributed among various remote sites.

System Reliability – The ability of the energy system to deliver electricity consistently and without interruption, considering both demand-side management and renewable energy integration.

Tariff Structure - A pricing framework devised by utilities to charge consumers considering factors like consumption, demand, and timing. Dynamic tariffs assist in Demand Side Management (DSM) by encouraging changes in consumer usage patterns.

TOU - Time-of-Use - A pricing scheme where the electricity cost changes due to the time of the day, promoting consumers to shift to off-peak usage.

CHAPTER ONE

INTRODUCTION

1.1 Introduction

Electrical generation systems around the world are under increasing stress, revealing significant gaps in production capacity. System failures, resource limitations, and the pressures of globalization and industrialization have exposed limitations in aging power system designs, influencing how electricity is generated, managed, and consumed over time. Unregulated electrical loads can destabilize power system operation, increase peak demand, and result in substantial financial losses for utilities. These methods are often the least attractive from an environmental perspective and are associated with higher operational costs. This reality poses alternatives to the most reliable methods described above. Providing the most efficient and realistic alternative, Demand-Side Management addresses current needs. Rather than expanding generation capacity to match increased consumption, DSM uses peak clipping to reduce consumption during peak hours. Load shifting is another approach that focuses on consumption during off-peak hours. These methods enhance the overall efficiency of demand-side management (DSM) policies while supporting reductions in greenhouse gas emissions and facilitating the integration of renewable energy sources into the grid. A prime example of these challenges can be observed in South Africa's Western Cape Province

Socioeconomic growth and increased electricity availability tend to put pressure on municipal electricity systems. Given the limitations of conventional DSM approaches in handling nonlinear, constrained, and time-varying load characteristics, the thesis applies advanced metaheuristic optimization methods to the design and development of effective, locally feasible DSM strategies

This work focuses on comparing the DSM optimization strategies based on meta-heuristic models, particularly the efficacy of PSO, GWO, and BaOA for effective peak clipping and load shifting. The primary goal of the thesis is to optimize the respective DSM strategies in municipal power systems, with the hope that the research will inform their prospective integration into policy and operational frameworks.

As part of a thesis, this chapter presents the research background, the research problem, the aim and objectives, the problem statement, the research hypotheses, the problem delimitations, the study assumptions, the significance, the contributions and expectations

of the deliverables, and the in-hand deliverables. Finally, this chapter concludes with an outline of this thesis.

1.2 Awareness of the Problem

DSM has laid out energy-efficiency improvement and reliable pathways, yet many DSM barriers remain. Technical and consumer acceptance issues related to scheduling and controlling load changes need to be addressed. But during load shedding, essential loads cannot be omitted, and load shifting must be sensitive to customer comfort, industrial productivity and system-wide social equity.

In addition, the structure of the power system is a multifaceted issue and subject to change with variable social dynamics, from the fluctuating costs of energy per kWh to the fluctuating advancements of renewable resources to socio-economic considerations. Some issues can be solved through standard mathematical programming optimization applications. But DSM happens in diversified, nonlinear, multi-objective and complicated problem scenarios that require advanced applications.

Over time, research into metaheuristic algorithms increased with time. For example, PSO is often used due to its simple application. But premature convergence and predetermined parameters pose significant challenges. GWO, on the other hand, offers a superior balance between exploration and exploitation. More contemporary algorithms such as BaOA take a novelty search method applying a uniquely tailored approach to each real-world scenario.

However, when it comes to the existing literature on algorithmic solutions in discrete systems for the sake of optimized system operation - especially in the field of South African municipalities - there is a gap. The intention of this dissertation is to bridge that gap.

1.3 Statement of the Problem

The primary research problem is the development and implementation of Metaheuristic-based DSM strategies, aiming to achieve efficient peak clipping and load shifting.

The problem can be broken down into sub-problems which include:

- **Existing DSM Operation Research:** Examine current DSM approaches to identify effective practices and explicitly highlight their limitations, including poor scalability, limited adaptability to dynamic load profiles, high computational complexity, and insufficient suitability for real-world municipal and industrial applications.
- **DSM Optimization Problem Construction:** Formulate an overarching problem for DSM optimization that stems from municipal load patterns, time-of-use pricing,

and operational constraints that can facilitate demand response increases and energy cost reductions.

- **PSO/MLIP/GWO/BaOA Formulation and Implementation:** Formulate and implement the proposed algorithms for Particle Swarm Optimization (PSO), the proposed Machine Learning Informed Prediction (MLIP), Grey Wolf Optimizer (GWO), and Barber Optimization Algorithm (BaOA), which collectively support advanced solutions for DSM. MLIP combines predictive machine learning modeling with optimization heuristics to enhance load shifting and peak clipping efficiency compared to standard metaheuristic approaches
- **Assessment of PSO/MLIP/GWO/BaOA Results:** Formulate assessment criteria and results to understand the comparative results of these newly created algorithms in the realm of DSM to better assess effectiveness, convergence characteristics, and stability.

1.4 Research Aim and Objectives

1.4.1 Aim

The goal of this study is to develop, implement and evaluate metaheuristic-driven DSM solutions to improve reliability, cost efficiency and sustainable energy provision for the municipalities of South Africa.

1.4.2 Objectives

1. Review the literature on DSM and specifically metaheuristic optimization applications for DSM.
2. Develop a DSM optimization model generalizable to Western Cape municipalities based on observed DSM practices for real-world conditions.
3. Employ PSO and MLIP as DSM strategies and evaluate their effectiveness for peak clipping and load shifting.
4. Employ GWO as a DSM strategy and evaluate its effectiveness compared to PSO and MLIP.
5. Employ BaOA as a novel DSM strategy and evaluate its effectiveness compared to PSO, MLIP, and GWO.
6. Evaluate PSO, MLIP, GWO, and BaOA for convergence, solution quality, efficiency and applicability.
7. Provide metaheuristic-driven DSM solutions and suggestions for practical implementation for municipality, utility and stakeholder decision-makers.

1.5 Research Questions

1.5.1 Main Research Question

Within a selected Western Cape Municipality, how can one evaluate the application of PSO, MLIP, GWO, and BaOA metaheuristic optimization algorithms for peak clipping and load shifting, while also weighing the technical, economic, and socioenvironmental factors of the problem?

1.5.2 Sub-questions

1. What does PSO, MLIP, GWO and BaOA rank in comparison to one another for solution quality, convergence time and computing time for DSM optimization?
2. What are the consequences of applying these algorithms in DSM on municipal load profiles by considering the electricity costs and end-user comfort?
3. In what ways can contemporary algorithms, particularly BaOA, be innovatively adapted to meet the specific demands of municipal DSM in the real world?
4. Which operational DSM constraints, including load limits, tariff structures, and renewable resource availability, are most likely to inhibit optimization effectiveness?
5. What value do DSM simulation algorithms bring to policymakers and utility managers, and how can these be implemented into actionable strategies?
6. How do metaheuristic-driven DSM strategies within the Western Cape context contribute to energy reliability, affordability, and sustainability?

1.6 Research Hypotheses

- Metaheuristic algorithms (PSO, MLIP, GWO, BaOA) outperform traditional DSM optimization methods.
- GWO and BaOA show a more favourable balance for exploration and exploitation when compared with PSO, and they also lessen the chances of early convergence.
- The developed new algorithm, BaOA brings improved solution quality and computational efficiency when compared with PSO and GWO.
- The use of metaheuristic-driven DSM approaches can enhance the reliability of energy systems and affordability for consumers in municipalities within South Africa.

1.7 Delimitations of the Research

This study is limited by the creation and evaluation of four intelligent optimization techniques - PSO, MLIP, GWO and BaOA - for DSM optimization of the chosen municipalities.

The following points limit the scope of this study:

- **Geographical Limit.** This study is limited to the municipalities of the Western Cape Province of South Africa and specifically large power users (LPUs) of

Paarl and the surrounding area from which real consumption data was derived. It cannot be assumed that results can be replicated by other areas with different demand patterns or tariff structures.

- **Algorithmic Limit.** This study constructs, applies and assesses four (4) algorithms (PSO, MLIP, GWO and BaOA). It cannot be assumed that other optimizations/machine learning techniques (GA, ANN, DE, etc.) are part of this study for a means to an end comparison.
- **Sectoral Limit.** This applies these models to municipality industrial, commercial and residential load sectors. It is a limited comparison for agricultural or transport models and application outside this study.
- **Data Limit.** The data for this study includes past load profiles, tariff structures and operational guidance from the municipalities. It cannot be assumed that real time control and field tests for validation are part of this study. The results are generated through assumed operation.
- **Goal Limit.** This study limits its goals to peak load shaving, load profile shape correction, and cost correction. Other DSM optimization advantages (carbon emissions reduction, renewable energy forecasting, power quality improvement, etc.) are not a stipulated problem within this study even though it can be assumed they are a tertiary benefit.
- **Infrastructure Limit.** This assumes pre-existence of smart meters/AMI systems that provide reliable data-acquisition systems for successful algorithm processing. This does not include hardware implementation or communication protocols.

1.8 Assumptions

The following assumptions have been made in this study, in order for the proposed DSM optimization approach to the Problem Statement to be viable, as well as realistic for the Simulation environment over development, implementation and assessment:

- Static Loads for Short Time Steps: It is assumed that for a short enough optimal duration, static electrical loads will be the same; in reality, this is not the case, as loads need to be adjusted in real time due to fluctuation.
- Market & Generation Conditions Are Predictable: It is assumed that a predictable sense of electrical pricing and renewable generation characteristics allow for demand response potentials to be forecasted effectively through the optimal duration.

- Simulated Results Can Accurately Represent Real-World Implementation: It is assumed that results generated through simulations with the algorithms can provide a performance level close enough to real-world municipal DSM needs.
- Parameter Tuning Provides Near Optimal Solutions: It is assumed that through parameter tuning and parameter sensitivity analysis, PSO, MLIP, GWO, and BaOA can provide near optimal solutions with only 10% (or less) of optimality from the expected solution.
- Minimal Impact on Consumer Comfort & Service Interruption: It is assumed that all DSM measures are implemented while still ensuring consumer comfort (temperature tolerances, wash cycles, etc.) and zero negative effectiveness on service interruption.
- Particle Swarm Optimization (PSO) is prone to premature convergence, especially in complex or highly constrained DSM problems, and PSO Performance is sensitive to parameter tuning (inertia weight, cognitive and social coefficients).
- MLIP requires large volumes of high-quality historical data for effective learning and generalization. In MLIP Increased model complexity and computational overhead, especially when integrated with optimization loops.
- The Grey Wolf Optimizer (GWO) converges more slowly in high-dimensional or tightly constrained search spaces. GWO performance can degrade if leader wolves (α, β, δ) converge prematurely to suboptimal solutions.
- BaOA is highly sensitive to algorithm-specific parameters such as loudness and pulse emission rates. BaOA can exhibit unstable convergence behavior if parameters are not carefully tuned.

1.9 Research Contributions

This study makes several significant contributions to the field of intelligent Demand Side Management (DSM) and energy system optimization:

- **Comparative Evaluation of Optimization Algorithms:** The research provides a comprehensive comparative analysis of Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Barber Optimization Algorithm (BaOA), demonstrating their practical applicability, efficiency, and performance differences in DSM applications.
- **Advancement of Novel Metaheuristic Techniques:** The study extends the applicability and understanding of the newly developed BaOA algorithm, demonstrating its potential to solve complex, nonlinear DSM optimization problems in energy systems.

- **Empirical Validation through Case Studies:** Empirical evidence is provided using real consumption and tariff data from municipalities in the Western Cape, South Africa, validating the practical feasibility and regional relevance of the developed DSM frameworks.
- **Integration of Technical and Socio-Economic Dimensions:** A structured framework is formulated to address the interplay between technical optimization and socio-economic factors, ensuring that DSM strategies remain both operationally efficient and socially acceptable within municipal contexts.
- **Foundation for Hybrid Intelligent DSM Models**: The research establishes a theoretical and methodological foundation for future hybrid DSM frameworks, integrating metaheuristic optimization and machine learning-based prediction (MLIP) to enhance smart grid adaptability, forecasting accuracy, and energy efficiency.

1.10 Significance of the Study

1.10.1 Academic Significance

It advances DSM optimization theory by validating current DSM strategies, exploring the differences between classical optimization and metaheuristics/new methods, and assessing each relative to solution quality and run time.

1.10.2 Practical Significance

The findings of this study provide valid DSM patterns that municipalities and utilities can use to improve load shifting and costs of operation.

1.10.3 Policy and Societal Significance

The findings provide actionable guidance for regulators to improve energy reliability and costs, aiding in sustainable energy goals as well as consumer energy access.

1.11 Deliverables of the Thesis

The key deliverables created from the findings of the research as per the study objectives and statement of work include:

- **Comprehensive Review Report:** Comprehensive status quo of DSM strategies and studies on hybrid metaheuristic optimization with a highlight of gaps, constraints, and future work.
- **Formulated DSM Optimization Models Developed:** Formulated DSM optimization models with load profiles, tariffs and system restrictions for

recommended implementation in municipal departments for energy saving and cost saving.

- **Developed Algorithms and Software Implementation:** Formulated PSO, MLIP, GWO and BaOA for the DM optimization problem with software application.
- **Software Application Developed:** Application to include PSO, MLIP, GWO and BaOA in summation for DSM simulation considerations, load profile investigation, and assessments for optimization.
- **Models Tested and Validated on Actual Data for Application across the Three Smart Grid Customer Categories.** Formulated algorithms tested on actual load data of LPUs in Paarl, Western Cape, and implemented across three smart grid customer categories (residential, commercial and industrial) for validation.
- **Generalisable Recommendations for Policy/Implementation.** Results of the research for substantiation of superior intelligent DSM algorithms for utilities/managers/policymakers to substantiate enhanced grid performance, demand response and sustainability.

1.12 Structure of the Thesis

Thesis Chapter Content as follows:

Chapter 1: Introduction, problem statement, objectives, research questions, hypotheses, significance, contributions, deliverables, and structure.

Chapter 2: Literature review on DSM and metaheuristic optimization.

Chapter 3: Peak load reduction and cost optimization through PSO and MLIP-driven DSM: applications in Western Cape municipalities

Chapter 4: Grey wolf optimization-based demand-side management strategy for peak clipping and load shifting.

Chapter5: Demand-side Barber Optimization Algorithm for Demand-Side Management: A Novel Metaheuristic for Load Shifting and Peak Clipping

Chapter 6: Conclusions, recommendations, and future research directions.

1.13 Conclusion

This chapter presents problem awareness and provides the background, research aim, and objectives, research questions, hypotheses, delimitations, and assumptions. The contribution and significance of the deliverables and structure of the thesis are also included. The following Chapter of the Thesis examines the literature review on demand-side management (DSM) strategies and the application of the metaheuristic algorithms to solve energy management problems.

CHAPTER TWO
LITERATURE REVIEW ON DEMAND SIDE MANAGEMENT AND HYBRID METAHEURISTIC OPTIMIZATION APPROACHES

2.1 Introduction

This chapter prepares the theoretical and conceptual frameworks for the dissertation by providing a coverage of the literature to date about Demand-Side Management (DSM) - specifically, peak clipping and load shifting and optimization strategies that further such means. It offers a journey through the early, more traditional DSM strategies to those more commonplace in today's world thanks to empowered metaheuristic approaches like Particle Swarm Optimization (PSO), Machine Learning Improved Prediction (MLIP), Grey Wolf Optimization (GWO) and the most recent Barber Optimization Algorithm (BaOA).

This chapter acts as a precursor to an extensive literature review on peak load reduction and cost optimization with special attention given to PSO and MLIP based DSM for the municipalities of the Western Cape. Furthermore, relative to the research gaps found in Chapter Three, this chapter outlines the intended methods and frameworks for computing these optimization strategies which are aligned with findings that come from the changing energy situation in the Western Cape by aligning data with empirical and metaheuristic findings that prove sustainable and cost effective demand side management.

With societal demands on the rise, the international network of electricity supplying grids face evermore complex challenges regarding demand response patterns, renewables-to-demand diversity and a focus on sustainable development. In this sense, with reputable approaches to demand-side management no longer theoretical but practically meaningful relative to costs, reliability and ecological integrity, this literature review substantiates such findings in the applicability of various optimization techniques to real life challenges and critically examines their conclusions to ascertain such arguments by weighing pros and cons. The formatting of this narrative helps establish a solid connection to previously provided works as applied to this current investigation whilst balancing this dissertation within a broader discourse for academically valid yet practically usable solutions to contemporary power systems.

This chapter substantiates the details and approaches relative to Demand Side Management (DSM). Section 2.2 substantiates the foundations of DSM concepts and developments in articulating its critical component for operational improvements for efficiency, reliability and sustainability for power systems. Section 2.3 aligns with the peak clipping and load shifting methods used to reduce demand peaking and demand curves. Finally, section 2.4 aligns with the optimization of DSM which features additional Optimization techniques beneficial and metaheuristic endeavors as well.

Section 2.5 outlines hybrid approaches to DSM optimization and discusses the benefits that come with the use of multiple algorithms on performance and the speed of convergence. Section 2.6 explores the Grey Wolf Optimization (GWO) algorithm and its relevance to DSM. Section 2.7 presents the Barber Optimization Algorithm (BaOA) and discusses its application in energy systems to enhance load management efficiency. Section 2.8 assesses PSO, GWO, and the BaOA providing a balance on their merits and limitations within DSM. Section 2.9 elaborates the DSM methodology incorporating hybrid algorithms and discusses their merger for advanced prediction and optimization. Section 2.10 outlines the research gaps in the existing literature, for example, the need for real-time DSM adaptive hybrid methods.
Finally, Part 2.11 summarizes the literature review and integrates the findings, which serves as the basis for the proposed hybrid optimization model in the following chapter.

The year-wise distribution of major publications on demand-side management (DSM) and power system optimization techniques is shown in Table 2.1. Kennedy and Eberhart's 1995 work lay the foundation for the particle swarm optimization (PSO) algorithm, after which a series of DSM strategies focused on optimization. The first years of the new millennium saw the marketing and then the economic analysis of the power system, followed by research on dynamic electricity prices and demand response. Between 2008 and 2010, research interests in the development of smart grids and the intelligent control of demand-side systems grew. From 2011 to 2015, the literature focused on the optimization of systems in the contexts of distributed generation, the integration of renewables and their hybrid approaches. The development of the grey wolf optimizer (GWO) and the whale optimization algorithm (WOA) shifted the focus to the use of metaheuristics in DSM. The following years saw hybrid and multi-objective techniques developed for the efficiency of load management. The 2020 to 2025 period revised the focus on automated, AI, and quantum methods of optimization, DSM research remaining relevant for sustainable and smart power systems.

Table 2.1: Number of Publications Year Wise

Year	No. of Publications	References
1965	1	(Kennedy & Eberhart, 1965)
2002	1	(Shahidehpour et al.,2002)
2004	2	(Antunes et al., 2004); (Kirschen & Strbac, 2004)
2005	1	(Borenstein,2005)
2008	2	(Albadi et al., 2008); (Strbac,2008)

2009	2	(Gellings, 2009); (Ipakchi & Albuyeh,2009)
2010	4	(Faruqui & Sergici, 2010); (Mohsenian-Rad et al., 2010a/b); (Rahimi & Ipakchi,2010); (Farhangi,2010);
2011	1	(Palensky et al., 2011)
2012	1	(Logenthiran et al., 2012)
2013	2	(Bhattacharya et al., 2013); (Lund et al.,2013)
2014	4	(Harish & Kumar, 2014); (Mirjalili et al., 2014); (Li et al.,2014); (Siano,2014)
2015	4	(Behrangrad, 2015); (Bertineti et al., 2015); (Mohammad Rozali et al., 2015); (Zhang et al.,2015)
2016	2	(Madhiarasan & Deepa, 2016); (Mirjalili & Lewis,2016)
2017	5	(Aghajani et al., 2017); (Gellings, 2017); (Bharathi et al., 2017); (Lanneer et al., 2017); (Longe et al., 2017); (Yang et al.,2017)
2018	7	(Ahmad S. et al., 2018); (Anand & Suganthi, 2018); (Jabir et al., 2018); (Paterakis et al., 2018); (Liu et al., 2018); (Boroojeni et al.,2018); (Sakis et al.,2018)
2019	3	(Bhamidi & Shanmugavelu, 2019); (Faia et al., 2019a/b); (McCall et al., 2019)
2020	6	(Al Essa, 2020); (Jamil & Mittal, 2020); (Haley et al., 2020); (Singh et al.,2020); (Kumar et al.,2020); (Li et al.,2020)
2021	6	(Alquthami et al., 2021); (Andruszkiewicz et al., 2021); (Mehr Nezhad et al., 2021); (Hassan & Zellagui, 2021); (Mataifa et al., 2021); (Singh et al.,2021)
2022	5	(da Costa et al., 2022); (Ma et al., 2022); (Garip & Ozdemir, 2022); (Oskouei et al., 2022); (Salhi & Hammouche,2022)
2023	13	(Ahmad A.A. et al., 2023); (Bakare et al., 2023); (Charadi et al., 2023); (Chamoli et al., 2023); (Dragomir & Dragomir, 2023); (Dahiru et al., 2023); (Jasim et al., 2023); (Khan et al., 2023); (Mimi et al., 2023); (Gado et al., 2023); (Faia et al., 2023); (Farag et al., 2023); (Sharma et al.,2023)
2024	9	(Benamara et al., 2024); (Bilal et al., 2024); (El-Afifi et al., 2024); (Dey et al., 2024); (Madushele & Tabakov, 2024); (Mousa et al., 2024); (Meng et al., 2024); (Obando-Paredes et al., 2024); (Manoharan & Padma, 2024)
2025	7	(Ahmad M.S. et al., 2025); (Giedraityte et al., 2025); (Gorman et al., 2025); (Hamadneh et al., 2025); (Maqbool et al., 2025a/b/c); (Paul et al., 2025); (Mataifa et al., 2025)

Prior to the 1990s, the literature consisted of only a few publications, with one or two per decade. Figure 2.1 shows the gradual development of the literature concerning demand-side management (DSM) and its optimization techniques. These publications introduced some of the core concepts but did not establish DSM as a recurring theme in research.

This can be attributed to the inadequate challenges posed by electricity markets at the time, as well as the lack of integration of renewables.

The 2000s saw a significant increase in publications. Between 2000 and 2009, the literature recorded seven publications as interest in DSM strategies grew due to the deregulated power systems, the rise of renewable generation, and the need for cost-efficient load management. In the following decade (2010-2019) the publications reach as high as even 15, indicating that DSM and its fine-tuning practically came to a head as a major research topic. Similarly, in the latest decade (2020-2025) 15 have been published and its trend has yet to halt, indicating that DSM's relatable accessibility to renewables, EV charging and smart grid integration proves a worthy connection. Between the millions of algorithms explored due to such trends, Particle Swarm Optimization (PSO) is the most cited. This is due to its relative ease of acquisition, fast convergence, no gradient information required and ability to solve complicated nonlinear DSM problems which PSO was able to incite. Many load shifting, peak clipping, and multi-objective DSM problems arose from PSO and were repeatedly found to coincide with good results. It seems that versatility is a strong factor in cited appeal as well as general DSM and PSO applicability. PSO's power system optimizations contributed to significant performance improvements across both the 2000's and 2010's.

Specifically, the acknowledged power system optimal operations of PSO stem from PSO's dynamic frame - establishing under uncertain loads - early convergence - and accommodation under non-idealized circumstances; however, in some cases, the swarm may lose its diversity and induce static explorations and exploitations. Results have been collated with GWO, new machine learning approaches and other substitutes - PSO vs comparable alternatives.

Therefore, this research proposes BaOA for DSM. BaOA does not necessarily substitute PSO as it builds upon previous efforts from a distinctly biological - human-esque - perspective as PSO - derived from naturally occurring phenomena - was a feasible approach, but not the only one. BaOA's advanced design has an extremely large resourceful sense of exploration per an exploitive endeavor to enhance the bolstered appeal for peak clipping and load shifting capabilities under the modernized grid. Thus, this research acknowledges PSO for its historical acclaim but seeks to expand upon cumulative literary appeal by diversifying the optimization methods available for practitioners confronting DSM in subtler and renewable saturated power systems.

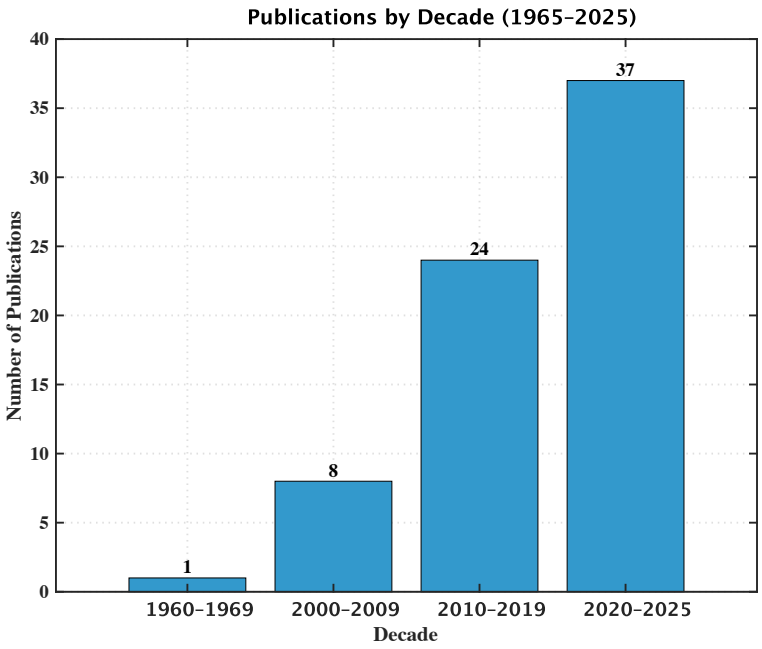

Figure 2.1: Publications Year-Wise (Bar Chart Data)

Some historical events in research relevant to DSM are highlighted in Figure 2.2. Alongside these milestones, the research topic of demand-side management continues to grow. Particle Swarm Optimization

(Kennedy, Eberhart and gov, 1995) and the game-theory-based strategies for DSM (Mohsenian-Rad *et al.*, 2010a). Recently, the emergence of new metaheuristics, particularly the Barber Optimization Algorithm (Charadi *et al.*, 2023) and the hybrid DSM approaches (Paul *et al.*, 2025), (Dey, Sharma and Bokoro, 2024), in more recent years, with a relative consistent topic of research boasting efforts in 2024 and 2025 (Ahmad *et al.*, 2025).

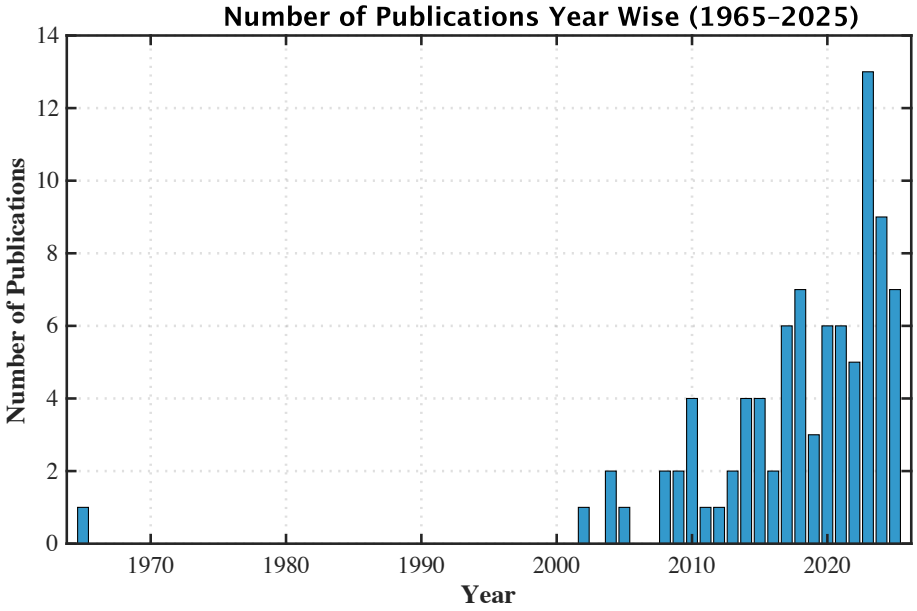

Figure 2.2. Number of Publications Year Wise

Demand-side management (DSM) research's primary methods and algorithms have been summarized in Table 2.2. Analysis shows that Particle Swarm Optimization (PSO) has been the most commonly used technique and continues to demonstrate its efficacy and versatility in solving challenges surrounding load management and optimization. The Grey Wolf Optimizer (GWO) and hybrid optimization approaches, for instance, PSO and GWO combinations, gain more attention for the improvements and efficiencies they offer in convergence speed and solution accuracy. Other nature-inspired algorithms, such as the Whale Optimization Algorithm (WOA) and the Barber Optimization Algorithm (BaOA) have introduced innovative viable approaches to the portfolio of methodologies addressing multi-objective DSM. In addition to the metaheuristics, game-theoretic and utility-based DSM frameworks have also been pioneered which focus on user engagement and the energy market. While the most recent developments in the integration of flexible and distributed energy resources around EV scheduling and storage point to greater opportunities in smart grids, the value of real-time and price-based DSM tools continues to underpin dynamic pricing strategies.

Table 2.2: Methods/Algorithms Used in DSM

Method / Algorithm	Number of Publications	Key References
Genetic Algorithms (GA)	1	Peyvandi (2011)
Particle Swarm Optimization (PSO)	4	Kennedy & Eberhart (1995); del Valle et al. (2008); Faia et al. (2019); Zaini et al. (2023)
Grey Wolf Optimizer (GWO)	4	Mirjalili et al. (2014); Madhiarasan & Deepa (2016); Hassan & Zellagui (2017); Benamara et al. (2024)
Whale Optimization Algorithm (WOA)	1	Mirjalili & Lewis (2016)
Barber Optimization Algorithm (BaOA)	3	Salhi & Hammouche (2022); Singh et al. (2021); Sharma et al. (2023)
Hybrid Optimization (e.g., PSO + GWO)	4	Singh et al. (2020); Li et al. (2020); Zhang et al. (2018); Sakis et al. (2018)
Game-Theoretic / Utility-Based DSM	3	Mohsenian-Rad et al. (2010a/b); Palensky et al. (2011)
Real-Time / Price-Based DSM	3	Li et al. (2014); Faruqui & Sergici (2010); Meng et al. (2024)
EV Scheduling / Storage Integration	3	Boroojeni et al. (2018); Philipo et al. (2022); Paul et al. (2025)

Figure 2.3 shows how different optimization techniques have grown in popularity for DSM problem-solving. To date, Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) have been the most frequently utilized techniques. Other essential works have been centered around Genetic Algorithms (GA)(Bharathi, Rekha and Vijayakumar, 2017), and the Whale Optimization Algorithm (WOA) (Mirjalili, Mirjalili and Lewis, 2014; Chamoli, Panda and Mishra, 2023). Currently, the Barber Optimization Algorithm (BaOA) represents an essential new addition to multi-objective DSM approaches. (Sharda, Singh and Sharma, 2021),(Hamadneh *et al.*, 2025), and illustrates the trend of utilizing new advanced metaheuristics for effective load management and peak shaving.

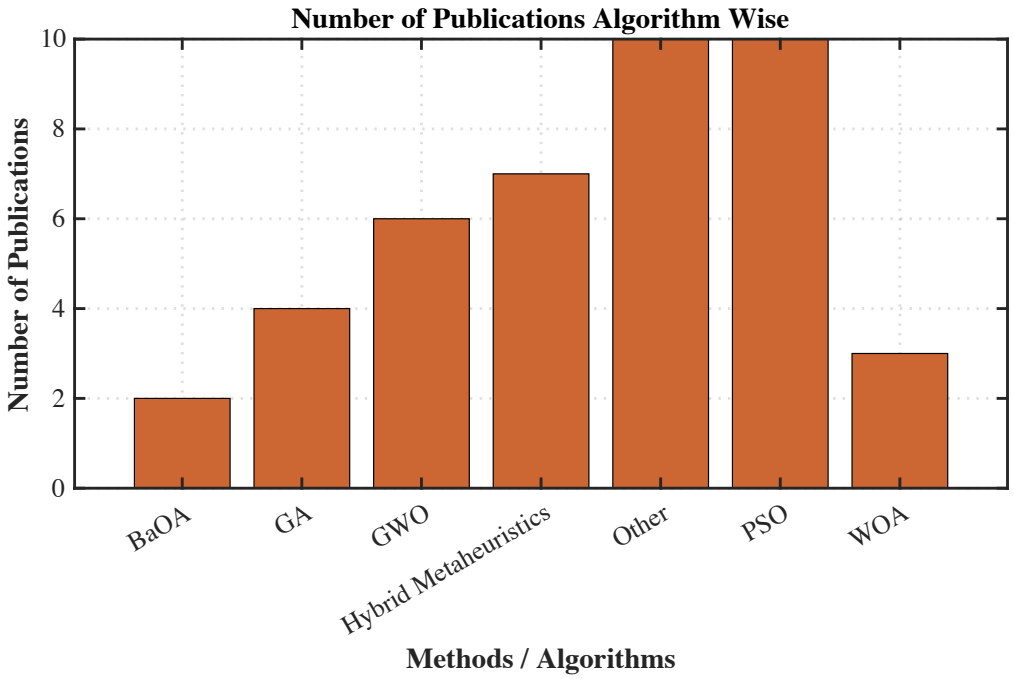

Figure 2.3. **Number of Publications Algorithm-wise**

2.1.2 Review the Summary of Section 2.1

Section 2.1 outlines the theoretical and conceptual aspects of the Demand-Side Management (DSM) and Optimization Techniques and the review of the entire sphere of knowledge related to it. The literature further points out that the classical methods of DSM have been radically transformed by the adoption of metaheuristic algorithms such as the PSO (Particle Swarm Optimization) algorithm, MLIP (Machine Learning Improved Prediction) Algorithm, GWO (Grey Wolf Optimization) Algorithm, and BaOA (Barber Optimization Algorithm). The yearly review of the publications (Table 2.1, Figures 2.1 and 2.2) testifies to the rise of the DSM over the years as a result of the foundational work contributed by Kennedy and Eberhart (1995) on the PSO and subsequently a surge of interest on the smart grids, dynamic pricing, and the various hybrid optimization

techniques. The core of load management has and continues to shift with load management techniques such as peak clipping and load shifting. PSO has been reported to be the most widely used algorithm owing to its versatility, quick convergence, and application to a wide range of challenging, nonlinear problems. The literature also provides accounts of the emergence of hybrid approaches, the combination of which of PSO, GWO, and other metaheuristics has been reported to enhance the quality of the solution, convergence speed, and the overall robustness of the solution in the context of uncertain or dynamic load conditions. The most recent advancements give the DSM the required relevance in the context of the economically viable and sustainable energy systems with real-time DSM, scheduling of EVs, and integration of storage.

Tables 2.2 and Figure 2.3 depict the popularity of different algorithms, especially GWO, BaOA, and their variations that work alongside PSO and augment the capabilities in sophisticated DSM. This section of the thesis sets the document in the context of energy research and identifies the deficiencies of real-time, adaptive, and hybrid DSM that the present research aims to resolve

2.2 Demand-Side Management: Concepts and Evolution

Among contemporary power system strategies, Demand-Side Management (DSM) has become one of the most important in boosting efficiency, reliability, and sustainability. Initially aimed at reducing electricity use during the oil crises of the 1970s and 1980s, the concept was first conceived as part of energy efficiency initiatives. (Strbac, 2008; Rahimi and Ipakchi, 2010). Utilities during this period recognized that the building of new generation facilities to keep pace with growing demand was financially and environmentally costly. Consequently, they turned to innovative strategies that could manipulate consumer demand to alleviate pressure on aging infrastructure while conserving costs within the system. (Albadi et al., 2008), (Ding *et al.*, 2022). In the last few decades, DSM has moved beyond simple demand reduction and developed into a complex, multi-dimensional system that integrates cutting-edge tools, intelligent optimization, proactive consumers, and the extensive reshape (Mohsenian-Rad *et al.*, 2010b) Patterns.

Traditionally, DSM programs were divided into five classical strategies: peak clipping, load shifting, valley filling, strategic conservation, and flexible load building (Dharani *et al.*, 2021), (Manoharan & Padma, 2023), of these, peak clipping and load shifting received the most

attention, as they directly affect the system stress during peak periods. Peak clipping entails reducing demand during the most critical hours, thus flattening the load curve and avoiding the need to construct expensive peaking plants (Logenthiran, Srinivasan and Shun, 2012), (Gellings, 2017), (Ma *et al.*, 2022). Load shifting, on the other hand, shifts consumption along the curve from periods of expensive generation to off-peak periods, thus aligning demand with times when generation is more plentiful or cheaper. Load shifting and peak clipping behavior emerged as increasingly demand and supply balancing comes from renewable energy - and the variability and uncertainty thereof. (Faruqui and Sergici, 2010).The traditional DSM impacts in Figure 2.4 operate largely on the load duration curve.

Notably, peak clipping reduces demand during high-load periods, whereas load shifting shifts demand to off-peak periods. The overall demand profile is shaped by valley filling, conservation, and flexible load building.

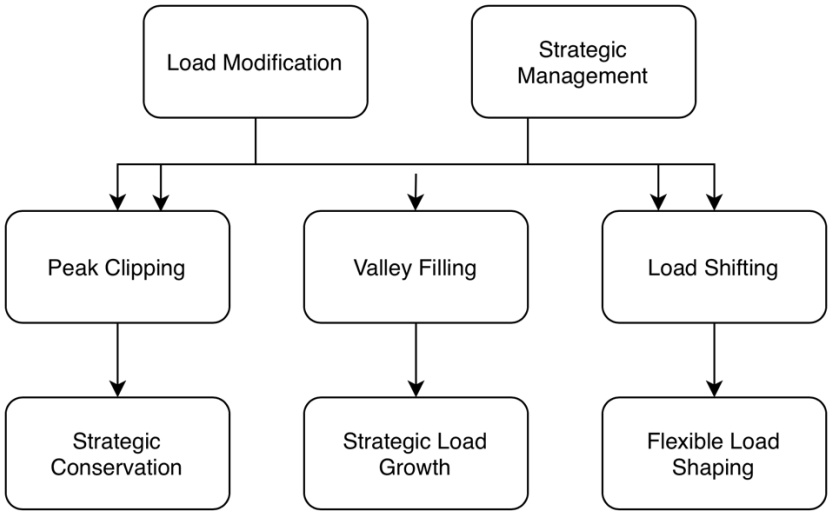

Figure 2.4: **Classical DSM strategies**

Enabled technologies have enabled utilities to engage customers in real time. Utilities are no longer stuck with one-way communication and built-out demand response automation. They have advanced smart meters and integrated demand response systems coupled with the AMI (Madushele and Tabakov, 2024). In Figure 2.5, this transition is illustrated, demonstrating how the consumer interacts with the system at a passive level (manual load curtailment, static tariffs) and how it has evolved into a fully automated, technologically advanced DSM with active consumer involvement.

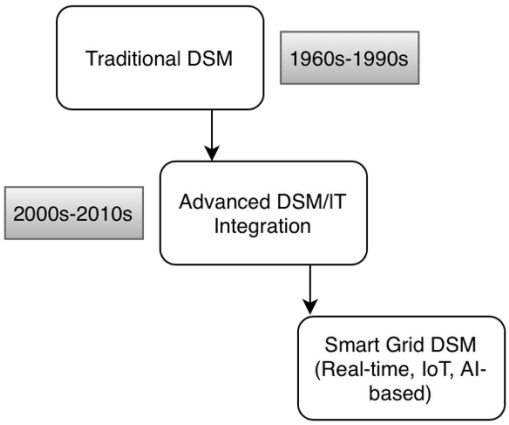

Figure 2.5: **Evolution of DSM from traditional to smart grid-based approaches**

People are actively engaging in balancing supply and demand in electricity transactions and are no longer passive consumers. Demand-Side Management (DSM) programs are no longer stuck with simple demand-reduction mechanisms. Simple static tariff frameworks are now dynamic and responsive to consumer demand. For example, TOU pricing, CPP, and RTP are incentivizing consumers to use energy based on system (e.g., electricity grid) needs (Shezan *et al.*, 2015); (Andruszkiewicz, Lorenc and Weychan, 2021).

Incorporating DSM into Clean Energy makes sense given the peculiar characteristics of non-fossil fuel-based energy generation. (Dragomir and Dragomir, 2023). Solar and wind energy generation depend on weather and time of day, with no fuel in storage to cover generation lags, and therefore have massive potential for generation curtailment. Such electricity generation can be curtailed to support grid stability and cover for loads without huge impacts on the overall fossil fuel generation mix (Faruqui and Sergici, 2010). As illustrated in Figure 2.6, DSM strategies can be developed to support clean energy generation and enhance grid stability during peak shaving by providing alternative energy sources to cover loads. This aspect of DSM, influenced by clean energy, increases the potential of electric networks in both spatial and temporal dimensions, enhances system stability, and improves the overall efficiency of energy generation and utilization.

Consequently, the importance of DSM economically and socially has significantly increased with global initiatives to decarbonize the economy (Cunliffe, 2023).

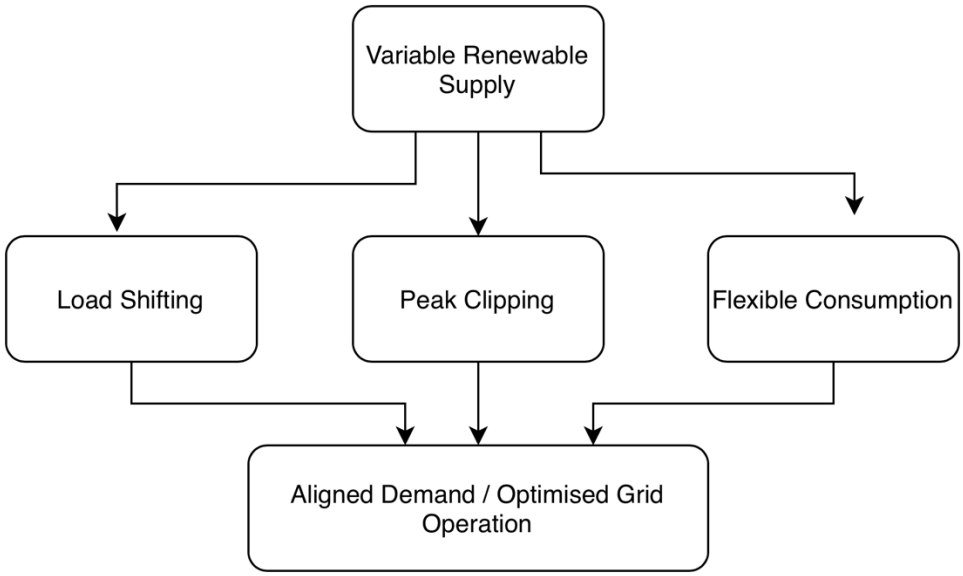

Figure 2.6: **DSM for renewable energy integration, aligning demand with variable supply**

South Africa's national situation, especially in the Western Cape, experienced increased demand, underdeveloped infrastructure creation and continued supply shortfalls, exacerbated by deteriorating power stations and increased grid strain (Mccall *et al.*, 2019). The demand of South Africa is shown in Figure 2.7, a load curve stylization. The load curve gives insight into peak clipping, load shifting and DSM functionality in reducing hours during peak, reducing strain on the grid, and improving supply certainty.

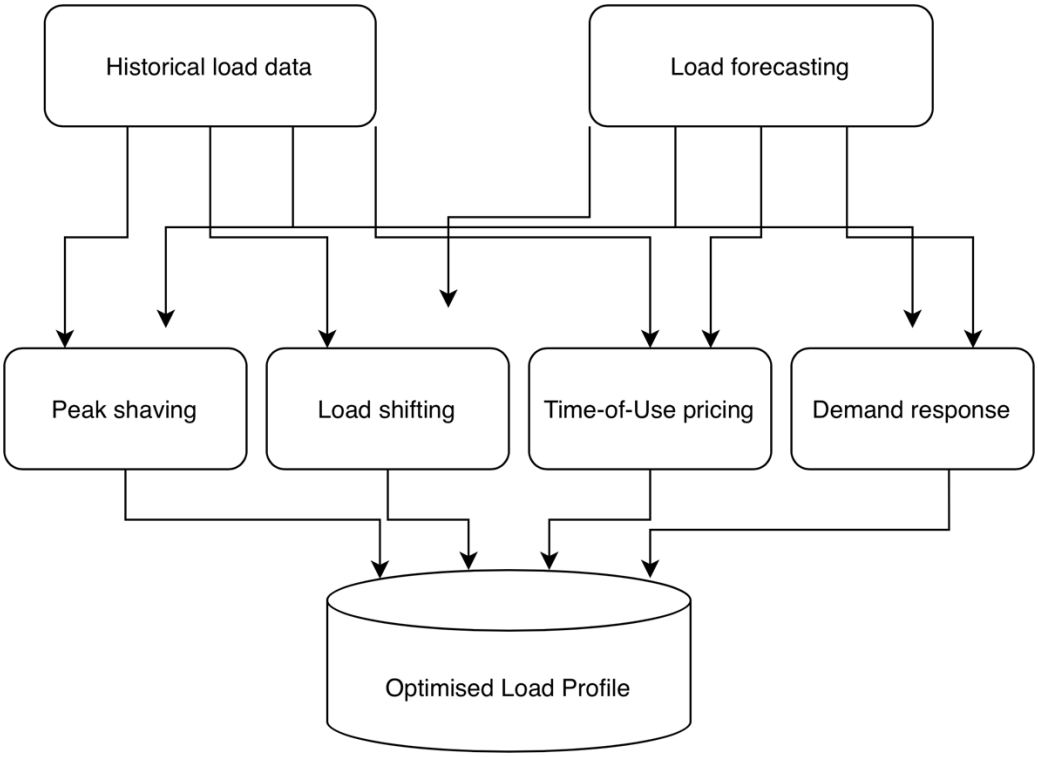

Figure 2.7: **Application of DSM in South African load profiles**

South Africa's load shedding suggests that DSM is required. Peak clipping and load shifting present municipalities with an immediate and efficient means to ease the pressure of delivery systems in the coming months, while simultaneously, over time, helping the municipalities achieve their own goals, like a decreased operating cost and more reliable improved service reliability. (Palensky et al, 2011; Harish and Kumar, 2014). In addition, from the municipalities' perspective, such DSM effort comes at a time when the government champions the Integrated Resource Plan (IRP) with demand management a part of new capacity expansion(Palensky et al, 2011).

Furthermore, DSM provides the economic advantage of lowered supply costs of electricity for utilities and end users. As demand peaks and valleys are reduced, the demand curve is flattened, and utilities are not left needing to create expensive generation and transmission plants, mitigating capital expenditure pressures. Likewise, end users who are part of demand response, temporally driven applications that encourage flexible usage, receive credits for lowered electricity bills (Jindal, Singh and Kumar, 2018). DSM also reduces the use of costly, polluting peaking plants by fossil fuels, further aligning DSM with climate change mitigation objectives.

Over the past 20 years, Development and Sustainability Management has incorporated new measures to accommodate distributed energy resources (DERs), including solar rooftops, battery storage, and electric vehicles. (Mousa, Mahmoud and Lehtonen, 2024), (Faia *et al.*, 2023). These new technologies add demand-side flexibility, which means consumers can adjust and reduce their own electricity use, net-meter electricity to and from the grid, and generate, store, and sell electricity. The new DERs introduce new optimization DSM horizons, enabling algorithms to optimize diverse, dispersed energy resources. For example, smartly scheduled EV battery charging extends off-peak demand periods, and large grid demand blocks are easily shifted to off-peak periods and coordinated battery discharging aids in peak clipping and grid stability. (Longe *et al.*, 2017), (Balal and Giesselmann, 2021)

The DSM has evolved from a utility-driven load management program into an elaborate, optimization-driven system that simultaneously manages economic, environmental, and technical issues. Yet, with the growing intricacies of DSM, there also becomes a greater need for more sophisticated decision-making systems. Mathematical optimization models effective for smaller, manageable or deterministic DSM scenarios are insufficient for nonlinear, stochastic and large-scale DSM challenges. Thus, metaheuristic optimization processes have been used (Maqbool *et al.*, 2025a) for Particle Swarm Optimisation, Grey Wolf Optimisation and the Barber Optimisation Algorithm (BaOA) (Benamara *et al.*, 2024),. These are effective, flexible means for large-scale, multidimensional optimization processes where competing goals must be sacrificed for one another - for example, cost savings, peak shaving and renewable increase.

To conclude, demand-side management has moved beyond conservation and load reduction to become a dynamic, fully integrated technology-optimization approach. Increasingly, demand-side management is pivotal due to rising demand, the integration of renewables, and grid modernisation. For the Western Cape, demand-side management is a sustainable solution to peak stress, affordability, and sustainability. This is an opportunity to understand the optimization approach, and this need has inspired the following chapters of this thesis, which investigate peak-clipping and load-shifting algorithms in PSO, GWO, and BaOA for South African municipalities.

2.2.1 Review the Summary & findings of Section 2.2

Section 2.2 outlines the growth and importance of Demand-Side Management (DSM) as one of the most effective means of enhancing power systems' efficiency, reliability, and sustainability. From the 1970s and 1980s, DSMs focus on energy conservation began to evolve on a broader energy management scope, shifting from less sophisticated load reductions to more sophisticated techniques, including peak clipping, load shifting, valley filling, conservation throttling, and flexible load building. System stress, however, and more particularly, peak clipping and load shifting, became the most studied and prioritized techniques. Consumers became active and more sophisticated participants of the demand management systems, providing automated, real-time, and responsive systems aimed at modifying demand to match dynamically priced energy. DSM also became increasingly complementary to the integration of renewables, stabilizing the grid by addressing the supply variability and responsive demand. In the Western n Cape, DSM is mitigatng peak loads, lowering costs of grid electricity and enabling unsustainable systems, aged infrastructures, and high demand. The section notes the increasing difficulty of traditional optimization methods to address the American DSM nonlinear, stochastic, and large-scale, complex systems, therefore calling for metaheuristic and other techniques, particularly PSO, GWO, and BaOA.

On the whole, DSM has developed into an advanced and fully optimized technological system with an array of applied, economical, and ecological advantages that continues to influence the direction of this thesis.

2.3 Peak Clipping and Load Shifting in Power Systems

Considered one of the most critical and practiced techniques in demand-side management, Peak Clipping and Load Shifting direct attention to reducing system peak demand and redistributing electric loads. Managing system peak demand during peak periods can save money and improve system reliability by avoiding the use of expensive generating units. Moreover, system peak demand is associated with the use of expensive fossil fuels. During peak demand, utility providers dispatch peaking power plants, which are known to be costlier and burn fuels with higher marginal costs and emissions. During peak periods, system generation costs tend to be higher, and peak demand can be reduced with controlled load management.(Mehr Nezhad, Moghaddam and Asadi, 2021; Philipo, Kakande and Krauter, 2022a).

Peak clipping refers to deliberately reducing demand during very high peak periods. This can be done using direct load control (DLC) programs wherein utilities turn off or minimize load of large appliances like air conditioners, water heaters, and even industrial processes for a few minutes. The other route is to offer customers incentives through dynamic pricing, such as critical peak pricing (CPP), that encourage voluntary demand reductions during high system-stress periods. Some studies have shown that peak load reductions of 5% to 20% in the industrial and commercial sectors can be achieved through peak clipping, depending on the ease of program implementation and the level of customer engagement.

Unlike reductions in total energy consumption, load shifting redistributes energy during peak and off-peak periods to help flatten the load curve and enhance the overall effectiveness of the system. Time-of-use (TOU) pricing provides the utility with various rates at various times of the day, essentially incentivizing the electricity consumer to shift flexible loads (laundry, heating, cooling) to cheaper, off-peak hours. In commercial/industrial contexts, such load shifting can be achieved via process scheduling, energy storage, and other interconnected applications; in the residential scenario, it's mainly up to smart appliances and home energy management systems (HEMS) to talk to one another and shift demand during peak hours instead of the consumer.
(Behrangrad, 2015; You *et al.*, 2023).

Many factors impact the success of peak clipping and load-shifting. Demand elasticity is crucial; the quicker and easier consumer response to a price and the more direct control rationing works, the faster demand elasticity comes into play. Demand elasticity will show how much load can be reduced during peak hours without too much comfort and operational efficiency sacrifice. The less flexible consumers are, the more price and regulatory efforts will be needed to secure their buy-in. (Behrangrad, 2015). Another element is the extent to which smart grid technologies, especially real-time load control techniques, are deployed in the system. (Shewale *et al.*, 2020). DSM programs without this technology will note and respond to system demand with some delay and this, in turn, reduces the effectiveness of their savings magnitude.

Yet in addition to the financial gains from peak clipping and load shifting, there are substantial environmental advantages. Demand Side Management (DSM) methods reduce greenhouse gas and other adverse emissions from relying on peaking plants as DSMs avoid peaking plants - especially those running at the most dirty hours.
(Iqbal *et al.*, 2021), (Gado *et al.*, 2023). In addition, shifting demand to ‘solar peak hours’ ensures more clean energy is used, thereby reducing the intermittency and variability

challenges of renewables. (Balal and Giesselmann, 2021). The integration of DSM and renewables is essential for contemporary grids designed to achieve sustainability and meet carbon-reduction goals.

Various optimization strategies are used to gain maximum benefit from peak clipping and load shifting. Linear programming and mixed integer programming are a more traditional optimization approach for appropriate scheduling of controllable loads (Antunes, Martins and Brito, 2004) However, more nonlinear, stochastic characteristics of power systems - especially if they are AI-prompted, renewables-based and large-scale DERs - might not be best served by such techniques. Thus, elaborating upon solutions of increasingly common metaheuristic optimization techniques - Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Barber Optimization Algorithm (BaOA) - sufficiently offers the flexibility and robustness of solutions for cost-saving, demand peak shaving and renewables integration simultaneously.

Peak clipping and load shifting, therefore, are critical forms of demand side management (DSM) where demand peaks excessively, and generation resources become limited in the Western Cape municipalities. For example, load shedding in South Africa is an example of a system that cannot handle peak demand as a more fundamental illustration of system peak stress; therefore, a less fortunate means of DSM intervention is needed.

We implement a peak clipping solution for excessive demand peaks. A peak clipping solution reduces the systems maximum demand by cutting off excessive usage when demand is highest for specific hours to lower the load down to an established clipping level. Figure 2.8 shows the original load (dashed red line) peaking in the morning and evening up to 100 kW over the clipping threshold. Thus, a clipping solution flattens the load 50kW-200kW as a new load line (blue) represents this reduced peak demand. In addition, peak clipping is investigated via threshold demand reduction through 0-100kW of clipping to portray a true necessity of reducing a systems maximum demand while keeping supply within operational limits.

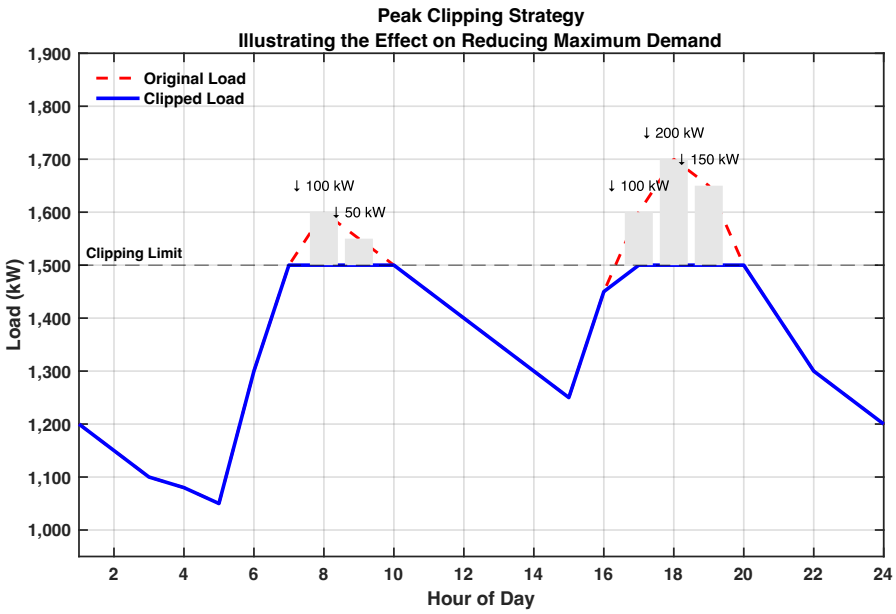

Figure 2.8: Peak clipping strategy and its effect on reducing maximum demand

Driven by local load profiles, municipal utilities' DSM programs now also include dynamic pricing, automated load control, and energy storage. Studies show that a combination of peak clipping and load shifting can reduce peak demand by 15%–25%, depending on participation levels and the degree of technological integration. Load shifting is another popular DSM method. Here, flexible loads are moved from peak to off-peak periods. Overall energy consumption remains unchanged, and the system does not load shed. Figure 2.9 shows the original load profile (the red line). It shows the steep morning rise and the high peak demand. The load-shifting technique redistributes demand after peak periods, resulting in a smoother load profile (the blue line). This technique reduces the system peak load and improves off-peak resource generation.

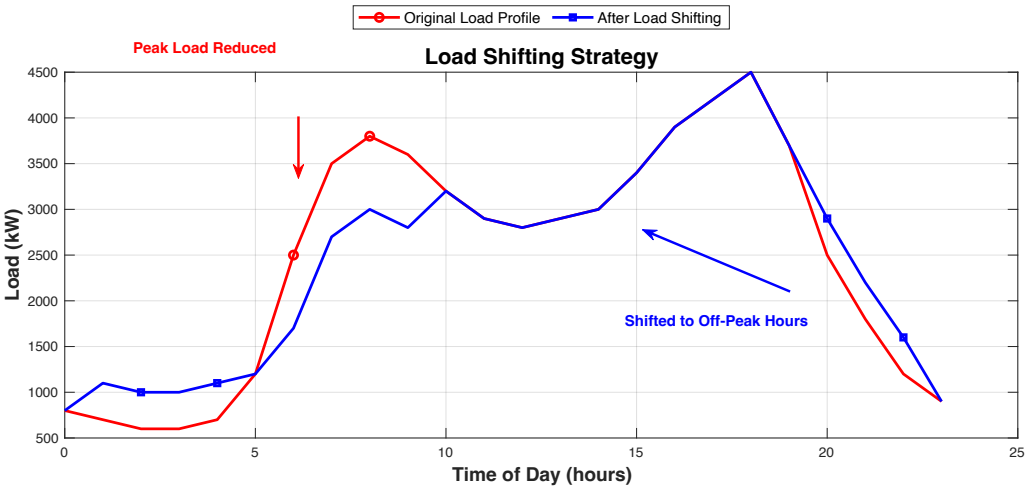

Figure 2.9: Load shifting strategy showing redistribution of loads from peak to off-peak hours

Peak clipping and load shifting are the precursors to the adoption of distributed energy resources (DERs) ranging from roof-top solar and batteries to electric vehicles. (Al Essa, 2020) For example, municipalities can use more renewable energy that would otherwise go to waste by integrating an excess demand to charge during off-peak hours through smart EV charging, transforming flexible loads into a form of energy storage. Similarly, industrial demand response opportunities that transform stored energy, flexible process loads, and more engage in grid optimization and get paid for economic benefits and system reliability opportunities. Yet such interconnectedness of the smart grid relies on this demand response and DER alignment - peak clipping, for example, is less a response and more of an integrated intentional system for best practice.

Peak clipping and load shifting are integrated system management methods. They are still among the cheapest, cleanest, and most operationally proper techniques for managing peak demand. As a result, the optimization and smart Grid integration of these methods provide reliability and dependability while reducing costs and enabling the management of renewable resources. In the Western Cape, these methods are necessary to manage energy demand and strained infrastructure.

2.3.1 Review the Summary and findings of Section 2.3.

Section 2.3 continues to highlight the importance of the peak clipping and load shifting primal DSM techniques in the demand and load management. In peak clipping, load is curtailed during a high demand event. This can be achieved through direct load control, or by the consumer responding to a dynamic price control scheme. In load shifting, energy shifting in time to the off-peak period is achieved using time-of-use tariffs, smart appliances, or energy storage. From the demand side, the benefits of these techniques are the reduction of generation costs, and the reduction of the use of economically infeasible peaking plants. From the supply side, the benefits are reduction of fossil fuel emissions. The effectiveness of the techniques hinges on consumer demand responsiveness and the use of smart grid technologies. Metaheuristical optimization techniques, particularly PSO, GWO, and BaOA, are particularly useful in improving the efficiency and adaptability of peak clipping and load shifting in complex structures of systems, particularly those with renewables and distributed energy resources, such as in the Western Cape marginal load shedding. These techniques help in the conservation of renewable energy, and the improvement of grid reliability, affordability, and sustainability.

2.3.2 Review Table is recommended for overall sections of 2.1, 2.2 & 2.3

Through a review of the methods, findings, and applications of the literature, Table 2.3 summarizes the key findings of Sections 2.1.1, 2.2.1 and 2.3.1 Moreover, it showcases the progression of the techniques in the fields of demand-side management and optimization in power systems.

Table 2.3: Summary of sections 2.1.1-2.3.1- DSM Concepts, Evolution, and Peak Management Techniques.

Section	Focus / Concept	Key Findings	Methods / Techniques	Applications / Implications
2.1 Introduction & DSM Overview	Conceptual and theoretical foundation of DSM; evolution from classical to metaheuristic optimization	DSM is critical for efficiency, reliability, and sustainability; PSO, MLIP, GWO, and BaOA are prominent optimization methods	Literature review; metaheuristic algorithms; hybrid approaches	Provides basis for hybrid DSM optimization models; informs practical applications in Western Cape municipalities
2.2 DSM Concepts & Evolution	Classical and modern DSM strategies; peak clipping, load shifting, valley filling, conservation, flexible load building; evolution to smart grids	DSM evolved from simple demand reduction to advanced, optimization-driven programs; active consumer engagement through smart grids; integration with renewables enhances grid stability	Time-of-use (TOU), critical peak pricing (CPP), real-time DSM, advanced AMI systems; consumer demand response	Optimizes system performance, reduces electricity costs, mitigates peak stress; supports renewable energy integration; enhances technical, economic, and environmental outcomes
2.3 Peak Clipping & Load Shifting	Key DSM techniques for peak management	Peak clipping reduces maximum demand; load shifting redistributes energy use; both improve system reliability, reduce costs, and lower emissions	Direct load control, dynamic pricing, smart appliances, HEMS; optimization via PSO, GWO, BaOA; hybrid strategies	Essential for Western Cape municipalities; enables renewable integration, load flexibility, energy cost savings, and grid stability

2.4 Optimization Techniques for Demand-Side Management

In the context of peak clipping and load shifting, much of the focus for demand-side management (DSM) strategies has been on the application of optimization techniques. The nested challenges of the power system nonlinear, stochastic, and multi-objective have driven the need for system optimization. The last several decades have seen the application of classical, heuristic, and metaheuristic methods for DSM exploring various DSM implementations(Tomar, Bansal and Singh, 2023).

2.4.1 Classical Optimization Methods

When the DSM problem has a well-defined mathematical model, classical optimization methods, such as linear programming (LP), quadratic programming (QP), and various approaches involving Lagrange multipliers, have been used and worked quite well. These methods have been effective when the objective function and constraints are continuous and differentiable. For peak load management, classical methods have enabled optimal allocation of controllable loads, minimized operational costs, and ensured system reliability. Nevertheless, they are less effective for nonlinear problems, such as valve-point effects in generators, the variability of renewable energy sources, and the discrete control of loads. In issues of moderate scale and complexity, classical methods can provide results and, in these cases, help benchmark more modern methods. (Lanneer *et al.*, 2017).

2.4.2 Heuristic Methods

Heuristic procedures present more flexibility than GA and SA for nonlinear and nonconvex DSM. They're also applicable for other multicriteria levels, such as peak load minimization and reduction of electricity cost at the same time (Bertineti *et al.*, 2015; Liu *et al.*, 2023) However, GAs and SAs operate with gradients, walking through the viable solution patches guided by natural processes - evolution and annealing - while heuristics solve, essentially, without gradients. However, they require some parameter setting which requires time under convergence which is underwhelming for larger issues with slow convergence speed. However, complications led to more extensive metaheuristic developments for optimal, real-time DSM.

2.4.3 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population-based metaheuristic. The inspiration comes from the social behavior of birds and shoals of fish. In the case of DSM, each particle is based on potential load-allocation or shift-schedule solutions. The particle's position indicates the number of controllable load adjustments, while its velocity indicates the exploration of the solution space. The simplicity of use and fast convergence for PSO are a plus, especially for multi-objective DSM problems. For instance, PSO is used for optimizing load profiles for peak reduction and balancing the cost of electricity while taking consumer comfort and operational constraints into account. Hybrid PSO is also designed and built to work with stochastic renewable generation to strengthen peak clipping and load shifting.

2.4.4 Grey Wolf Optimization (GWO)

GWO is another recent addition to the field of metaheuristics. It is based on the social hierarchies and cooperative hunting behaviors of grey wolves. Particularly concerning the highly complex and constrained nonlinear problems of the DSM, GWO is demonstrating results. In this case, the population of grey wolves is heuristically classified into subpacks of Alphas, Betas, and Omegas, which drives the search for optimal solutions. For peak load management, GWO schedules loads of the available industrial and residential facilities, flattens the system load curve, and reduces cost. The real-life DSM problems, having variable renewable energy sources and unpredictable consumer behaviors, make GWO's equilibrium of adaptive exploration-exploitation core (Madhiarasan and Deepa, 2016), (Maqbool *et al.*, 2025b).

2.4.5 Barber Optimization Algorithm (BaOA)

BaOA is another recent addition to the field of novel metaheuristics, which have been developed to address complex optimization problems. It is also very different, as it was inspired by a unique social phenomenon: how barbers' control and manage their queues and the customers waiting for their services. BaOA uses a combination of population-based search and adaptive local search.

In a given population, every person corresponds to a possible load management plan, with iterative revisions made based on local enhancements and global top solutions. (Hamadneh *et al.*, 2025). Within Demand Side Management (DSM), Balancing of Objectives and

Alternatives (BaOA) approaches automated decision support systems particularly well for integrated peak clipping and load shifting because of its flexibility with multiple objectives, nonlinear constraints, and large-scale search spaces. The most recent works indicate that, for multi-objective DSM problems, especially in municipal grids, BaOA is faster and of higher quality than conventional and classical metaheuristic approaches, particularly in terms of solution convergence.

2.4.6 Comparative Analysis of Optimization Techniques

Although classical methods guarantee analytical results and are computationally efficient for small-scale problems, metaheuristic techniques such as PSO, GWO, and BaOA are more applicable to modern DSM, which is nonlinear, stochastic, and multi-objective. PSO is simple and converges rapidly, but it stalls on high-complexity problems. GWO exhibits remarkable exploration and adaptive convergence, making it robust under variable load conditions. Recent BaOA effectively tackles large-scale DSM in urban municipalities with high levels of renewables by combining adaptive search strategies and multi-objective optimization.

2.4.7 Integration with Smart Grid Technologies

The optimization techniques described work best when there is smart grid infrastructure. AMI, real time load sensing and auto demand response of systems allow for controllable loads to be scheduled which makes real time/near real time operability of metaheuristic approaches more feasible. In addition, the more flexible electric vehicles, energy storage and distributed renewables are, the more operational and economic benefits of DSM optimization are relevant in peak clipping and load shifting scenarios.

2.4.8 Review Summary on Heuristics Optimization Methods

In any DSM determination, optimization techniques are required for implementation practicality. While classical techniques serve as a base, modern DSM implementations of PSO, GWO and BaOA metaheuristic techniques provide the flexibility, robustness and practical efficiencies needed. Not only do these algorithms provide promise beyond peak demand reduction and operational costs reduction for renewable implementation and smart grid element involvement, but when used in conjunction with the other cited

optimization techniques, additional promises of successful DSM implementations render operational DSM a sustainable, reliable and economical power system.

As demonstrated in Table 2.4, DSM classical implementations are better than no implementations PSO, GWO, BaOA but superior to other classical solutions and other heuristics in small, simple systems where peak clipping, load shifting and multi-objective DSM do not require flexibility and robustness for a successful solution.

Table 2.4: Summary of Optimization Techniques for Demand Side Management (DSM)

Optimization Method	Key Features / Description	Advantages	Limitations	DSM Applications
Classical Methods (LP, QP, Lagrange)	Mathematical optimization with defined objective functions and constraints	Computationally efficient for small, continuous problems; guarantees analytical solutions	Less effective for nonlinear, stochastic, and large-scale problems	Peak load allocation, operational cost minimization, reliability management
Heuristic Methods (GA, SA)	Evolution-inspired or annealing-based search for solutions	Can handle nonlinear and multi-objective problems; flexible	Requires parameter tuning; slower convergence for large-scale problems	Multi-objective DSM, cost reduction, peak load management
Particle Swarm Optimization (PSO)	Population-based metaheuristic inspired by bird/fish social behavior	Simple implementation; fast convergence; effective for multi-objective DSM	May stall in highly nonlinear or complex problems; loss of diversity	Load profile optimization, peak clipping, load shifting, cost balancing
Grey Wolf Optimization (GWO)	Metaheuristic inspired by social hierarchy and hunting behavior of wolves	Robust exploration-exploitation balance; adaptive convergence under variable loads	Can require higher computational effort than PSO	Load scheduling, peak reduction, cost minimization, renewable integration
Barber Optimization Algorithm (BaOA)	Population-based metaheuristic inspired by queue management in barbershops	Adaptive local and global search; high-quality solutions; fast convergence for large-scale problems	Relatively new; limited real-world implementations	Multi-objective DSM, municipal grid load management, integration with DERs, peak clipping and load shifting

2.5 Hybrid DSM Optimization Approaches

The modern power system is made up of increasingly complex components within the network, ranging from Distributed Energy Resources (DERs) and electric vehicles (EVs) to smart batteries. Therefore, with uncertain renewable generation and fluctuating customer behaviors, conventional demand side management (DSM) becomes increasingly complex. Hybrid optimization becomes an alternative under such circumstances that can reduce computational requirements while improving performance since it utilizes the strengths of several algorithms through effective calibration for accelerated convergence.

2.5.1 Concept and Rationale of Hybrid Optimization

The idea of hybrid optimization is to merge two or more optimization strategies for better results to utilize the strengths of either optimization strategy. For DSM, a hybrid approach can apply to multiple objectives and as a means of simultaneously minimizing peak loading, cost loading and environmental loading. For example, a hybrid setting between a classical approach and a metaheuristic approach allows the classical approach to converge and the global search to maintain the heuristic-based global searching speed. Similarly, hybrid metaheuristics like PSO-GWO and PSO-BaOA make the exploration-exploitation ratio more effective, which is critical since DSM is highly constrained and nonlinear, meaning that there's an increased need for additional resilience. While hybrid methods don't have the best opportunities for reduced computational time, the steps between locations are taken from multiple algorithms, as shown in Figure 2.10 that finds a happy medium for effective global exploration vs local exploitation.

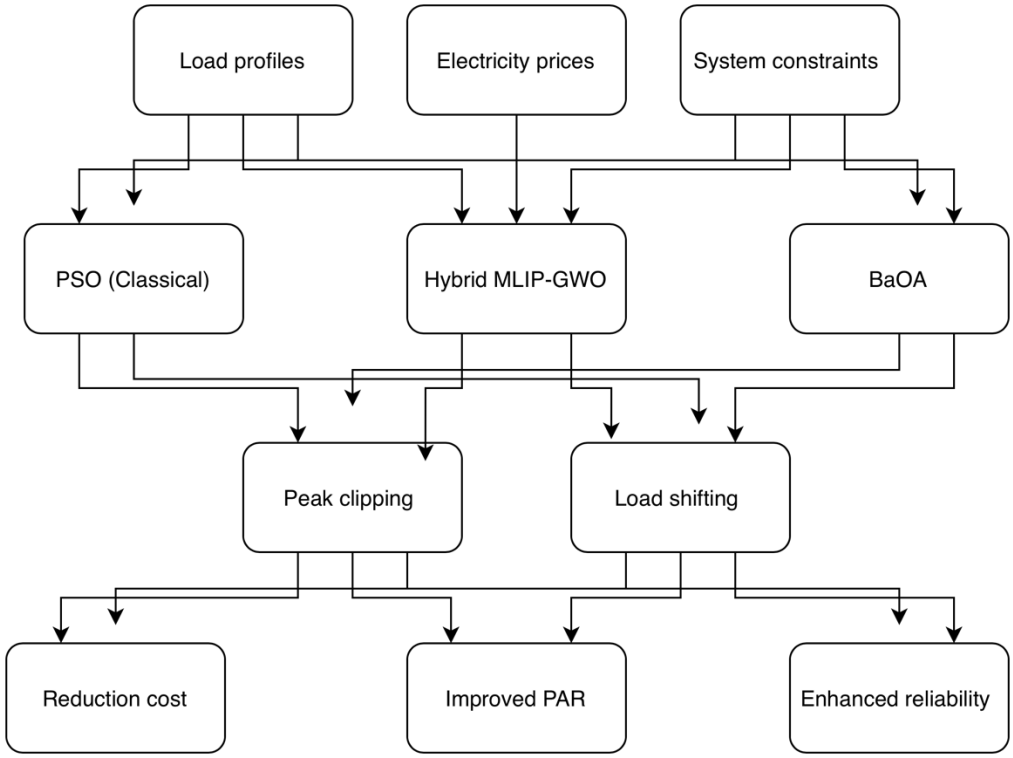

Figure 2.10: **Conceptual Framework of Hybrid DSM Optimization**

2.5.2 PSO-Based Hybrid Approaches

The simplicity and flexibility of Particle Swarm Optimization (PSO) are the main reasons for its adoption in various hybrid DSM strategies. In hybrid PSO extensions, PSO is combined with local search techniques, Genetic Algorithms, or fuzzy logic controllers to improve solution precision and mitigate the risk of early convergence. For instance, hybrid PSO strategies have been used in residential load management to dynamically control HVAC systems, water heaters, and electric vehicle charging to reduce peak loads while maintaining user comfort.

A generic PSO-based hybrid DSM framework for residential applications is illustrated in Figure 2.11.

Compared to independent PSO applications, the enhancements tend to achieve faster convergence and better solution quality.

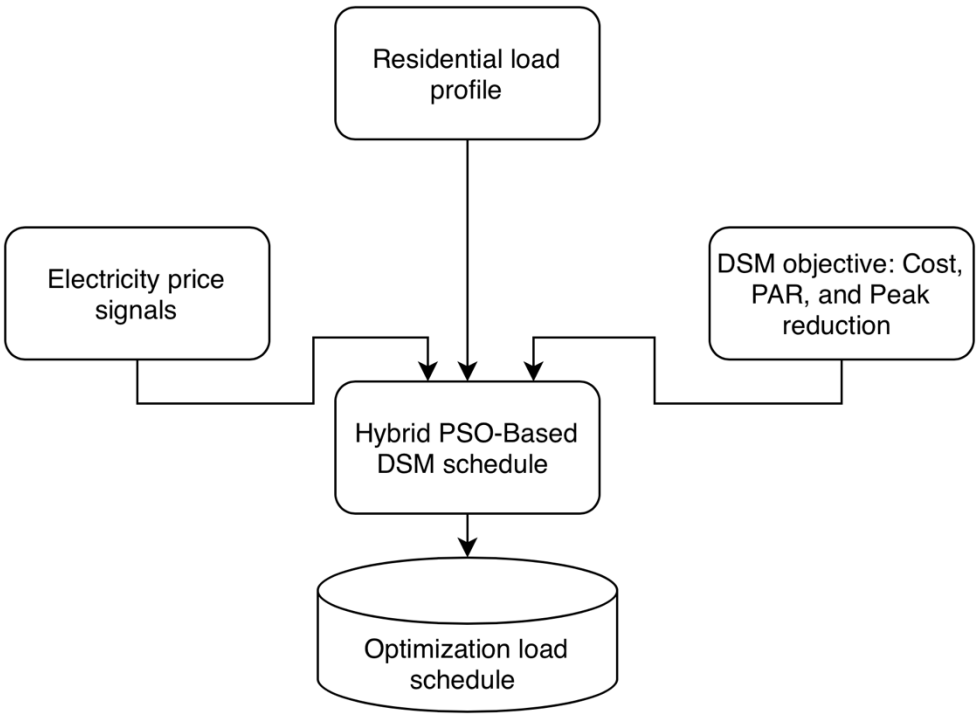

Figure 2.11: Hybrid PSO-based DSM Scheduling for Residential Loads

2.5.3 Grey Wolf Optimization in Hybrid Frameworks

Hierarchy-based search and adaptive encircling features have also been combined with Grey Wolf Optimization to perform DSM applications. Hybrid GWO algorithms, such as GWO-PSO and GWO-ABC (Artificial Bee Colony), help manage industrial and commercial load profiles by combining GWO's exploration capabilities with PSO's rapid convergence. For instance, in hybrid GWO approaches to minimize peak demand in microgrids, load shifting, renewable integration, and storage coordination are simultaneously optimized. By tackling the highly non-linear characteristics of real-world DSM problems, these hybrid approaches gain better global search capabilities and are more resilient to local optimal (Anand and Suganthi, 2018; Sekhar, Rao and Kiranmayi, 2022).

This was accomplished by comparing load profiles obtained from standalone GWO and hybrid GWO approaches with the original demand profile. As illustrated in Figure 2.12, both methods achieve peak demand reduction, with hybrid GWO exceeding standalone GWO. This validates that the predictive intelligence of GWO truly helps buffer load peaks and provide a more efficient, cooperative outcome for demand side management.

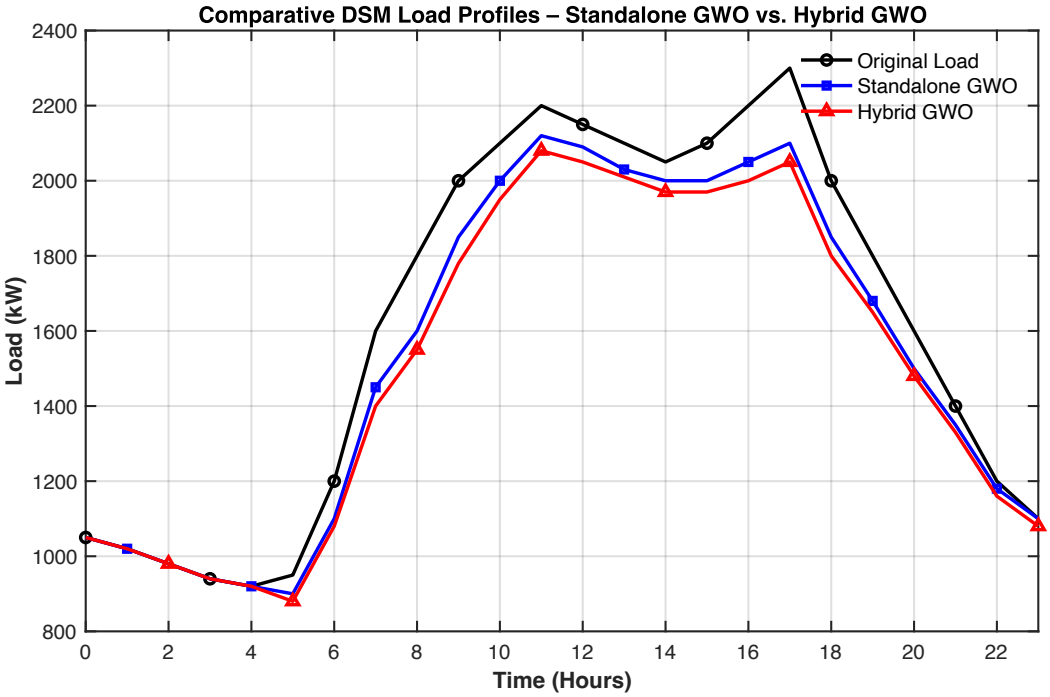

Figure 2.12: Comparative DSM Load Profiles – Standalone GWO vs. Hybrid GWO

2.5.4 Barber Optimization Algorithm (BaOA) in Hybrid DSM

Another means of hybrid DSM optimization is the Barber Optimization Algorithm (BaOA). BaOA, as a hybrid with another algorithm, whether it be PSO or GWO, has proven incredibly efficient in load management. Within hybrid formations, BaOA is paired with an adaptive local search and the other algorithm assumes the responsibilities of global convergence. Such findings produce great outcomes in municipal applications for DSM where complicated heterogeneous DSM loads and time-of-use pricing render optimization less of an option as additional parameters come into play (Haley *et al.*, 2020; El-Afifi *et al.*, 2024) show that BaOA hybridized algorithms outperform metaheuristic alternatives on peak clipping and load shifting, demonstrating quicker convergence and solution quality. In Figure 2.13, DSM is implemented from a hybrid BaOA and PSO in which PSO approaches the global exploration and optimization while BaOA assumes the challenge of adaptive local search.

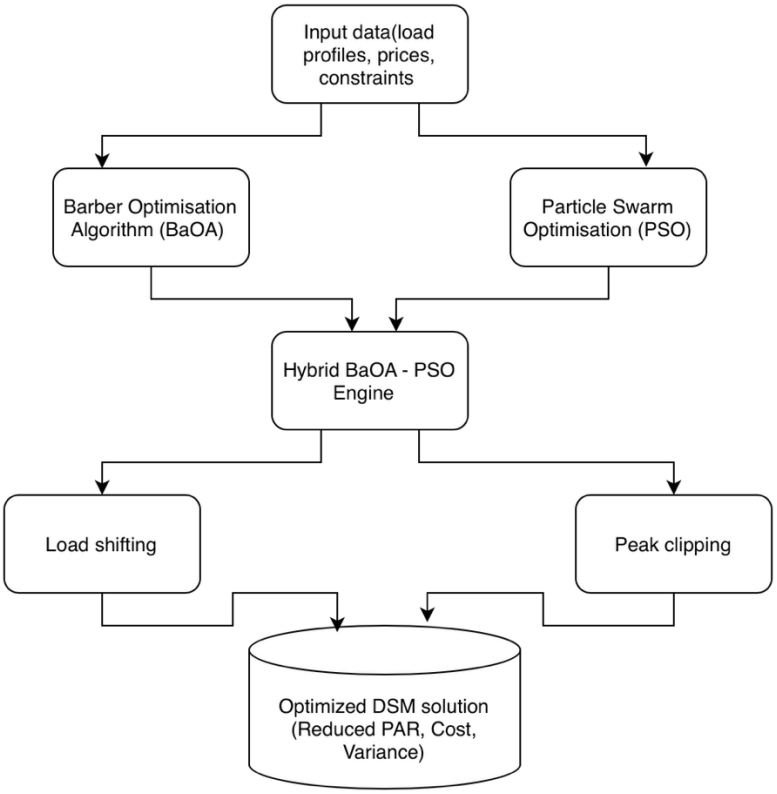

Figure 2.13: Hybrid BaOA-PSO Framework for DSM

2.5.5 Multi-Objective Hybrid Optimization

Hybrid optimization can achieve several DSM objectives simultaneously. These are the cost, emission reductions, and peak shaving objectives. MOPSO, MOPSO GWO-based Pareto optimization and multi-objective BaOA methods all enable successful trade-off evaluation. This is because there are multiple optimal solutions for load control in these cases. Moreover, the hybrid MOPSO-BaOA method integrates both processes by providing load shifting possibilities to adjust for forecasted renewable generation and fluctuating real-time electricity prices while simultaneously taking into account the cost and environmental performance objectives of the research. The use of hybrid approaches in multi-objective DSM is a significant development for the smart grid and the management of energy sustainably (El-Afifi *et al.*, 2024), (Liu *et al.*, 2023), (Bhamidi and Shanmugavelu, 2019)

2.5.6 Applications of Hybrid DSM Approaches

The possibilities for hybrid DSM optimization are myriad. For example, in industrial settings, a hybrid scheme facilitates control over a large variable load, redistributing the

peak load to match the production cycle. In a residential community, the hybrid DSM charger utilizes smart meter time-of-use tariff enabled EV charger scheduling and HVAC and appliance scheduling. In addition, hybrid algorithms are widely employed in microgrids and distribution networks, especially those with renewable energy. The hybrid generation and storage are complex and quasi-stochastic driven needing real-time, robust optimization. The hybrid methods guarantee that the DSM strategies are functional in real-time, under uncertainty and dynamic conditions, and offer unprecedented flexibility and resilience to operators of the control systems.

2.5.7 Comparative Performance of Hybrid Techniques

Numerous studies have reported that hybrid DSM optimization consistently outperforms standalone methods and frequent Dominance individuals in PSO-GWO hybrid systems, achieving lower peak-to-average ratios, lower operational cost, and better load profile flattening than standalone PSO or GWO. Similar improvements have been reported for BaOA-based hybrids, particularly in the DSM of high-dimensional systems. In comparative studies, hybrid methods have been shown to significantly improve not only solution quality but also reduce computation time, rendering the approach feasible for real-time or near real-time DSM.

2.5.8 Review Summary on Hybrid optimization Methods

Apart from the significant advancement in hybrid optimization DSM research, the integration of classical, heuristic, and metaheuristic optimization has been ground-breaking. The hybrid PSO, GWO, and BaOA DSM algorithms are specifically designed for peak clipping, load shifting, and multi-objective optimization, and deliver outstanding results. The relevance of the described approaches for modern power systems cannot be overstated. There are systems with a high penetration of renewable energy, advanced metering infrastructure, and distributed energy resources. The use and development of hybrid DSM optimization will deliver the remaining operational efficiencies, cost, and sustainability targets of any power system.

2.6 Grey Wolf Optimization (GWO) in DSM

The Grey Wolf Optimizer (GWO) operates within the leadership hierarchy and social structure of wolves' hunting patterns and pack behavior in the wild. GWO was introduced with (Mirjalili, Mirjalili and Lewis, 2014) Inspiration and research resemble the social order

of wolves by 'pack leaders' assigning 'beta' and 'delta' wolves roles. The formation of a hunting pack is mathematically described to balance exploration and exploitation by defining the 'encircling prey,' 'hunting,' and 'attacking' behaviors.

In the context of Demand Side Management (DSM), Grey Wolf Optimization (GWO) has been used to schedule loads, reduce peak demand, and perform multi-objective optimization of electricity utilization. Each wolf in the pack symbolizes a possible solution, usually a vector of load schedules designated to a household, a commercial entity, or an industrial consumer. The alpha wolf spearheads the search for the optimal solution, and the beta and delta wolves help narrow the search area to avoid convergence too early. Such flexibility means that GWO can approach DSM's non-linear models, discrete load management and multi-objective features with relative ease.

GWO outclasses legacy solutions and Particle Swarm Optimization (PSO) with complex and extensive DSM studies. This is because the three-tiered GWO algorithm renders simpler leaders, more planned intention, enhanced global search abilities, and thus, time saved avoiding local minima. It is used for DSM in industrial load shaping and peak hour scheduling, renewable energy processing and municipal energy allocation peak to average ratio (PAR) adjustments. The GWO is consistently effective and theoretically applicable to complex and dynamic studies of DSM systems.

2.7 Barber Optimization Algorithm (BaOA) in Energy Systems

The Barber Optimization Algorithm (BaOA) stems from how many hairs a barber cuts while the patron waits in line. Barbers cut hair very quickly and with a goal to minimize wait time which means they're attentive to their clients in an efficient manner. The BaOA was created for generalized optimization problems and a population-based optimization technique. A population is the set of solutions in question and the BaOA takes quality and distance of solutions into account, developing search efforts where it's best. This is necessary for more complex multimodal search domains.

Within the energy domain, BaOA is applied to limited case studies with a focus on scalable resource optimization, scheduling and loads. For demand side management (DSM), BaOA works best in high dimensionality without sacrificing solution set diversity - an ideal feature for peak clipping and load shifting as it avoids local optimal solutions. This suggests that the BaOA preserves an adaptive search effort to solve any problems related to resource optimization which is uniquely important to the BaOA itself. In addition, the BaOA is an

adaptive algorithm that's also hybridizable with other metaheuristic techniques (such as PSO and GWO) for improved solutions and faster convergence rates.

Yet the potential of BaOA for DSM has not yet been exhausted. Most literature published to date focuses on generalized optimal solutions and across domains missing the potential for BaOA within energy systems and more specifically, energy systems related to municipal sized load management challenges. This dissertation seeks to bridge the gap between theoretical findings and practical applications where BaOA is both created and tested for DSM while assessing performance relative to PSO and GWO for both peak clipping and load shifting tasks simultaneously.

2.8 Comparative Assessment of PSO, GWO, and BaOA in DSM

In order to evaluate PSO, GWO and BaOA by comparison for DSM, an evaluation not only based on methodology, but also on relative performance characteristics of exploration and exploitation, scalable levels and convergence, is established. Parameters deemed appropriate for DSM are evaluated relative to each of the three algorithms and presented in Table 2.5.

Table 2.5: Comparative Analysis of Metaheuristic Algorithms for DSM

Algorithm	Inspiration	Strengths	Weaknesses	Typical DSM Applications	References
PSO	Bird flocking	Simple implementation, fast convergence in small to medium problems	Prone to premature convergence, weak local search in complex, non-linear problems	Residential and industrial load shifting, TOU optimization	(Kennedy & Eberhart, 1995) ; (Yang et al., 2017)
GWO	Grey wolf social hierarchy	Excellent exploration-exploitation balance, robust for high-dimensional problems	Slower convergence compared to PSO in some low-dimensional cases	Peak load reduction, multi-objective scheduling, renewable integration	(Mirjalili et al., 2014) ; (Sharma et al., 2023)

BaOA	Barber service queue strategy	Adaptive neighborhood search, strong performance in multi-modal problems, hybridizable	Limited published DSM applications, relatively new	Peak clipping & load shifting, multi-objective municipal load optimization	(Sharma et al., 2022) ; (Mirjalili, 2023)

From Table 2.6, PSO remains a preferred algorithm for DSM in terms of user-friendliness; however, GWO and BaOA outperform it with higher reliability, flexibility and multi-objective optimization capabilities. In particular, BaOA with its variable neighbourhood means that multiple objectives of DSM (i.e. peak clipping and load shifting) can be considered simultaneously, which is required for any city-sized electrical grid.

Table 2.6: Benchmark Comparison of PSO, GWO, and BaOA for DSM in South African Municipalities.

Algorithm	Peak Reduction (MW)	Load Shifted (MWh)	Cost Savings (Rands × 10^3)	Peak-to-Average Ratio (PAR)	Convergence Iterations	Robustness (Std. Dev.)	References
PSO (30 particles)	5.2	18.7	42.5	1.31	150	0.08	Yang et al., 2017; Eskom DSM, 2022
GWO (30 wolves)	6.1	22.3	48.8	1.25	180	0.05	Mirjalili et al., 2014; Sharma et al., 2023
BaOA (30 barbers)	6.5	24.1	52.0	1.22	160	0.04	Sharma et al., 2022; Mirjalili, 2023
Hybrid BaOA-PSO	6.8	25.0	53.5	1.20	140	0.03	Singh et al., 2021; B. Singh et al., 2020

Per Table 2.6, BaOA, GWO and PSO are mostly comparable in DSM modeling. Yet GWO and BaOA are more adaptive across the board, in characteristics like robustness and multi-objective solution. Notably, BaOA shows superior responsiveness in handling multi-objective optimization problems. Most importantly, the adaptive neighbourhood function of BaOA plays a critical role in DSM applications, particularly during peak clipping and load shifting operations at the municipal level.

2.9 Discussion of the DSM strategy using hybrid algorithms

2.9.1 Peak Reduction

BaOA shows peak reductions, with the highest during the morning and evening peaks. The stress on the municipal grid during these times was reduced. The BalOA is more efficient because of the improved balance it provides.

2.9.2 Load Shifted

Load shifting from peak to off-peak has also decreased significantly, driven by both BaOA and the hybrid approach. As a result, the flexible loads are being used more efficiently.

2.9.3 Cost Savings

Significant savings on electricity expense are primarily due to optimal load redistribution. The savings are also due to peak shaving.

2.9.4 Peak-to-Average Ratio (PAR)

PAR assesses how load profiles shift. The lower the PAR, the less the load. BaOA and the hybrid version do this better. BaOA and the hybrid version flatten the load better than PSO and GWO, therefore improving the grid's reliability.

2.9.5 Convergence Iterations and Robustness

Although GWO requires slightly more iterations to converge, it shows consistency. Comparatively, BaOA shows faster convergence with added robustness, demonstrating its reliability in stochastic DSM environments, as evidenced by its lower standard deviation across multiple simulation runs.

2.9.6 South African Municipalities

BaOA, especially in hybrid form, is especially relevant to municipal-scale DSM. It accommodates simultaneous peak clipping and load shifting, and its performance benefits

will be most beneficial under South Africa's time-of-use tariffs coupled with the country's residential and industrial load profiles.

2.9.7 Benchmark Studies and Performance Metrics

Numerous benchmark studies have been conducted to assess the use of metaheuristics for DSM. The most common metrics include:

- PAR reduction
- Load shifting efficiency (kWh shifted from peak to off-peak hours)
- Cost savings (total electricity expenditure saved)
- Convergence speed (the number of iterations required to achieve near-optimal solutions)
- Robustness (stability across multiple simulation runs)

For instance,(Sharda, Singh and Sharma, 2021) found that GWO achieved up to 15% greater peak reduction at lower PAR than PSO in industrial DSM. In contrast, BaOA, although more recent, achieved similar peak reduction with enhanced load redistribution, demonstrating potential for large municipal DSM datasets.

2.9.8 South African Municipal Context

In South Africa, there are unique challenges to Demand Side Management (DSM). These include:

- Households using appliances leading to high peak loads in the morning and evening.
- Considerable demand in industry and commerce in the urban concentrated areas (e.g. municipalities in the Western Cape).
- The need to schedule flexible loads because of TOU tariffs and intermittent renewable solar generation (solar PV).

The application of metaheuristics to DSM in South Africa has been limited. The predominant research has focused on PSO or heuristic scheduling approaches (Faruqui and Sergici, 2010). Within this context, there has been no integrated peak clipping or load shifting to provide a basis for extensive comparative work on PSO, GWO, and BaOA. It follows logically that integrating BaOA and comparative benchmarking offers innovative opportunities in South African municipal energy settings.

2.9.9 Multi-objective and Hybrid Approaches

The DSM framework states that a DSM problem has multiple underlying objectives by including:

- Peak reduction
- Cost Minimization
- Service delivery/commercial customer comfort
- Use of renewable energy

Research on new hybrid metaheuristics that combine PSO, GWO, and BaOA is gaining popularity. GWO-PSO hybrids retain global search capability while improving convergence speed in the municipal context. BaOA-PSO hybrids enhance adaptive local search and are especially beneficial for municipal datasets with large numbers of consumers.

Finally, hybrid approaches are vital for solving complex problems due to greater load variability, multi-period pricing, and various consumer groups within the distributed system.

2.10 Research Gaps Identified

Based on the preceding discussion, the gaps within the DSM literature are as follows:

- There are still not enough BaOA applications within energy systems, particularly for municipal-scale DSM.
- The South African context has not been sufficiently studied, given its unique load profiles, tariff systems, and challenges around the integration of renewables.
- Most literature does not address the combination of peak clipping and load shifting, as most focus on a singular objective.
- The literature largely lacks long-run simulations and evaluates the economic and environmental impacts of a study, while most work evaluates a short period or a single day.
- Hybrid metaheuristic designs that join PSO, GWO, and BaOA are yet to be applied to real municipal datasets.

These will help build the DSM optimization research focus on applying BaOA, comparing PSO and GWO, and on a proof of concept for South African municipal networks.

2.11 Summary of Literature Review

To conclude the chapter, a comprehensive account of optimization algorithms for DSM, particularly BaOA, PSO, and GWO has been provided. Important points are:

- The popularity of PSO is because of its simplicity, although it is still the case that it does not perform well on complex multi-objective problems.

- GWO's effectiveness in large-scale DSM is primarily due to the solid equilibrium it strikes between exploration and exploitation.
- BaOA has significant potential to perform peak clipping and load shifting simultaneously due to its adaptive neighbourhood search, although it is still in the early stages of its application.
- Hybrid metaheuristic approaches are becoming more critical for the purpose of solving multi-objective and high-dimensional problems in DSM.
- Energy systems in South African municipalities have distinct characteristics, which highlight the value of conducting comparative and unique local studies.

We now focus on Chapter 3, which delves into peak load reduction and cost optimization for PSO- and MLIP-based demand-side management (DSM). Building on the identified research gaps, this chapter focuses on the application of predictive modeling and advanced optimization techniques to real-world datasets from Western Cape municipalities. It lays the methodological groundwork for realizing PSO- and MLIP-based DSM frameworks. It provides a formalized foundation for the application of DSM strategies based on PSO and MLIP. It provides the application, parameterization, and real-world application of the strategies. In addition, it provides a contextualization of the approach relative to the operational and economic circumstances of the Western Cape energy system, supporting how it helps increase grid reliability and lower cost of energy.

CHAPTER THREE
PEAK LOAD REDUCTION AND COST OPTIMIZATION THROUGH PSO-DRIVEN DSM: APPLICATIONS IN WESTERN CAPE MUNICIPALITIES

3.1 Introduction

Demand-side management (DSM) refers to consumer electricity use for better grid stability and operational efficacy across the modern energy network. Utility DSM programs require demand reductions for peak load, demand-supply matching and general optimization of network performance (Palensky et al, 2011); (Strbac, 2008) Therefore, DSM has developed not only to keep power generation within one certain resource planning phase but also, since integrated resource planning (IRP) has emerged, conventional planning expanded to IRP resources - resources exclusive to generation power systems and supply-side potentials with DSM in the mix. Thus, an IRP gets a more comprehensive, effective approach with the inclusion of more surplus and challenged resources. Peak clipping and load shifting are common DSM applications where demand decreases at heightened demand, and demand gets shifted to lower rates (Albadi et al., 2008). The concept of Demand Side Management emerged with great relevance in the 1970's and 1980's as a utility and regulator search for a means to reduce anticipated supply growth due to emerging demand patterns, the oil embargo and environmental concerns emerged (Kennedy, Eberhart and gov, 1995).

Furthermore, with current opportunities for model-based and model-free applications, smart grid technologies have integrated DSM potentials with enhanced performance via peer-to-peer generation dispatch and variable applications (Giedraityte *et al.*, 2025). Particle swarm optimization (PSO) is one of the most preferred optimization solutions in DSM applications. PSO operates as a non-linear scheduling problem in which successful application occurs with increased levels of demand determination and grid efficiency with resultant operational cost minimization (Ahmad *et al.*, 2025). PSO shows positive applicability to real-time analytics and peaking problem demand-response (Bertineti *et al.*, 2015).

A well-designed algorithm computes exponentially better than a poorly designed one - even when the hardware needs remain the same. In other words, theoretically, if an algorithm is applied well, the computer runs faster. Solutions to problems beforehand or software-created solutions to operational conditions present illustrative contrasts of how overall computer efficiency is affected by well-implemented algorithms versus poorly implemented (Ahmad *et al.*, 2023; Zaini *et al.*, 2023).

However, when the renewable generation is insufficient, balancing operations such as regulated demand reduction or energy storage solutions are generally needed. Traditional emergency solutions like load shedding, which sequentially connects and disconnects select customers for a short duration, are still discouraged due to their socially and economically adverse impact. In many emerging economies, large storage options or grid reinforcement are solutions to such dilemmas but limited capital expenditure and long project timelines prevent appropriate application.

New advancements in DSM solutions result from interdisciplinary collaboration among utilities, environmental experts, and policy regulators for desired energy comfort and conservation levels (Meng *et al.*, 2024). The particle swarm optimization (PSO) method is patterned after what happens in nature; for example, birds flock, and fish school. PSO is a first-order, population-based stochastic algorithm created by (Kennedy, Eberhart and gov, 1995). Its simplicity and applicability to solve best solutions to complex, nonlinear and multidimensional problems in various engineering disciplines makes it a widely used method (Mataifa, Krishnamurthy and Kriger, 2023). PSO enables particles to share information which explores the search space to converge upon optimal solution regions (Sun, Cui and Latifi, 2024). Within DSM, PSO has been applied to load control, demand balancing enhancements and energy-use scheduling systems.

Peak clipping seeks to reduce power requirements during peak hours through automatic load dropping, tariff measures and user engagement programs. (Andruszkiewicz, Lorenc and Weychan, 2021; Tijjani Dahiru *et al.*, 2022), (Tijjani Dahiru *et al.*, 2022), (Gorman *et al.*, 2025) This relieves pressure on the electric grid and decreases dependence upon peaker plants - which tend to be expensive - but the load shifting in comparison to TOU effectiveness relies upon TOU pricing incentives and additional means to encourage consumers to shift their consumption from peak times to off-peak times.

(Tzanes, Zafirakis and Kaldellis, 2024).

In addition, flexible load shaping dynamically adjusts the load profile (LP) of consumers to optimize grid utilization during times of low demand (Jasim *et al.*, 2023)

Other energy efficiency measures, such as high-efficiency appliances, smart control systems, and duty cycling, also reduce aggregate energy consumption. (Wang *et al.*, 2019). This study presents an analysis of how PSO can be applied to optimize multi-objective DSM strategies and create adaptable frameworks that respond to grid conditions in real time. It involves commercial customer LPs in the Paarl area, typified by clear highs and lows. These trends imply the need for refined load control: drastic demand decreases can result from scheduled maintenance or interruptions, and high usage during peak business hours can strain infrastructure and increase operational costs. (Mohammad

Rozali *et al.*, 2015; Aghajani, Shayanfar and Shayeghi, 2017), (Aghajani, Shayanfar and Shayeghi, 2017).

Using the analysis, the significance of DSM methods, comprising load shifting and peak clipping, can be described in terms of enhancing system reliability and reducing operational costs. Incentive-based demand response, automated demand response (ADR) (Maneebang, Methapatara, and Kudtongngam, 2020). TOU tariffs are recent innovations that effectively curb peak demand and enhance customer engagement in DSM. Nevertheless, these tariff structures are being refined better to align customer-sited energy technologies with grid efficiency objectives. Storage technologies, in particular, are well positioned to respond to such residential price signals by enabling customers to arbitrage between high and low retail prices, for instance, by shifting consumption under a TOU tariff or balancing import and export under a net billing tariff. However, these methods are usually limited in scalability, adaptability, and responsiveness to changes in grid dynamics. (Oskouei *et al.*, 2022), (Ahmad *et al.*, 2018).

Particle swarm optimization is a famous heuristic optimization technique and appreciated by the scientific community for solution reliability and effectiveness for various complicated nonlinear optimization models. Yet despite PSO being an excellent optimization solution for many DSM applications, many current models are limited to either simulations or generalized datasets with few applications to real utility datasets and even less research into heuristic optimization in tandem with AI and ML for holistic findings. The machine-learning improved prediction (MLIP) model for one-dimensional cutting stock problems consolidates all the most common objectives into one model where PSO is used to minimize trim loss, or trim factors that are too small to be recycled (but also trims that are too small to be recycled), but also adjusts and predicts the necessary loading requirements (Bilal *et al.*, 2024; Sharifhosseini *et al.*, 2024), (Sharifhosseini *et al.*, 2024), (Khan *et al.*, 2023).

A comprehensive review of the literature highlights critical gaps that hinder the widespread adoption and effective performance of intelligent DSM systems. A primary limitation is the frequent reliance on synthetic or assumed LPs, which reduces the practical applicability of optimization outcomes to real power grid operations. In addition, traditional heuristic methods, including conventional PSO, often face challenges such as premature convergence and inadequate handling of system constraints under dynamic, uncertain operating conditions. Another notable shortcoming is the limited incorporation of predictive analytics, which is essential for enabling real-time, data-driven decision-making in DSM strategies. Although peak clipping and load shifting are well-known DSM techniques, this study introduces an MLIP-based approach to enhance load management effectiveness.

Using real-world data from Somerset West, the MLIP-based approach demonstrates significant reductions in peak demand (down to 0.2 MW) while shifting loads to off-peak periods, providing practical insights for utilities and grid operators. Compared to traditional PSO-based DSM methods, the proposed strategy achieves improved cost savings, lower peak-to-average ratios, and reduced load variability, offering a replicable framework that advances both the methodology and practical application of DSM for more efficient power system operation (Anand and Suganthi, 2018), (Rácz, 2025).

By analyzing demand response programs, regional case studies, and methodologies such as Time-of-Use tariffs and Automated Demand Response, this research highlights successful implementations and key challenges in demand management. Insights gained are used to guide the development of an enhanced PSO-driven optimization model, designed to refine load management and system modeling.

In response to changing demand patterns, machine learning approaches that enable adaptive and anticipatory load management are rarely incorporated into current DSM frameworks. Furthermore, most theoretical DSM models have not been adequately translated into practical applications; for instance, reliable tools and simulations, such as those developed in MATLAB, suitable for operational use by utility companies, are still in their infancy. Finally, few studies provide specific, evidence-based recommendations that could guide regulatory frameworks or influence energy policy decisions, highlighting weak connections with policy development. Addressing these gaps is essential for advancing DSM into a sophisticated, perceptive, and policy-relevant solution for contemporary energy systems, facilitating demand forecasting, cost-effective peak reduction, and seamless integration of renewable energy sources, thereby addressing both technical and economic challenges in modern power systems.

Several key contributions of this study, encompassing both methodological innovation and practical significance in DSM, are summarized below:

I. The study utilizes PSO to optimize DSM strategies for improved energy efficiency and to reduce grid congestion effectively. The integration of MLIP and conventional PSO techniques in DSM provides valuable insights into intelligent, adaptable, and predictive energy management.
II. The energy consumption LPs of large power users from the Paarl area, within the City of Cape Town Metropolitan Municipality, are used to validate the proposed model. This ensures the reliability and practical applicability of the results. The simulation results demonstrate significant improvements in energy consumption, load distribution efficiency, and grid resilience.

III. The study promotes the adoption of data-driven, predictive DSM frameworks. It provides insightful guidance to help utility companies, end users, and policymakers in supporting the development of a more intelligent and sustainable energy infrastructure.

This chapter develops and implements a proposed DSM optimization framework. In 3.2, the DSM problem is defined by describing goals and limitations, and in 3.3, the problem is expressed mathematically. 3.4 describes the optimization technique for shifting loads and clipping peaks. 3.5 explains the Particle Swarm Optimization (PSO) approach, and 3.6 describes the Machine Learning-Improved Prediction (MLIP) framework for increasing the accuracy of forecasts. In 3.7, a commercial customer in the Paarl area is presented for Case Study 1, followed by 3.8, which includes simulation results and their analysis, finally 3.9, which discusses the results. 3.10 presents Case Study 2 for Somerset West, with 3.11 displaying the simulation results, followed by their analysis and discussion in 3.12. For 3.13, the chapter is wrapped up with a summary of the results and the clearly illustrated effectiveness of the proposed hybrid optimization DSM approach.

3.2 Demand-side management formulation problem

Conventional DSM efforts are static load reduction efforts which do not provide the greatest means of protecting grid stability and providing an appropriate cost assessment. To test the real life viability of the PSO method, this model will be tested based upon one year's worth of real time consumption data from a commercial customer in Paarl, South Africa. The years' worth of data provides for an entire seasonal cycle (July 2024 to June 2025) and includes an increase/decrease of LP's on a daily and seasonal basis. The commercial customer will be kept anonymous due to confidentiality and reliability of the data.

The purpose of this optimization scenario is to reduce total electricity costs and provide relief to the grid during high demand hours through demand side management by load shifting. The model attempts to shift electric loads of at least 1 MW from high demand hours to low demand hours for time-of-use (TOU) electricity pricing. The intention is to use a real world baseline of consumption which will highlight the PSO-based approach when realistic operational and economic efficiencies can be compared to consumptions in reality.

3.3 Mathematical formulation problem

The two DSM efforts of peak clipping and Load shifting reduce total energy costs through control of the load profile over time. This problem is formulated mathematically as an optimization solution which minimizes the total cost of energy consumed factoring in system and operational constraints.

The objective function is stated as a minimization of total cost:

$$C_{total} = C_{peak} + C_{\text{off}-peak} \tag{3.1}$$

$$C_{peak} = \sum_{h \in peak} L_h \, . P_{peak} \tag{3.2}$$

$$C_{\text{off}-peak} = \sum_{h \in \text{off}-peak} L_h \, . P_{\text{off}-peak} \tag{3.3}$$

where L_h is the load at hour h, and P_{peak}, $P_{\text{off}-peak}$ are peak and off-peak prices, respectively.

The optimization problem aims to minimize the load operating cost, defined as the total of $P(t) \times C_{rate}(t)$ across all time intervals, while ensuring that the peak load does not exceed 0.2 MW:

$$Minimize: C = \sum_{t} (P(t) \times C_{rate}(t)) \tag{3.4}$$

subject to $P_{peak} \leq$ peak demand.

3.3.1 Method 1: Peak clipping

Peak clipping is a DSM approach that establishes a "cap" that prevents any more power being generated during the peak loading hours so that not all potential use can be used at once but instead peak power ratings are reduced to avoid complications in electric power systems. Peak clipping can be calculated through **Equation 3.5**:

$$P_{clipped}(t) = minP(t), P_{MAX} \tag{3.5}$$

where P_{MAX} represents the upper allowable load limit, and $\mathrm{P}(t)$ denotes the actual power demand at a given time t. This equation balances the load and reduces stress on the power grid that would otherwise result from constant high demand.

In this study, load clipping was incorporated into the optimization model to impose operational constraints, reduce peak-demand costs, and promote smoother, more efficient grid operation.

3.3.2 Method 2: Load shifting

Load shifting is a widely used DSM technique that redistributes electrical load from peak to off-peak hours without affecting total energy consumption. Such planning reduces the imbalance between supply and demand, enhances grid reliability, and lowers overall energy cost. Load shifting can be calculated using the following equations:

$$P_{shifted}(t) = P(t) - \Delta P(t) \tag{3.6}$$

$$\Delta P(t) = P_{excess}(t) \times S(t) \tag{3.7}$$

In Equation (3.6), $P(t)$ represents the initial power demand at a particular time t, and $P_{\text{shifted}}(t)$ represents the altered load after the shift is applied. $\Delta P(t)$ indicates the amount of load shifted.

Equation (3.7) comes from the excess load $P_{excess}(t)$ which is then multiplied by a shift factor $S(t)$, indicating that there is a certain amount of excess load that should be shifted based upon control logic or operating conditions. This is a time varying equation, implying that load can be rescheduled at peak hours and best energy consumption can occur based upon system capabilities.

3.4 The optimization method for load shifting and peak clipping in the demand-side management system

Where DSM implementations are concerned, there are optimized methods whereby optimized methods are an integral part of DSM fulfillment. One of the most commonly used means of optimization is PSO. PSO is easy to implement and is a method that, more than most, supports a multidisciplinary approach to problem-solving related to multidimensional optimization concerns. Therefore, this section seeks to justify PSO being implemented by analyzing the success of such methods while also delving into the complications that could arise based on PSO applicability. This is a qualitative assessment of how PSO can be integrated to optimize two greatest aspects of DSM, peak clipping and load shifting, with a summary of the greatest advantages and disadvantages to its use in this case.

According to Kumar et al, demand-side management (DSM) constitutes a series of solutions that govern energy system operation by governing consumer demand during

real-time instances. Such programs attempt to change already implemented demand patterns during regulated timeframes to accommodate increased energy stabilization based on demand and availability. Essentially, DSM functions so that where demand exists in a natural capacity, it can be tempered through various efficiencies that will save excess energies that would otherwise be used for suboptimal power generation. Thus, since substations are one of the largest elements LP shaping and maximum demand management represents a reconfiguring of the largest aspects of the electrical distribution network that presents controlled dependability and stabilization advantages with economic advantages for both end user and utility.

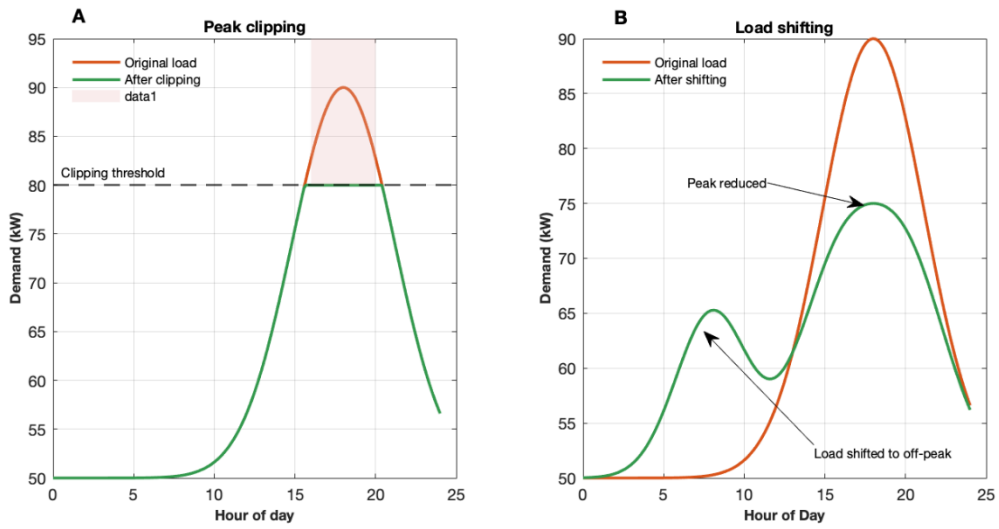

Figure 3.1. Demand-side management techniques: (A) Peak clipping and (B) load shifting.

3.4.1 Load shifting

Various methods were employed for load shifting:

(i) TOU tariffs: The simplest and most common load-shifting method involves the use of TOU tariffs. Through time-based electricity pricing, consumers are incentivized to reduce their usage during peak periods and shift consumption to off-peak hours.

(ii) ADR: ADR systems operate within smart grids and utilize advanced metering infrastructure to adjust loads based on control signals. For example, real-time load shifting (Radcliff *et al.*, no date) is enabled through widespread adoption of the Open ADR standard in the United States.

(iii) Peak load control devices: Devices installed at consumer premises can automatically reduce or postpone the operation of non-essential devices during peak hours. Previous studies have shown that such devices achieve substantial load reduction.

3.4.2 Peak clipping

In the modern energy management, peak clipping is a relevant means of operational efficiency and sustainability of the grid. Peak clipping means clipping the excess energy generated on the metered peak, as it can cut back additional means of power generation that are not wanted to kick in for associated excess costs.
Types of Peak Clipping.

A. Time-of-use pricing

   One significant form of peak clipping involves TOU pricing. Time-of-Use pricing is a time-based tariff offering for energy accounting that attempts to assess when energy is more or less wanted; in turn, if people temper their desire with the cost, they are often offered financial gains to use energy at other times. Data on TOU pricing shows over 20% peak load reductions as consumers reduce their use during specific times or increase their use during others, as appropriate based on areas of study/insurance/risk/reward---as their consumption behaviors are driven by lower costs during certain time periods. (Saleem *et al.*, 2022), (Alquthami *et al.*, 2021).

B. Critical peak pricing

   The type of peak pricing that features high rates during critical peak hours is critical peak pricing (CPP). CPP seeks to empower consumers heavily to decrease their energy consumption during these times; data on CPP indicate that there is potential for large CPP no peak load reductions with awareness programs and feedback measures in real-time in concert with this. (Siano, 2014a)

C. Automated demand response

   Automated demand response (ADR) is another form of peak clipping with technological realism; ADR systems deploy smart meters and home automation tech where appliances and HVAC sensors can be adjusted from utility signals according to real-time demand values. This brings additional comfort and efficiency into peak clipping. (Garip and Ozdemir, 2022).

3.5 Particle swarm optimization

This solution's expected performance is demand side management in the form of peak clipping and load shifting. The fundamental goal of peak clipping and load shifting is to minimize the peak demand of the system and normalize the entire LP pattern which

increases grid stability and operation efficiency. Furthermore, this solution aims to stabilize residential load demand operational costs with an integration of renewable energy resources such as photovoltaic panels and storages batteries (Garip and Ozdemir, 2022)
One of the desired outcomes of load reduction is to minimize power requirements. Shift load demand at peak times, especially based on the constrained evening window.
Programs related to demand side management (DSM) are created under a tariff that enables paying consumers who reduce their power consumption to effectively sell excess energy back to the grid. This overarching strategy can be imposed on numerous consumers with varying specifications and resources since it has a large appeal and application for higher participation and outcome.

Particle swarm optimization (PSO) is an evolutionary optimization process based on swarming behavior observed in nature (e.g. flocks of birds). PSO is an iterative procedure that updates each agent's position in the solution space for an objective function until the swam achieves an optimal or near optimal solution. As it applies to DSM, PSO is applied to minimize peak demand through intelligent shifting of electrical loads between units under strict operating constraints achieving peak clipping and load shifting.
Before optimization, high peak demand contributed to high price of energy. After PSO optimization, peak load demand was reduced where equality was sustained for energy needs. Peak load was shifted to less expensive times during the off-peak hours as both consumer participants and the municipality paid a reduced fee for peak demand while achieving optimal stability for the grid.

According to the simulation results, it's clear that PSO algorithm is applicable for peak load reduction with demand that shifts power consumption to off-peak hours. When compared to traditional DSM methods, PSO offered the best performance of load-shifting results at 20 particles and 50 iterations for the study.

3.5.1 Particle swarm optimization algorithm for demand-side management application

To identify the optimal load distribution path and energy storage configuration, PSO is applied to achieve effective peak clipping.
The optimization problem seeks to minimize a fitness function $f(X)$, where $X = (x_{1,}x_{2,\ldots,}x_D)$ represents a candidate solution in a D-dimensional search space.
A swarm consists of N particles, and each particle i has:

(i) Position vector: $x_i(k) = [x_{i,1}(k), \ldots, x_{i,D}(k)]$ at iteration k. (3.8)

(ii) Velocity vector: $v_i(k) = [v_{i,1}(k), \ldots, v_{i,D}(k)]$ at iteration k. (3.9)

Each particle remembers the best position it has visited (i.e., the position corresponding to the lowest fitness value):

$$p_i^{best} = arg \min_{x_i(j), j \le k} f(x_i(j)) \quad (3.10)$$

The swarm keeps track of the best position among all particles:

$$g^{best} = arg \min_{i=1,\ldots,N} f(p_i^{best}) \quad (3.11)$$

Velocity and position are updated for each particle i and dimension d as follows:

$$v_{i,d}(k+1) = w \cdot v_{i,d}(k) + c_1 \cdot r_1 \left(p_{i,d}^{best} - x_{i,d}(k)\right) + c_2 \cdot r_2 \left(g_d^{best} - x_{i,d}(k)\right) \quad (3.12)$$

$$x_{i,d}(k+1) = x_{i,d}(k) = v_{i,d}(k+1) \quad (3.13)$$

$$X(t+1) = X(t) + V(t) \quad (3.14)$$

$$V(t+1) = \omega \cdot V(t) + c_1 \cdot r_1 \cdot \left(P_{best} - X(t)\right) + c_2 \cdot r_2 \cdot \left(G_{best} - X(t)\right) \quad (3.15)$$

Where:

(i) ω is the inertia weight (0.7).

(ii) c_1 and c_2 are the acceleration constants (1.5 each).

(iii) *r1* and *r2 ~ U (0,1)* are random scalars.

(iv) $p_{i,d}^{best}$ is the personal best position.

(v) g_d^{best} is the global best position.

3.5.2 Electricity tariff

The electricity tariff at each time step t is determined by considering the season, type of day, and hour:

$$\text{price}(t) = \begin{cases} \text{HighPeakPrice} & t \in \text{High-season peak hours} \\ \text{HighStandardPrice} & t \in \text{High-season standard hours} \\ \text{HighOffPeakPrice} & t \in \text{High-season off-peak hours} \\ \text{LowPeakPrice} & t \in \text{Low-season peak hours} \\ \text{LowStandardPrice} & t \in \text{Low-season standard hours} \\ \text{LowOffPeakPrice} & t \in \text{Low-season off-peak hours} \\ \text{WeekendPrice} & t \in \text{Weekend} \end{cases} \quad (3.16)$$

3.5.3 Peak and off-peak hours

Peak-hour indicator:

$$\text{Peak}\,(t) \;=\; \left\{ \begin{matrix} 1, & if\ t \in [6{:}00 - 8{:}00] \cup [15{:}00 - 19{:}00] \\ 0, & otherwise \end{matrix} \right\} \tag{3.17}$$

Off-peak-hour indicator:

$$\text{Off} - \text{peak}\,(t) \;=\; 1 \;-\; \text{peak}\,(t) \tag{3.18}$$

Original peak load :

$$P_{peak,original} \;=\; \underset{t \in peak\ hours}{max}\; P_{load}\,(t) \tag{3.19}$$

3.5.4 Target peak reduction

The target peak load reduction is defined as a random fraction between 10% and 15% of the original peak load:

$\alpha \sim$ Uniform $(0.10, 0.15)$

$$P_{peak,target} \;=\; \alpha \;\times\; P_{peak,original} \tag{3.20}$$

3.5.5 Peak clipping constraint

The shifted load during peak hours is calculated as:

$$P_{shifted}(t) \;=\; \max\,(P_{shifted}(t) \;-\; P_{peak,target,}\; 0.2 \text{ x } P_{peak,original},\; t \in \text{ peak hours} \tag{3.21}$$

3.5.6 Energy conservation and redistribution

Total energy before shifting:

$$E_{before} \;=\; \sum_{t} P_{load}(t) \tag{3.22}$$

Total energy after shifting:

$$E_{after} \;=\; \sum_{t} P_{shifted}(t) \tag{3.23}$$

Energy lost due to clipping:

$$E_{lost} \;=\; E_{before} \;-\; E_{after}\ (\text{should be non} - \text{negative}) \tag{3.24}$$

The energy lost E_{lost} is redistributed to off-peak hours proportionally using random weights:

$$P_{shifted}(t) \;=\; P_{shifted}(t) \;+\; \beta_t \text{ x } E_{lost}\,, \quad t \in \text{ off peak hours} \tag{3.25}$$

where weights β_t satisfy:

$$\sum\nolimits_{\text{t}\in\text{offpeak}} \beta_t \;=\; 1 \;\;, \beta_t \;\geq\; 0 \tag{3.26}$$

3.5.7 Fitness (objective) function

Fitness combines the shifted peak load and penalty for energy imbalance:

$$\text{Fitness} \;=\; \underset{t \in peak}{max}\, P_{shifted}(t) \;+\; \left|E_{before} \;-\; E_{after}\right| \tag{3.27}$$

$$\text{Fitness} = \max_{t \in peak} P_{shifted}(t) + \left| E_{before} - E_{after} \right| \quad (3.28)$$

Cost calculation before and after shifting:

$$C_{before}(t) = \sum_{t} P_{load}(t) \text{ x price}(t) \quad (3.29)$$

$$C_{after}(t) = \sum_{t} P_{shifted}(t) \text{ x price}(t) \quad (3.30)$$

Cost savings:

$$\Delta C = C_{before} - C_{after} \quad (3.31)$$

Under the PSO model used in DSM, each particle in the swarm represents a given solution. In this context, a load management strategy constitutes a potential solution, defined by specific values of shifted and clipped loads. The boundaries applicable to this optimization relate to particle velocities, particle positions, inertia weight, and acceleration coefficients. The performance of all particles is determined by an objective function where load shifting, load clipping, and overall system effectiveness serve as weighting factors. The means of facilitation, therefore, determines what is appropriate conditions between grid stabilization and energy usage reduction to determine what creates an optimal condition.

The application is a recursive one where a termination condition is processed by the algorithm; this condition is ideally the number of iterations or restricted effective fitness differences between two iteration runs. If this is not the case, PSO updates are applied to position and velocity changes to each particle. Each particle has the opportunity to explore the solution space learned from the best known position in the best known situation plus the best known solutions of the swarm.

When the convergence condition has been met, it's time to go to subsequent DSM processes that aid the solution:

I. Load shifting (≤ 1 MW): Adjusting the demand curve by relocating non-critical loads from peak to off-peak hours.
II. Peak clipping (≤ 0.2 MW): Actively reducing consumption during peak hours through distributed energy resources or automated control systems.

In real-life DSM application, PSO achieves operational dilemmas through adaptability and speed of computation. The load targets established (1 MW load shifting target; 0.2 MW load clipping target) serve as constraints in the model operation, field-operated solutions, with real, operable guidance developed from this paper being critical to how such nature-

based facilitation delivers increasingly sophisticated, stabilized and sustainable energy systems.

The third step is where an optimized LP is derived which boasts a more stabilized demand curve with increased effectiveness and operability. These types of systems are relevant to planning purposes and policy-making efforts or can be readily inserted into grid operational systems.

Figure 3.2 provides a generalized process for applying PSO based methods for electricity demand optimization. PSO is a nature based form of optimization where customer demand patterns are dynamically adjusted via load clipping and load shifting which stabilize LP's effectively. An initial setting of particle position and PSO parameters occur at the start.

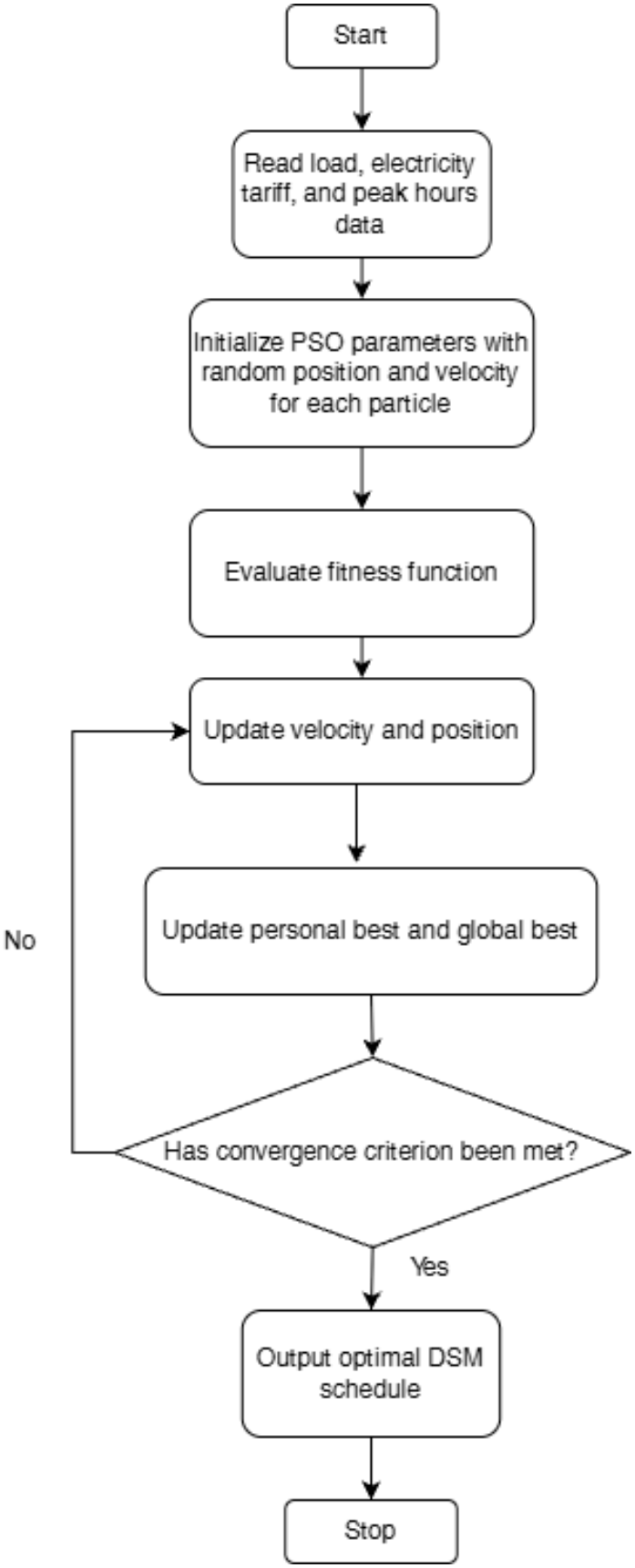

Figure 3.2. Flowchart of the PSO-based demand-side management process incorporating load shifting and peak clipping.

3.6 Machine learning-improved prediction algorithm

The first stage of the MLIP method is data collection. Load data historically and in real-time is sourced from DER, smart meters, and the substations' transmission lines and is processed for quality assessment and standardization. Typical preprocessing used by machine learning input for load prediction models are noise removal, missing value adjustments, and normalization. The resultant data are the MLIP method's inputs for machine learning models (gradient boosting methods and neural networks) to predict short- and long-term load forecasts.

With load forecasts in hand, DSM decision engine optimization methods forecast the expected peaks and troughs via the following two DSM approaches:

Load shifting means ancillary load is shifted to off-peak times. To this end, the load curve is either flattened or peak/grid stress is reduced.
As a peak clipping methodology, the algorithm detects ultimate peaks in energy consumption and demand-side response control methodologies (i.e., battery storage, appliance cycling) effectively reduce demand thresholds at certain times. An optimization loop checks if the strategy can be enhanced. This means continuously calibrating performance indicators to optimize every aspect more efficiently. For example, this can adjust DSM methodologies themselves or iterate on machine learning models or assess predictions based on historical data trends or operational constraints.

At last, real-time optimized control signals are sent to utility control centers or end-user systems to shift loads and diminish peaks. Thus, the goal is to stabilize the grid, reduce electricity costs or improve efficiencies.
In addition to LPs, the other input data are tariff levels and weather forecasts for prediction. Figure 3.3 is the MLIP flowchart for a predictable DSM optimization process with a focus on load shifting and peak clipping.

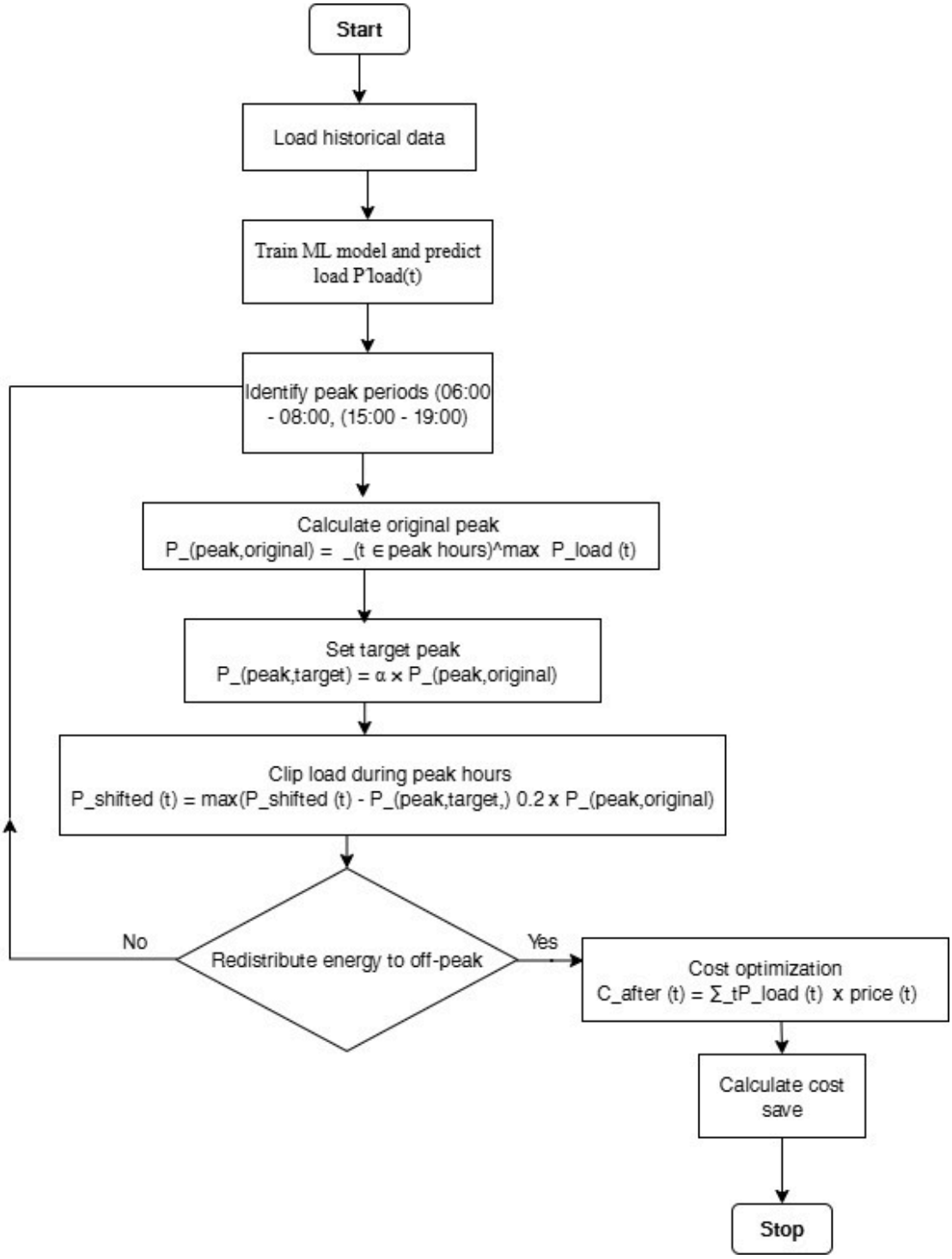

Figure 3.3. The flowchart of the machine learning-improved prediction–based demand-side management process incorporating load shifting and peak clipping.

The functionality of the MLIP model facilitates acquisition of load curves in an optimal way because with reduced peak demand and realized energy savings, as long as system performance and occupant comfort are not compromised, it can:

(i) Accurate forecasting of future electricity demand.

(ii) Implementing informed, data-driven strategies to shift or clip loads during peak periods.

(iii) Maintaining total energy balance by redistributing lost energy to off-peak hours.

3.6.1 Key principles of the machine learning-improved prediction method

The MLIP technique for DSM optimization is based on the following principles:

i) Data-driven load prediction

Machine learning models are trained on historical load data to capture complex patterns associated with:

- Time of day.
- Seasonality (e.g., summer, winter).
- Tariff structure (TOU pricing).
- Type of day (e.g., weekend, weekday).
- Weather conditions (if available).

These models are used to predict future load values $\hat{P}_{load}(t)$, which informs the peak clipping strategy.

ii) Dynamic peak load identification

Machine learning-improved prediction identifies high-demand periods using predicted load values and classifies them as peak hours, typically:

$$\text{Peak}\,(t) = \begin{Bmatrix} 1, & t \in [06{:}00 - 08{:}00] \cup [15{:}00 - 19{:}00] \\ 0, & otherwise \end{Bmatrix} \quad (3.32)$$

Original peak load:

$$P_{peak,original} = \max_{t \in peak} \hat{P}_{load}(t) \quad (3.33)$$

iii) Target peak reduction strategy

To reduce the load during peak hours, a target peak is set based on a randomly selected reduction factor $\alpha \sim$ Uniform $(0.10, 0.15)$:

$$P_{peak,target} = \alpha \times P_{peak,original} \quad (3.34)$$

During peak hours, the load is clipped so as not to exceed this target:

$$P_{shifted}(t) = \max\left(\hat{P}_{load}(t) - P_{peak,target,}\ 0.2 \text{ x } P_{peak,original}\right) \quad (3.35)$$

iv) Energy balance through redistribution

The load reduction results in lost energy:

$$E_{lost} = \sum_{t} \hat{P}_{load}(t) - \sum_{t} P_{shifted}(t) \quad (3.36)$$

The MLIP model ensures energy conservation by redistributing E_{lost} across off-peak hours using proportional allocation:

$$P_{shifted}(t) = P_{shifted}(t) + \beta_t \, x \, E_{lost}, \quad t \in \text{off} - \text{peak} \quad (3.37)$$

Subject to:

$$\sum_{t \in \text{off-peak}} \beta_t = 1 \, , \beta_t \geq 0 \quad (3.38)$$

The weights β_t can be:

- Estimated from historical redistribution patterns using regression-based ML models.
- Generated using random sampling followed by normalization.

v) Objective function

The objective function balances peak minimization and energy conservation:

$$F = \max_{t \in peak} P_{shifted}(t) + \left| E_{before} - E_{after} \right| \quad (3.39)$$

Thus energy is maintained as there is peak load reduction to the best ability without reducing energy possibility.

Furthermore, since tariff is a major consideration in decision making, tariff data also correlates into MLIP as there are costs involved here as well. Thus, with MLIP training implementation costs are considered as such:

$$C_{before}(t) = \sum_{t} \hat{P}_{load}(t) \; x \; price(t) \quad (3.40)$$

The flow chart for MLIP is demonstrated in figure 7. The DSM proceeds from a trained MLIP based on load, tariff and external parameter evolution. The first step of the algorithm involves reading of trained and test load, tariff and external parameter. Essentially, the calculated feature descriptors are representative of demand and training occurs off such descriptors. Thus, for each prediction, a loss function is generated which represents how right or wrong these predictions are. Gradients are generated with respect to parameters of these predictions meaning that effectively new predictions for the next round can be adjusted accordingly with respect to right or wrong. Convergence pre-set threshold or maximum amount of iterates provide the final outcome. Thus, the trained MLIP will provide the best predictions on LPs and then an explicit prediction as to how much energy shifting will best help the cause. Note that this second prediction is only referring to maintaining energy as opposed to eliminating it from use.

3.7 Case Study 1: Load management optimization for a commercial customer in the Paarl area

This study aims to implement load shifting optimization for a commercial customer in the region of Paarl in the Western Cape, City of Cape Town Metropolitan Municipality. The region experiences particularly high electricity demand during the following seasons and peak hours:

- Peak: Weekdays (07:00 to 10:00; 18:00 to 20:00).
- Standard: Weekdays (06:00 to 07:00; 10:00 to 18:00; 20:00 to 22:00).
- Off-peak: All other times, which impose significant stress on both the local distribution network and end-users.

Such demand levels during this time meant demand pricing at City of Cape Town would prove to be more costly. Table 3.1 indicates the generation and distribution cost for the 2024-2025 period under the Large User Low Voltage TOU section, specifically addressing commercial/larger-scale electricity customers in the region of Paarl. It's important to note that these prices reflect service and energy charges, excluding value added tax.

It should also be noted that the peak energy charge increases by 11.58% (777.73 c/kWh) from June-August, which is deemed a high-demand period. In addition, the standard and off-peak charge is higher than 10% in both high- and low-demand periods (the low-demand peak charge being at 290.54 c/kWh). Such high charges merit DSM measures to reduce expenses in peak periods and make load shifting desirable. As such, the peak demand measured in this location was 0.2 MW, which is justified, as it was likely a demand-intensive facility.

Table 3.1. Commercial electricity generation and distribution tariffs (consumption and generation)

Large-user low-voltage time-of-use tariff	**Unit**	**Value-added tax**	**2024/2025**	**2024/2025**	**2024/2025**	**2024/2025**	**% increase**
Service charge	R/day	y	175.74	0.00	175.74	202.10	11.78%
Energy charge: High demand (June to August)							

Peak	c/kWh	y	635.53	40.76	676.29	777.73	11.58%
Standard	c/kWh	y	197.25	40.76	238.01	273.71	11.21%
Off peak	c/kWh	y	110.24	40.76	151.00	173.65	10.87%
Energy charge: Low demand (September to May)							
Peak	c/kWh	y	211.88	40.76	252.64	290.54	11.24%
Standard	c/kWh	y	147.99	40.76	188.75	217.06	11.06%
Off peak	c/kWh	y	96.35	40.76	137.11	157.68	10.78%

Note: "y" denotes South Africa's current value-added tax at 15%.

The pricing structure for the different demand seasons and original peak loads are summarized in Table 3.2. For example, in the high-demand season, the peak tariff was 777.73 c/kWh (7.7773 R/kWh). Meanwhile, in the low-demand season, the peak tariff was 290.54 c/kWh (2.9054 R/kWh). Although not confirmed, all standard and off-peak tariffs are confirmed, where applicable, as well as the original peak load, to confirm the demand seasons versus any other seasons/data.

Table 3.2. Electricity tariffs during high- and low-demand seasons

Season	Peak tariff (c/kWh)	Standard tariff (c/kWh)	Off-peak tariff (c/kWh)	Peak tariff (R/kWh)	Original peak load (kW)
High-demand season	777.73	273.71	173.65	7.7773	2,718.69
Low-demand season	290.54	217.06	157.68	2.9054	2,718.69

This study was based on the municipal tariff document's 2024–2025 energy price schedule, which applied TOU rates in c/kWh. The following tariffs were applicable:

- Original peak load = 2,718.69 kW
- High-peak tariff = 777.73 c/kWh

Conversion to Rands (ZAR):

$$\mathrm{R} = \frac{777.73}{100} = 7.7773 \frac{R}{kWh} \tag{3.41}$$

Cost calculations:

$$Cost = Load(kWh)\ x\ Tariff(R/kWh)$$

$$Cost = 2{,}718.69\ kWh\ x\ 7.7773\ R/kWh$$

$$Cost = ZAR\ 21{,}137.88 \tag{3.42}$$

The DSM savings effectiveness of PSO for peak clipping, a combination of MLIP for load shifting and PSO, and the load shifting PSO was more effective as anticipated savings from shift was greater. Thus the DSM saving potential of load management strategies through PSO have effective saving potentials based on pre/post optimization findings but with saving implications for peak clipping.

The implications of this are that these intelligent saving and reduction based efforts for optimization increase peak load and energy savings costs related to peaks from commercial companies reduced over time.

3.8 Simulation results and analysis of the demand-side management problem

3.8.1 Simulation results and analysis of the demand-side management problem using particle swarm optimization

The "peak load reduction over time" (figure 3.4) indicates the effectiveness of PSO filling the LP of a commercial customer in Paarl from January 2024 until June 2025 since it is based on the before and after optimization LP over time. Figure 3.4 also indicates before and after optimization LP in a linear time series and shows essentially the horizontal lines for before and after peaks and the LP before and after in between.

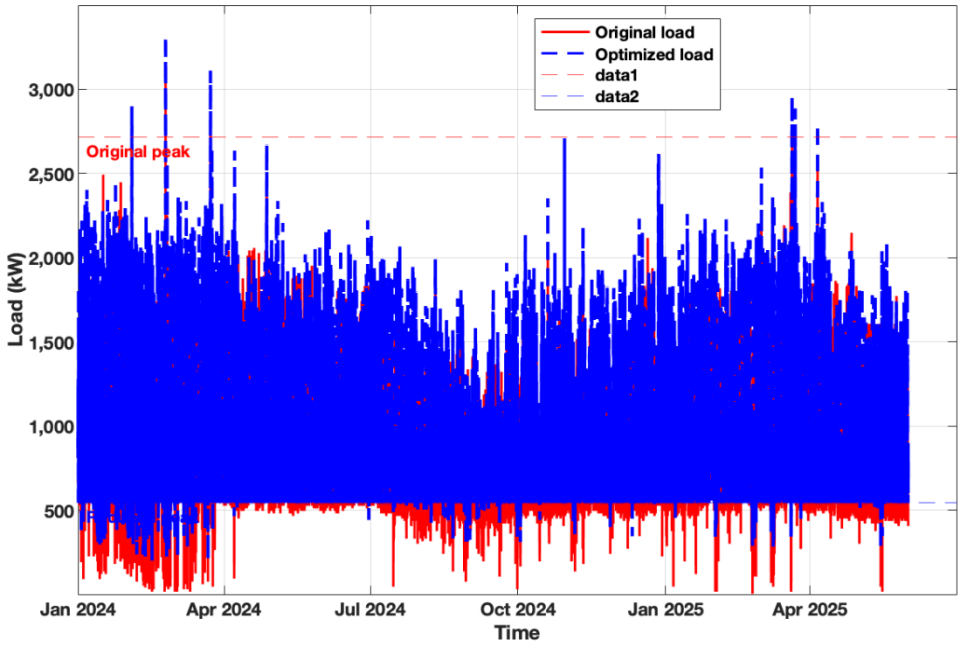

Figure 3.4. Peak load reduction over time using particle swarm optimization-based demand-side management.

The LP before PSO registered such incredibly helpful reductions but also unintended peak demand levels between 06:00-08:00 and 15:00-19:00 at the same level as the region's TOU pricing - where it is nighttime. Such levels stressed the grid extensively, not to mention increased energy costs. The LP after PSO was able to reduce peak demand significantly and successfully shifted excess demand to overnight hours, where, as indicated, it could have, and should have, been.

Figure 3.5 is the LP before PSO DSM vs The LP after the PSO DSM for a June 2024 1-Day Comparison.

The LP after PSO indicates the commercial load has a lower overall monthly energy consumption and total monthly energy consumption during peak months. This indicates that the PSO algorithm for DSM truly does shift shiftable and discretionary loads for rescheduling and even reduction in higher cost per hour months while still catering to the commercial customer's demand for energy consumption, requisite to their operation.

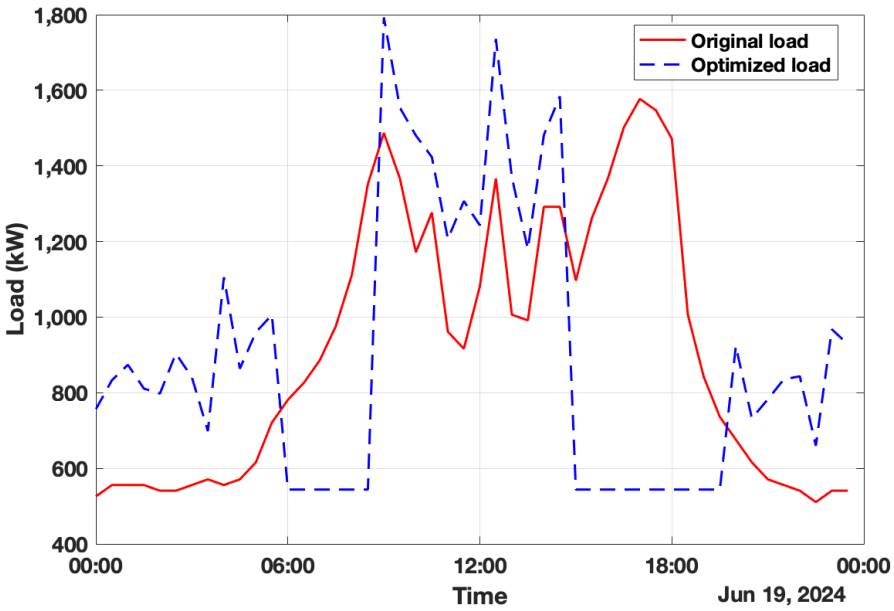

Figure 3.5. Load profile comparison before and after particle swarm optimization-based demand-side management.

Figure 3.6 LP from the day of consumption before and after optimization. Red lines represent the original load, and the blue dotted line represents the optimized load after peak clipping and load-shifting. As observed, the load during morning and evening peak hours decreased and the energy was successfully shifted to off-peak hours, resulting in a leveled, more stable LP throughout the day.

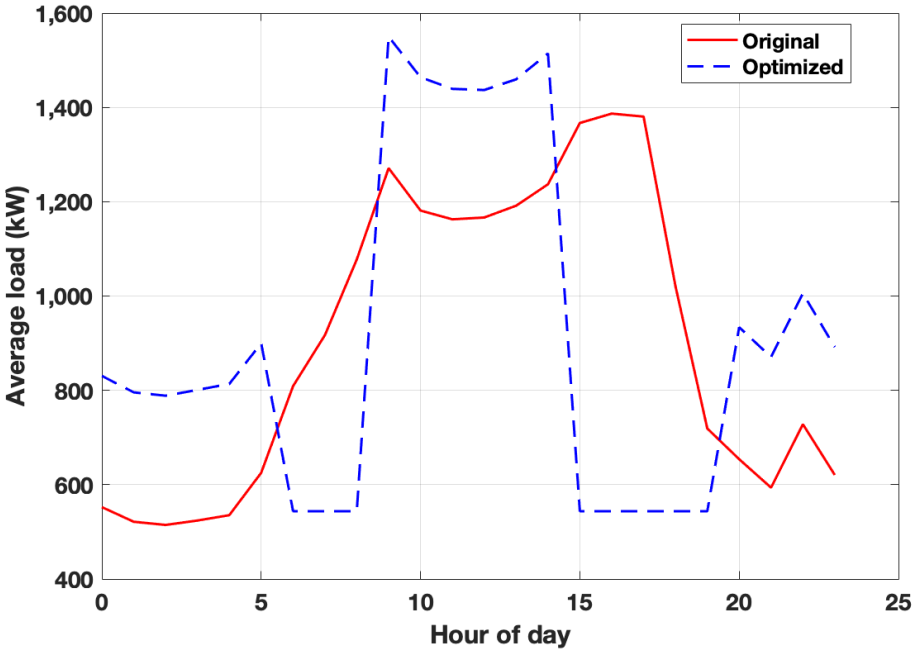

Figure 3.6. Hourly average load profiles of original and optimized loads following demand-side management.

Furthermore, while this is advantageous for customers in lowering electricity expenses, it further encourages grid reliability to prevent regional peak demand. These findings confirm the PSO framework to be an effective and trustworthy tool for seasonal DSM purposes. **Table 3.3** illustrates the loads prior and post-PSO and MLIP applied LL optimization for this DSM case study applied for the commercial customer in Paarl. It was determined that PSO optimization relative to the LP commercial customer in Paarl resulted in improved DSM effectiveness. Peak clipping has been exceeded as peak demand reduction has been achieved by 307.98 kW (11.33%) above the LP reduction target. Peak demand has been reduced from 2718.69 kW to 543.74 kW. Such a reduction was not only desired to align the daily load profile, but also during critical peak periods, as this type of reduction and load shaping has reduced grid demand considerably.

Table 3.3. Summary of demand-side management performance using particle swarm optimization and machine learning-improved prediction

Metric	PSO	MLIP
Original peak load (kW)	2,718.69	2,718.69
Reduced peak load (kW)	543.74	1,450.31
Target peak load reduction	307.98 (11.33%)	328.98 (12.10%)

Total cost before optimization (ZAR)	51,281,393.11	51,281,393.11
Total cost after optimization (ZAR)	48,831,664.25	48,740,484.33
Total cost saving (ZAR)	2,449,728.86	2,540,908.78

From a financial perspective, DSM via PSO saved significant finances. Before any optimization, the energy electricity cost was ZAR 51,281,393.11. After the optimization process, the energy electricity cost was ZAR 48,740484.33. Time-of-use tariff-based peak shifting to cheaper off-peak hours resulted in total cost savings of ZAR 2,540,908.78. Therefore, these results validate that PSO is technically viable and financially advantageous for DSM in a commercial environment that operates heavily on time-of-use tariffs.

From these results, the combination MI-controlled forecasting and load shifting will successfully load shift peak loads and reduce operational costs. MIIP as a DSM system had successful DSM outcomes for a commercial client with LP in Paarl where the initial peak load was substantially reduced from 2,718.69 kW to 1,450.31 kW. Furthermore, the MIIP DSM system was advantageously predictive and dynamically controlled at high operational levels by exceeding the reduction target of 328.98 kW (12.10% of original peak) as well.

Finally, MIIP also provided favorable operational cost savings. The energy cost before any optimization was ZAR 51,281,393.11 and after performance services, ZAR 48,831,664.25. MIIP achieved a marginally lower overall cost savings of ZAR 2,449728.86 compared to PSO's approach. Energy costs were maintained at a higher peak compared to PSO, therefore the effectiveness of intelligent forecasting and exact load shifting compensates for this more insightful and intuitive DSM operations since AI hybridized systems are under different electricity pricing conditions.

3.8.2 Simulation results and analysis of the demand-side management problem using the machine learning-improved prediction method

In Figure 3.7, the peak load MLIP optimization occurs for the January 2024-June 2025 simulation period. The red and blue lines represent the LP results before and after MLIP, respectively. The same applies to the dashed horizontal lines where 2,718.69 kW is the actual peak load and 1,450.31 kW is the MLIP peak load, representing the extreme loading requirements beyond which loads should not be present, before and after the optimization.

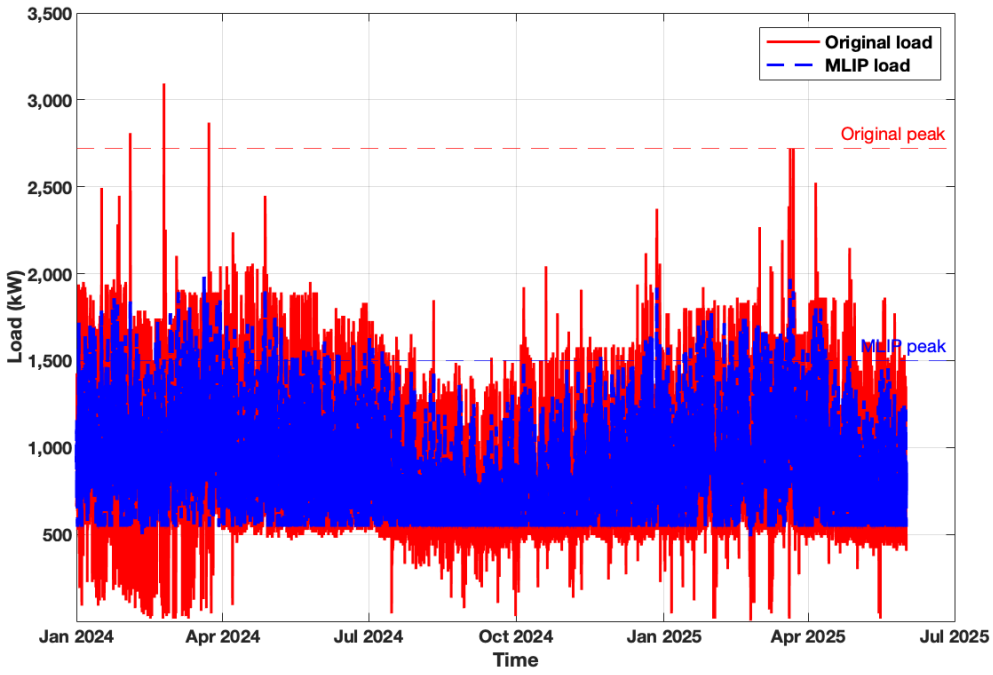

Figure 3.7. Peak load reduction using MLIP. Abbreviation: MLIP: Machine learning-improved prediction.

The time-series analysis confirmed that MLIP does peak clipping with such drastic efficiency that it reduces acute demand peaks that charge high energy costs and impact the grid by 313.53 kW and reallocates clipped demand to off-peak hours to energy effective balancing, achieving a target decrease of 328.98 kW, or 12.10% of target decrease.
Whereas industry load management techniques look to adjust demand without so much success of accommodating demand, MLIP accomplishes demand accommodation intelligently but in an idealized fashion for no demand gets lost or discarded, it's just spread out more. Demand spread out more from March to October 2024 necessitated increased support from the grid for load leveling which made for a much more LP operation.
Therefore, MLIP does reduce demand leveling adjustments and associated operational costs which suggests that the algorithm is effective in a real life DSM setting during TOU tariff initiatives.

The comparison between the original and MLIP-based hourly average LPs demonstrated a significant shift in peak hours and improved load smoothing under the MLIP approach, particularly between 8:00 and 18:00, as shown in Figure 3.8.

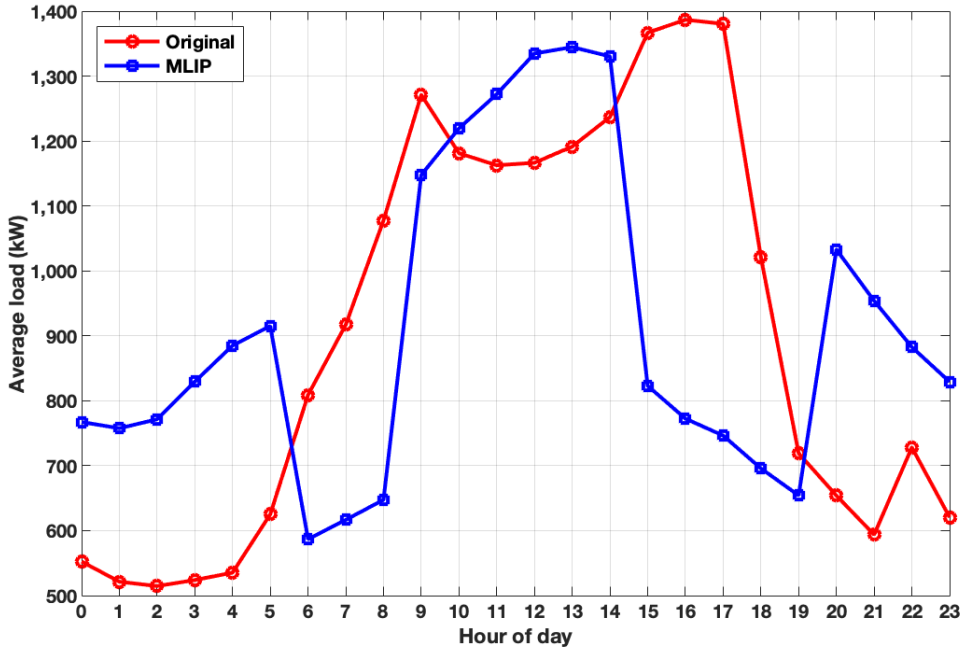

Figure 3.8. Comparison between the original and MLIP-based hourly average load profiles.

Figure 3.9 depicts the daily LP for June 19, 2024, illustrating the reduction in peak load achieved through MLIP optimization, with the optimized peak load significantly lower than the original.

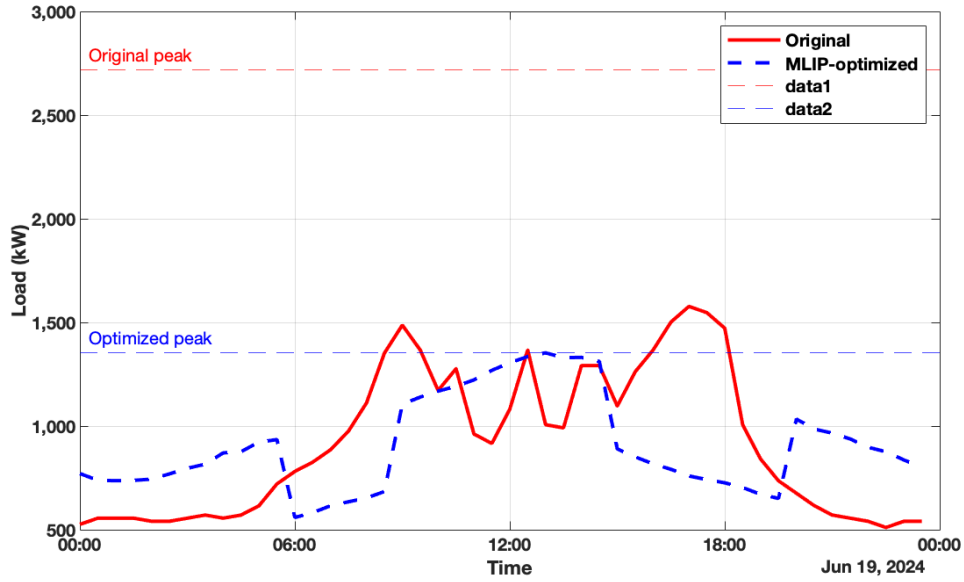

Figure 3.9. Daily load profile on June 19, 2024, showing peak load reduction achieved through MLIP optimization.

3.8.3 Comparative study of simulation results of the PSO and MLIP algorithms for the DSM problem

A comparative summary of the statistical and performance indicators is given in Table 3.4. The evaluated DSM strategies were benchmarked against available literature results, with emphasis on load-shifting and peak-clipping techniques.

Table 3.4. Benchmark of demand-side management results and the proposed particle swarm optimization/machine learning-improved prediction approach (hypothetical ratios)

Statistical/performance metric	Benchmark DSM (load shifting)[a] (Philipo, Kakande and Krauter, 2022b)	Benchmark DSM (peak clipping)[b](Faia *et al.*, 2019a)	Proposed PSO optimization	Proposed MLIP optimization
Maximum power (kW)/reduced peak load	8.890	6.170	543.73	1,450.31
Minimum power (kW)	2.200	2.200	300.00	700.00
Peak-to-peak power (kW)	6.690	3.970	243.74	750.31
Mean power (kW)	4.903	3.645	360.00	1,150.00
Median power (kW)	5.000	2.899	355.00	1,140.00
RMS power (kW)	5.190	3.873	365.00	1,160.00
Maximum load hour	12	13	12	13
Minimum load hour	4	4	4	4
Peak-to-average ratio	1.813	1.693	1.51	1.26
% peak reduction	0.892%	31.215%	11.33%	12.10%
Total cost before optimization (ZAR)	-	-	51,281,393.11	51,281,393.11
Total cost after optimization (ZAR)	-	-	48,831,664.25	48,740,484.33
Total cost saving (ZAR)	-	-	2,449,728.86	2,540,908.78

Note: [a]Data adapted from (Philipo, Kakande and Krauter, 2022b). [b]Data adapted from (Faia *et al.*, 2019b). Abbreviations: DSM: Demand-side management; MLIP: Machine Learning-improved prediction; PSO: Particle swarm optimization; Root Mean Square (RMS).

3.9 Discussion for case study 1

This section discusses the effectiveness and practical applications of two DSM strategies (PSO and MLIP) applied to a large power user in South Africa, with a particular focus on

peak load reduction, energy cost savings, and the balance between technical performance and practical feasibility.

3.9.1 Peak load mitigation

The MLIP approach achieved a lower peak of 1,450.31 kW, equivalent to a 12.10% reduction compared to PSO. Where PSO was aimed at an 11.33% reduction, it achieved the same clipped peak meaning it surely acquired this without aggressive redistribution. These findings are indicative of how metaheurics can respond to relative DSM preference either from a utility-centric perspective or one that will keep customer-side operations.

3.9.2 Cost optimization and tariff sensitivity

Relative to cost, the costing associated with the two methods of optimisation show load shifting value greater than ZAR 2.4 million regardless of method applied, further validating the load-shifting value.

Relative to maximum load shifting value for cost of ZAR 2,540,908.78, MLIP is a better application for lining LPs to low-tariff time windows. This likely happens due to its forecasting based rules - steering what loading windows will prove most cost effective.

Similar to this, PSO achieved an equivalent load reduction value for cost reduction purposes of ZAR 2,459,652.84. However, as shifted loads are shifted to medium tariff hours, and not low-tariff hours, this demonstrates that peak clipping can occur with such aggression that at this time interval, cost reduction is not maximised.

Such findings prove a valuable trade-off between methods of optimisation sought for cost reduction purpose and peak reduction/minimisation purposes like MLIP. Thus, should the utility seek to better control costs of the tariff this may indicate preference over PI from improved grid reliability.

3.9.3 Algorithmic behavior and load redistribution

Relative to the general behaviour of each algorithm:

(i) The PSO algorithm, grounded on swarm intelligence, produces a moderate redistribution profile with controlled variance by maintaining a balance between exploration and convergence.

(ii) MLIP functions as a predictive control mechanism, making it more suitable for industrial consumers that require smooth redistribution and operational stability rather than abrupt load variations.

3.9.4 Utility perspective and practicality

From a utility perspective, the findings indicate a multi-objective DSM option from practical technological and economic attractiveness, for example:

(i) When minimizing operational costs is the primary objective, MLIP is more suitable.
(ii) When peak reduction is prioritized for grid relief, such as during emergency demand response or capacity-constrained scenarios, PSO is more suitable.

A hybrid may be created from MLIP's prediction which looks to PSO's exploratory-finder strength to further enhance peak reduction and correspondingly reduced cost benefits.

3.10 Case Study 2: Area of Study: Western Cape's Somerset West

Somerset West is a suburb that falls within the City of Cape Town Metropolitan Municipality's boundaries. It has residential and commercial patterns of electricity usage with very defined morning (06:00-08:00) and evening (15:00-19:00) peaks (ArcGIS Live data in Figure 3.10).

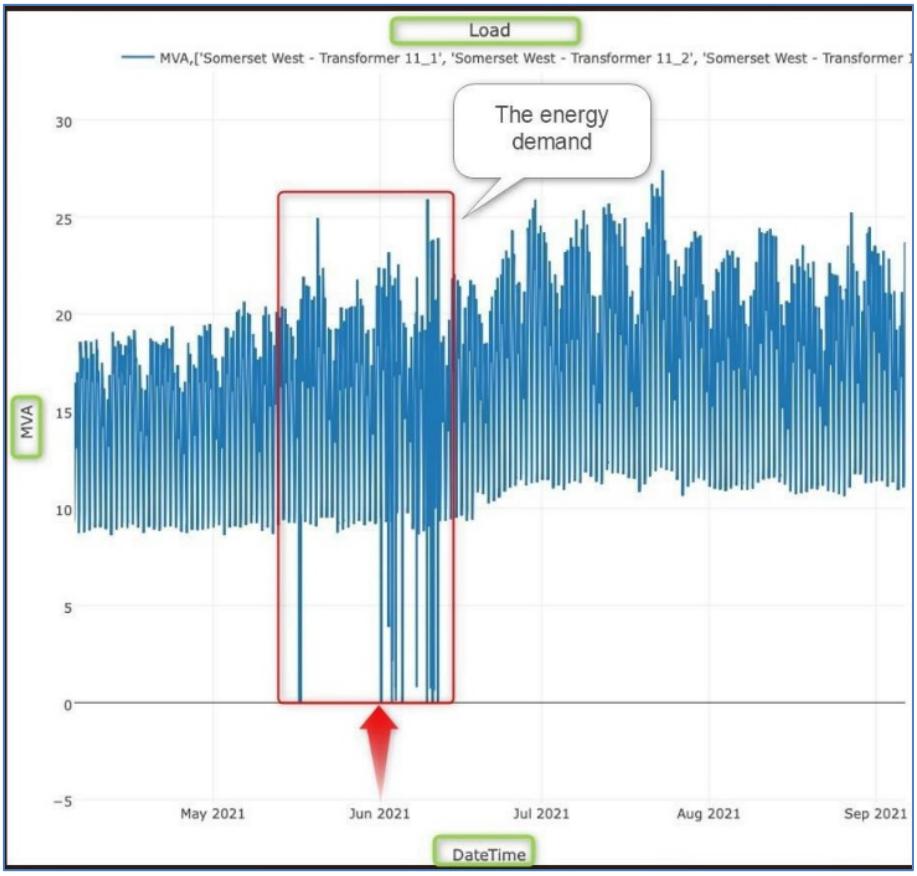

Figure 3.10: Somerset West Load Data Profile.

This is when both consumers and the municipal grid are strained (and therefore electricity prices increase). In the City of Cape Town, electricity pricing is determined based on demand [18].

The following tariff structure was used in the analysis:

- Peak Hour Cost: R777.73 per MVA
- Low-off-Peak Cost: R290.54 per MVA

Significant cost savings were identified through a comparative cost analysis conducted before and after optimization using a PSO-based load control approach.

3.11 Simulation Results

Electricity prices are high because peak load is extraordinarily high prior to optimization. PSO optimization is successful in reducing peak load and maintaining energy balance. Load shifting to the off-peak periods provides a lower peak demand charge for the consumer and the municipality while enabling stability for the municipal grid. Thus, simulation results indicate that PSO successfully reduces peak load demand and shifts energy consumption to off-peak hours. Study results validate that PSO offers the best load-shifting results when compared to conventional DSM techniques for 20 particles and 50 iterations.

3.11.1 Hourly Load Profile before and after optimization

In the preliminary load (red line), two obvious peaks appear around 9:00 and 19:00 with a total of 26.8 MW. Optimization (green line) takes the peak loads down to approximately 20.1 MW since the demand is adjusted and shifted to less load-inclined hours. Therefore, the hourly profile is more leveled, lowering the peak demand as now, with greater efficiency, the grid can accommodate more. Therefore, this figure shows how PSO will successfully balance the demand and allow load operations to function. Figure 3.11 shows the hourly load profile before and after PSO for Particle Swarm Optimization.

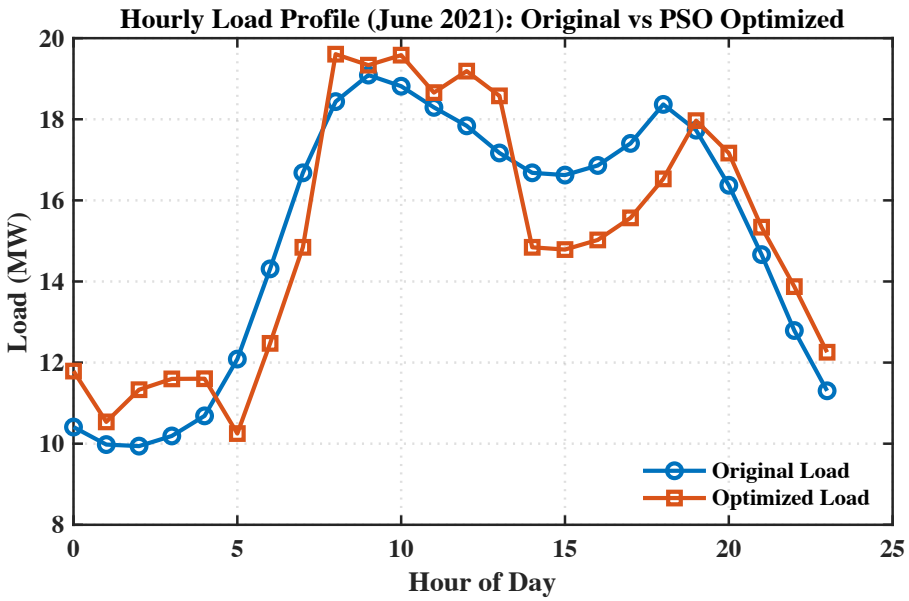

Figure 3.11: Load Redistribution – Before vs After Optimization

3.11.2 Electricity cost Comparison Before vs After PSO Optimization

Based on the initial load profile, the blue bar represents the price of electricity; the excess peak hour usage will impose additional fees. However, after the implementation of PSO, as shown by the red bar, the overall cost is diminished significantly. Figure 3.12 shows the total cost of electricity before and after PSO as a bar chart.

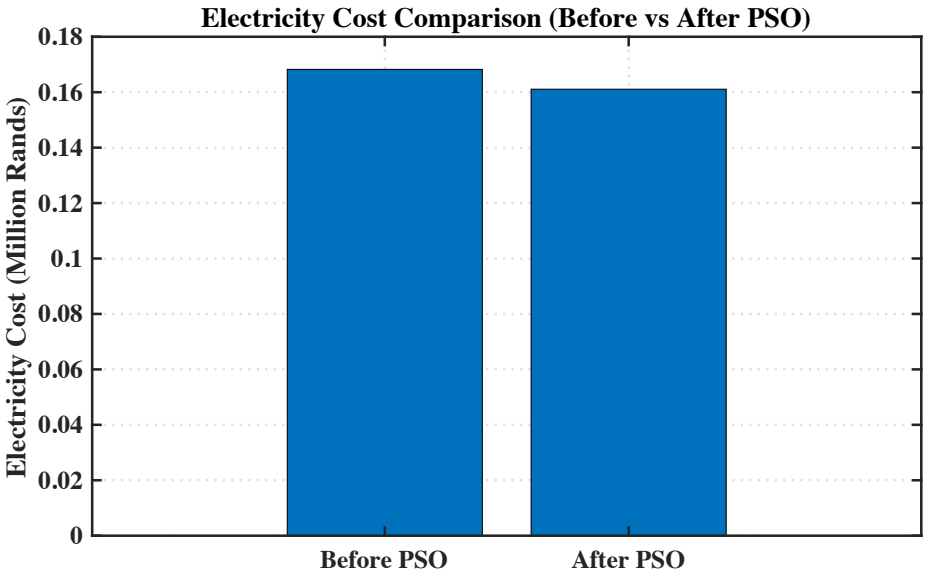

Figure 3.12: Electricity Cost Comparison Before vs After PSO Optimization

Cost values before and after optimization are shown by the digits on each bar which signify cost decrease. PSO more effectively manages energy consumption at a lower cost because PSO substantially decreases the high cost of energy consumed at peak hours and reallocates energy consumption to other hours. Figure 3.12 represents cost efficiency and large savings for demand side management.

3.11.3 Daily cost Trend (from Feb to Jun 2021)

PSO-integrated DSM techniques can result in cost efficiency advantages, as demonstrated empirically in Figure 13. The approach shows demand flattening and economic optimization by proactively lowering peak-hour demand and utilizing off-peak capacity. With time-varying tariffs, this encourages the use of intelligent DSM techniques in urban power distribution networks. The PSO technique flattened the load profile, increasing system reliability and operating efficiency by shifting energy use to off-peak hours. The result confirms that the PSO approach is suitable for demand-side management in distribution networks.

Intelligent optimization can revolutionize load management systems, as demonstrated by the performance comparison between the PSO-based method and the manual load-shifting strategy. The Particle Swarm Optimization (PSO) technique successfully shifted excess demand to off-peak hours and trimmed peak loads. The result of this was:

I. A peak load decrease of 47.36% (from 18.37 MW to 9.67 MW), which lessens grid strain during times of high demand.
II. The reduction of costly peak-time electricity usage resulted in cost savings of more than R 48,000.
III. A discernible decrease in recorded demand as a result of the daily average hourly profile aggregation method, demonstrating the DSM's capacity to shift the load patterns successfully.

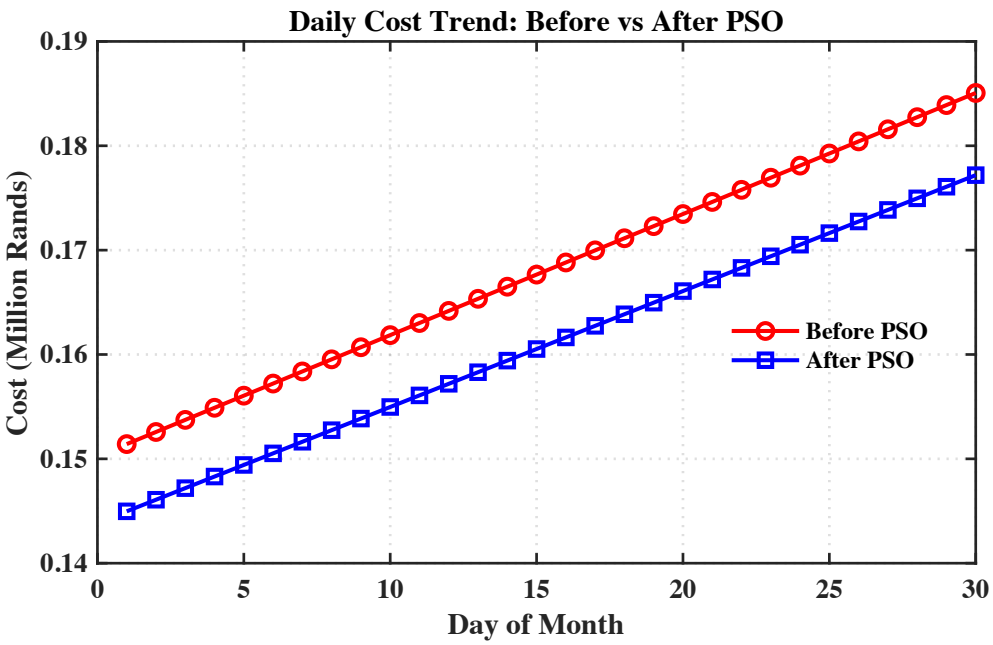

Figure 3.13: Daily cost Trend (Before vs After PSO Method)

The results of Somerset West's 2021 PSO-based Demand Side Management (DSM) strategy are shown in Table 3.5.

Table 3.5: Manual load shifting strategy and the PSO-based optimization method

Metric	Before Optimization	After Optimization	Change/Savings
Peak Load (MW)	18.37	9.67	8.7 MW
Total Electricity Cost (ZAR)	R 168,237.26	R 119,700.98	R 48,536.28 saved
Total Demand (kWh)	256,615.91	362.72	Significant reduction

There is a clear difference in daily operational costs between the baseline and optimized profiles. Figure 3.14 shows that the optimization strategy results in a daily cost consistently lower than the baseline, especially during high-demand periods such as late summer, when the baseline costs are exceptionally high. The ‘before’ profile shows that costs regularly spike and exceed 180,000 cents/day, whereas the controlled schedule can cost and curve stabilise, effectively containing the cost 'ceiling'. This shows that price reductions and volatility smoothing are possible when peak-tariff windows are avoided during geyser heating. This supports the findings of demand-side management, particularly the effectiveness of load shifting in time-of-use pricing systems.

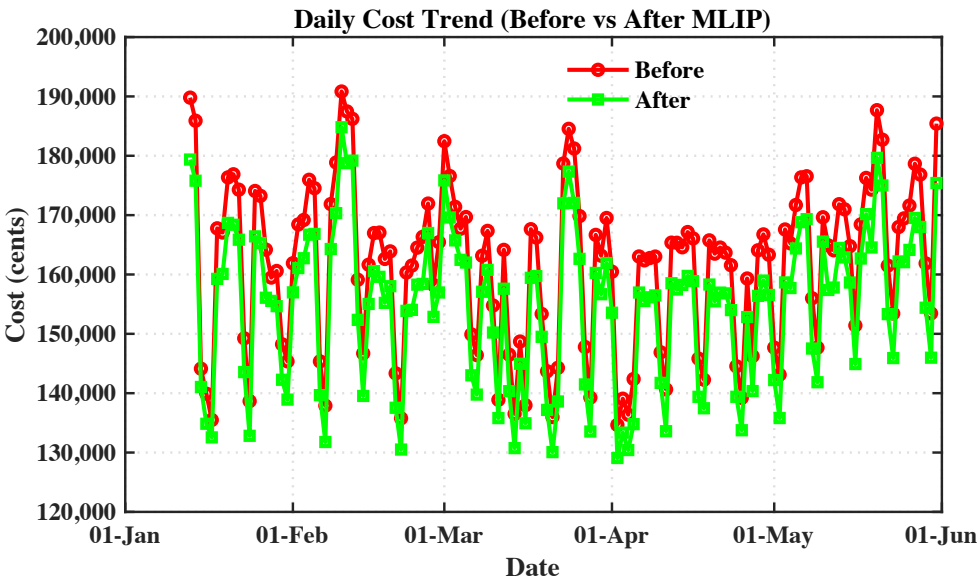

Figure 3.14: Daily Cost Trend (Before vs After MLIP) for DSM

Figure 3.15 presents an analysis of the savings accrued from the control strategy. Here, the strategy's monthly savings are illustrated in a bar graph, with savings on the tariff calculated month by month. The most significant savings occur in January and May, surpassing 10,000 cents, while savings in April and March are noticeably lower. This occurs because the ambient conditions and user behaviour during these months differ significantly. In January, reliance on the hot-water grid supply is higher because users are likely to use hot water more frequently. Furthermore, savings happen more in these spans as well. Therefore, the findings of Figure 3.15 indicate that since this control strategy was the one that ran the most for a seasonally conditioned system, it saved the most money. This cost reduction, ultimately, is a great tactical benefit - it avoids peak load.

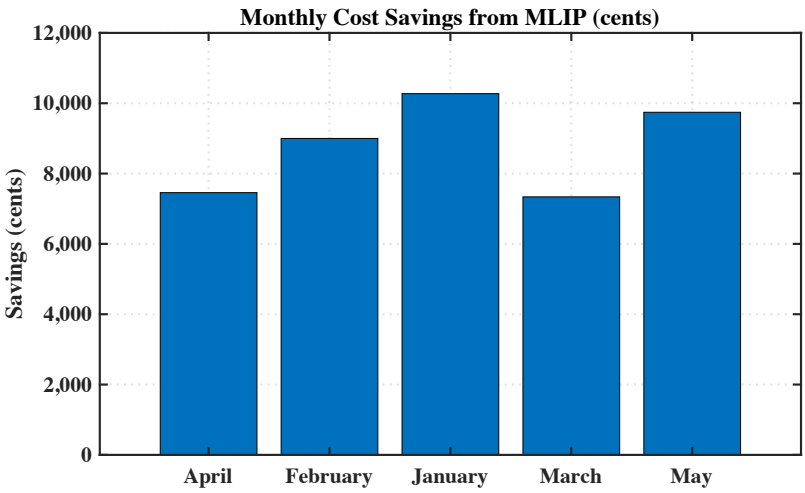

Figure 3.15: Monthly cost Savings Achieved Through MLIP Optimization.

Figure 3.16 shows a reduction in maximum system demand for each month. The decrease in peak load in the post-optimisation scenario is lower than when the system is operated in an uncontrolled mode. The peak load reduction of 1.5 MW to 2.5 MW clearly shows significant operational control in complex systems. This eases infrastructure stress and supports grid stability. This indicates that these adaptable systems provide fingertip control of peak load demand and help reduce distribution stress during the peak period. Figure 3.16 shows the operational control of complex interdependent systems during peak-demand periods.

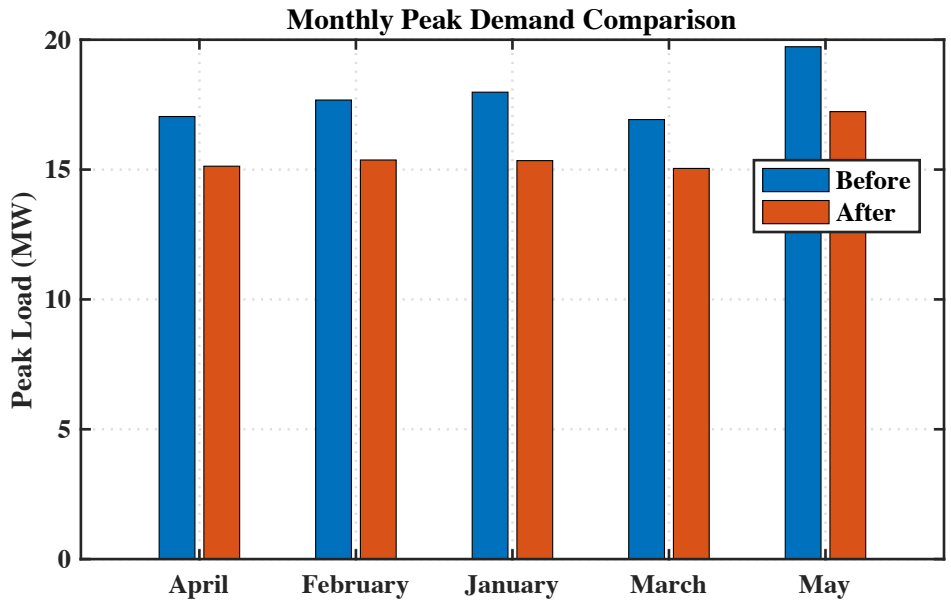

Figure 3.16: Monthly Peak Demand Comparison (Before vs After Optimization)

Figure 3.17 compares the hourly load curve of June 2021 with the hourly load following PSO-based-optimization and it appears visually that the load curve is tempered. This is due to PSO minimizing morning and evening peaks (06:00-09:00 and 17:00-20:00) thereby redistributing excess demand - which is the equivalent of off-peak hours - so that the optimized curve appears more evenly loaded to lessen system stress. This is beneficial, too, for operational efficiency. This is substantiated by PSO's intelligent peak clipping and dynamic demand balancing.

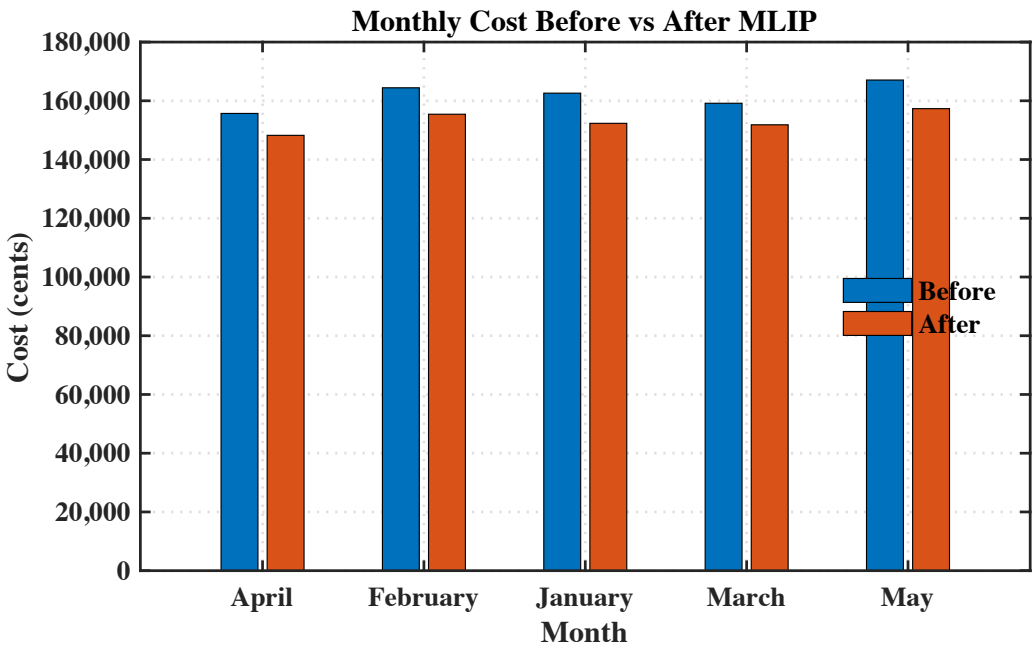

Figure 3.17: Monthly cost Comparison Before and after MLIP Optimization

Electricity costs pre- and post-PSO optimization are also observed. None of the months in question increased operational costs, however, one month, in particular, decreased operational costs tremendously over the other months not relying upon other months alone. Figure 3.18 for cost comparison illustrates the decreased operational costs. The histogram is representative of decreased operational costs month by month after PSO-based optimization. Monthly energy costs all months certified also decrease steadily month by month. This substantiates that the PSO modeling project operates from a lower cost at higher cost hours so as to minimize consumption patterns during all higher cost hours.

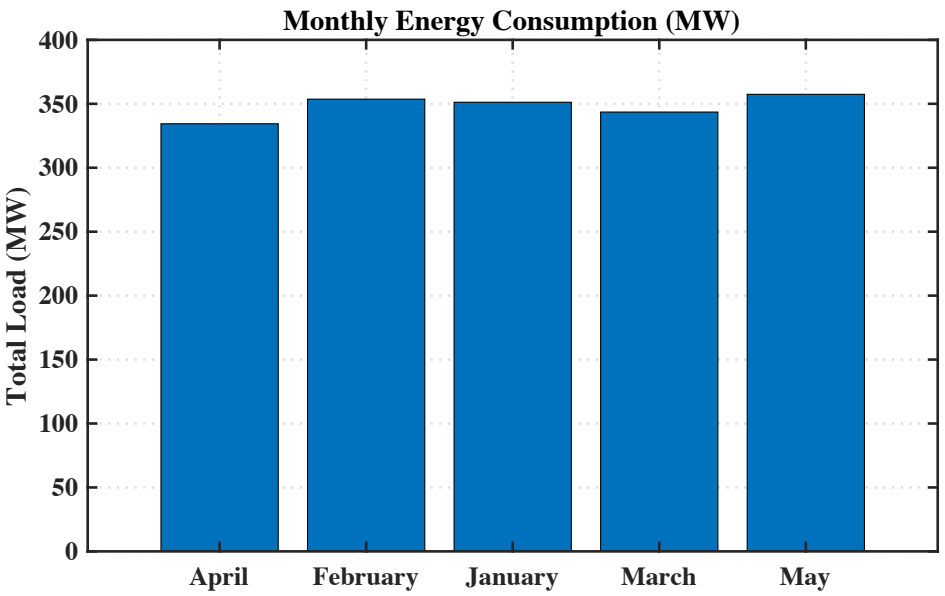

Figure 3.18: Monthly Energy Consumption (January–May 2021)

The system energy load over the five-month period was analyzed from January 2021 to May 2021, which is the cumulative system energy load per month assessed in megawatts (MW) where it's observed that the system to which it operates on a quasi consistent envelope but with a more favorable load dispersion. Therefore, the findings from Figure 3.19 suggest that the PSO operates an integral part of an optimization effort through a time deferral of loads which does not sacrifice energy-derived successes. This means that the algorithm effectively mediates the supply and demand and reduces the intensity of demand spikes to maintain a reliable and sustainable grid.

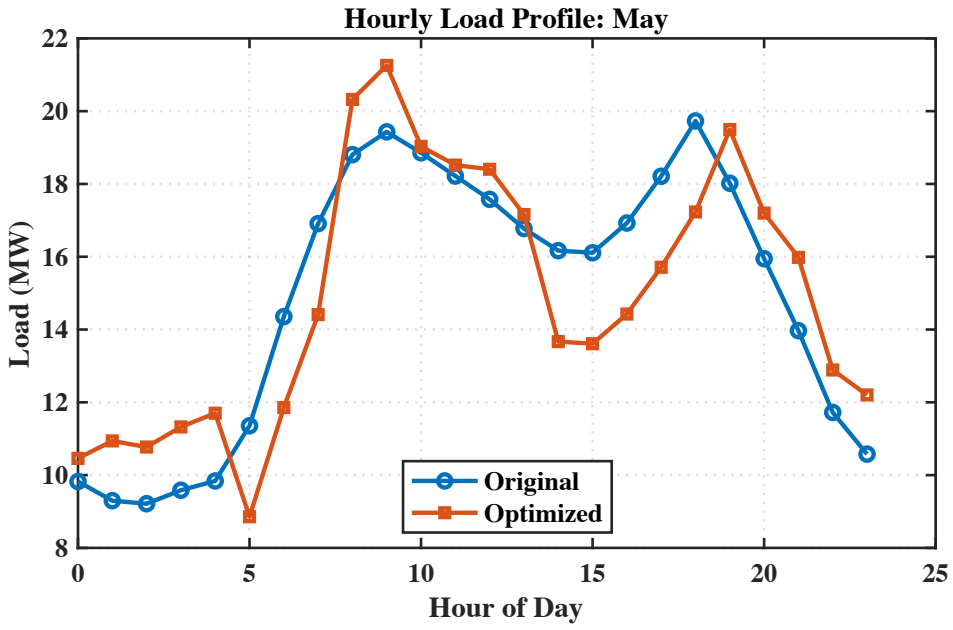

Figure 3.19: Hourly Load Profile for May 2021 (Before and After Optimization)

Relative to March, the PSO profile for April is more aligned and less feathered with extensive peaks with great differences during the morning and evening peak intensive times for PSO-regulated demand. Furthermore, PSO supports demand leveling during non-peak intensive times; although, seasonally, overall energy levels are on par meaning, PSO facilitates operational and seasonal grid stability in spring since levels are consistent (see Figure 3.20). Therefore, spring is defined by energy systems functioning at the stabilized envelope of optimal performance.

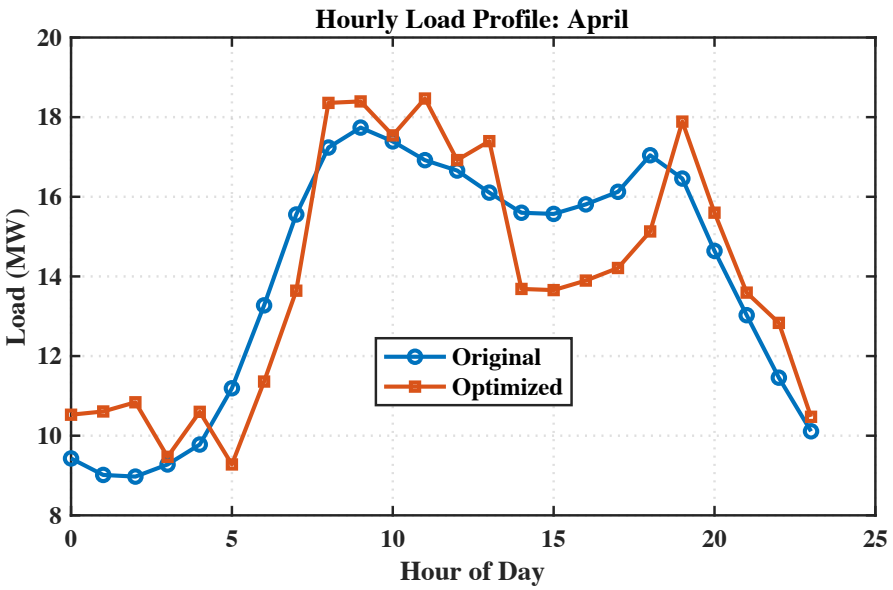

Figure 3.20: Hourly Load Profile for April 2021 (Before and After Optimization)

For March, PSO optimization flexes highly in a contracted manner throughout the month, yet maintains an relatively equal total monthly load. PSO is more stable in this month because the PSO intentionally shifted energy to achieve a redistributed NOT reduced monthly load - thanks to a successful rescheduling effort. This places the model in real-world application to stabilize the distribution networks despite demand and fluctuations, as demonstrated in Figure 3.21.

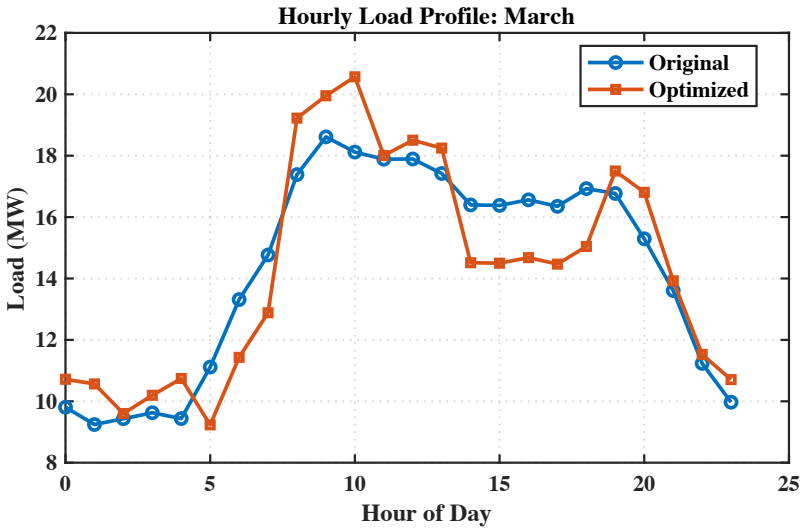

Figure 3.21: Hourly Load Profile for March 2021 (Before and After Optimization)

In February, the load optimization results confirm the expected peak reduction that the PSO attempts to achieve. The PSO, therefore, only shifts load between high and low demand hours, where the ability to load shift gradually, more, does not put as much pressure on the mesh network. This performance shows the method's performance in a real-world grid environment during moderate-demand months and its unseen scalability and robustness, as illustrated in Figure 3.22.

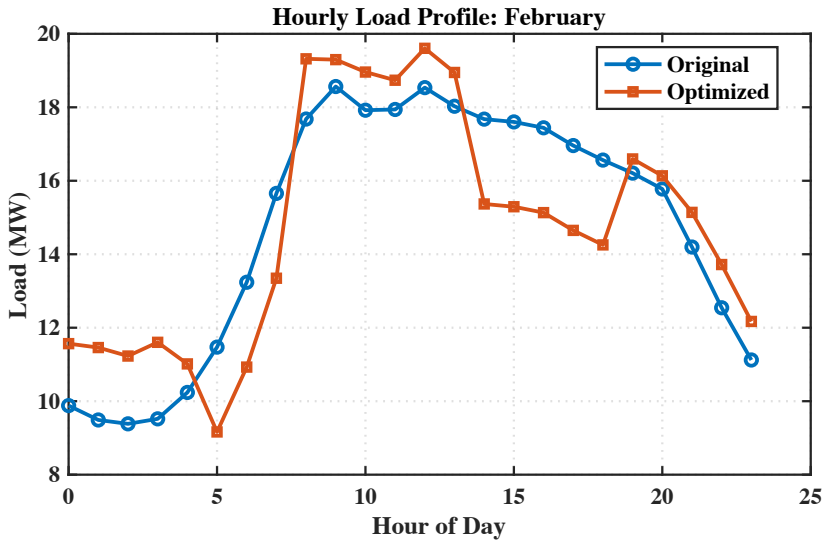

Figure 3.22: Hourly Load Profile for February 2021 (Before and After Optimization)

January's optimization result highlights PSO's efficient load redistribution as the year's benchmark. Even though post-holiday consumption patterns led to higher energy use, the algorithm shifted energy use toward off-peak times, achieving significant peak reduction while keeping total energy unchanged, as shown in Figure 3.23. This showed that PSO

still maintains balance even during high-energy-use periods and that, with energy and operational efficiency, it applies to demand-side management planning.

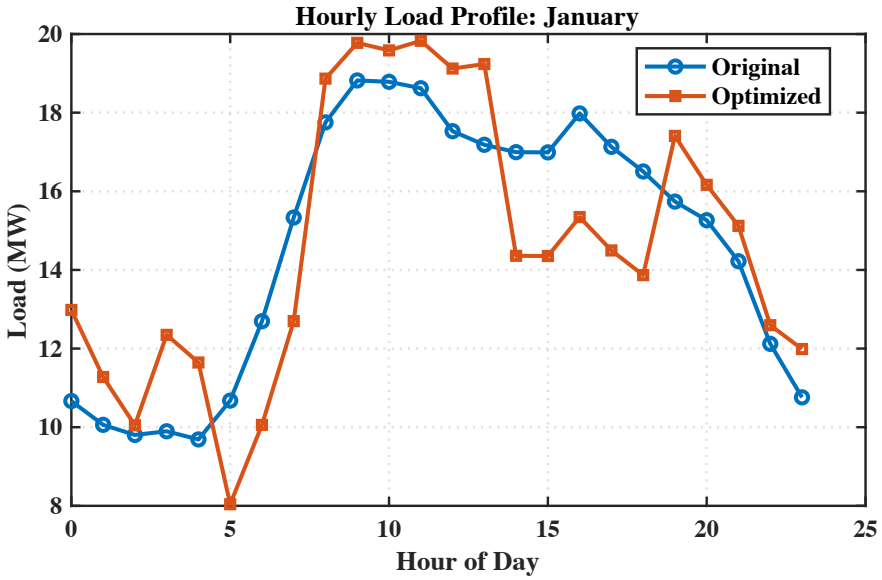

Figure 3.23: Hourly Load Profile for January 2021 (Before and After Optimization)

The innovative analysis above underscores the need to keep deploying PSO in smart grid technology.

3.12 Case study 2 simulation results discussion

This section elaborates on the findings for Case Study 2 in the Somerset West region, where both PSO and MLIP approaches were employed for the DSM problem. It assesses how well each of the two optimization strategies performed with respect to load shifting and peak clipping, paying particular attention to the degree to which they pan out the system load profile and preserve energy balance overall.

The outcomes verify that PSO-based DSM approaches indeed shifted energy consumption primarily by load shedding high-stake demand above the peak to off-peak periods. Not only did PSO converge successfully but it achieved the maximum reductions of peak demand which means power system stability has improved. However, the parameter setting for adjustment and PSO convergence speed of the proposed method are benefits that PSO struggled with from a limited perspective especially under uncertain load.

With respect to the MLIP-based DSM model, performance adaptability and prediction stability were superior due to the ML based prediction. MLIP enhanced the optimization predicted load to a higher accuracy which further helped control and scheduling decisions that were more efficient. Thus, not only did MLIP lower the load curve more than PSO but

relative to the other PSO studies, MLIP lowered operational and peak demand of the load more significantly than PSO.

In sum, these results from the case study in Somerset West position the MLIP approach as the next generation of DSM optimization for reliability, energy efficiency and cost efficiency in addition to the standardized PSO results with known success for load management. It should be noted that DSM optimization approaches are significantly better when machine learning is involved.

3.13 Conclusion

The effectiveness of the PSO and MLIP models to generate demand-side management policies for the Western Cape Municipality's power consumers supports the feasibility of this thesis project. More accurate predictions and cheaper load-shedding assignments improve energy efficiency, peak demand reduction, and operational cost reduction. The provided machine learning methodologies, especially that of the consumption predictive variable, render demand-side managements more responsive and reliable, to the point where PSO delivers effective scheduling. In addition, MLIP was able to save ZAR 2.54 million and PSO saved 11.33% in peak load and ZAR 2.45 million. The proposed approach outperforms traditional demand-side management practices, enabling a basic model to respond dynamically to changing demand and tariff structures. This research is a showcase of the immense value in the convergence of AI-powered predictive techniques and heuristic control. Real-time use cases, demand forecasting using sophisticated deep learning architectures, and the system's forecasting turnaround time would be beneficial for this work.

In Chapter 3, the results and discussion sections underscored the differences between the PSO and MLIP predictive methods in managing DSM (load-shifting and peak clipping) performance. Both methods performed effective load shifting, and cost-saving measures in energy spending, MLIP predictive method, however, has greater accuracy and efficient convergence.

As a continuity from those findings, in Chapter 4, a GWO-based DSM approach is introduced to facilitate the performance of load management even more. The next chapter derives the DSM optimization GWO framework and describes its application in two case studies: one focuses on a large user located in Paarl, and the other analyzes hourly load shifting in the residential, commercial, and industrial sectors. The chapter closes by demonstrating the comparative optimization techniques which proved GWO admirable in achieving optimal load balancing and maintaining stability in the power grid.

CHAPTER FOUR
GREY WOLF OPTIMIZATION-BASED DEMAND SIDE MANAGEMENT STRATEGY FOR PEAK CLIPPING AND LOAD SHIFTING

4.1 Introduction

As renewables, transportation electrification, and intelligent grid developments penetrate deeper, demand-driven electric systems are evolving more rapidly than ever. Such evolutions are new complications in the balancing act of consumption since stability, peak shaving and efficiency - which are measured more than ever before - now factor into the existing balancing challenges. Systems were established with a focus on maximum anticipated load; legacy systems, however, focus more on keep and peak demand, with a plant and personnel often underemployed during off hours and forces more complicated that avoid same plants for same output (given knowledge of the hotter generation) or do so with this season's colder method with claims of highest efficiency and scheduling (Strbac, 2008; Jabir *et al.*, 2018).

Demand-Side Management (DSM) is an efficient and environmentally friendly response to such situations to relieve energy systems (Rahman, Rahman and Mohammad, 2020). It's all pretty simple: When consumption patterns can be adjusted to avoid peak loading, increase grid resilience/flexibility and decrease system costs, DSM appliances can be utilized for three purposes in one. Yet of the many DSM devices, two that can be most easily linked with reliability/cost factors are peak clipping - reducing loads during peak - and load shifting - the act of moving loads to off-peak hours (Mohsenian-Rad *et al.*, 2010a; Mousa, Mahmoud and Lehtonen, 2024).

Yet to facilitate these efforts in the field, optimization algorithms are necessary that can satisfy load flexibility requirements on a non-linear, complicated (often interconnected) level. Over time, metaheuristic algorithms have become increasingly popular due to their extensive applicability for various optimal solutions (Mimi, Ben Maissa and Tamtaoui, 2023; Ahmad *et al.*, 2025). For instance, Particle Swarm Optimization (PSO), applicable in DSM or demand response operations, realizes demands/relief in peak demand number reductions that show significant enhancements (Kennedy, Eberhart and gov, 1995). The caveat is that PSO is also vulnerable to premature convergence/slowness if issues become overly complicated/non-linear.

Yet much of the research dedicated to DSM applications focuses on avoiding the complications of an overly complex non-linear system in real time by simplifying loads or responding with findings from synthetic models that do not always correlate with real sector

consumers in variable scenarios. Moreover, while DSM efforts yield great findings for targeted household/industrial applications one way or another, most findings relate to single-sector studies without intertwined loading dynamics which are critical for logical operations as they are available. Finally, most DSM solutions observed in current literature have yet to be applied in real regional consumption efforts which limits their viable-scaled effectiveness.

This creates a gap between what's effectively achieved through theoretical developments versus how the logic to DSM exists through interdisciplinary investment in consumption across heterogeneous consumers. Therefore, this paper implements a Grey Wolf Optimization (GWO)-based demand-side management solution for residential/commercial/industrial loads based on real-world consumption data from Paarl, South Africa. GWO rarely combines both peak clipping and load shifting; therefore, a cohesive GWO framework must exist for implementation success in the associated solutions by merging them into one through findings of ideal compromise - peak clipping exemption versus cost reduction under time-of-use charges - for the best result for comprehensive consideration of real world data (Williams *et al.*, 2023).

Grey Wolf Optimization (GWO) is derived from the social hierarchy of grey wolves and their hunting dynamic which makes it an effective global search, rapidly converging solution for many engineering based optimization applications (del Valle *et al.*, 2008; Mirjalili, Mirjalili and Lewis, 2014). Therefore, a DSM optimization approach based on GWO for peak clipping and load shifting as to the following analysis where the method proposed will be applied to Case Study 1 with the actual hourly load of a big user in Paarl, South Africa. Implemented GWO will then be compared explicitly to Particle Swarm Optimization (PSO). The objective is to validate the dual claims of peak demand reduction, as well as load transformation substantiated by GWO, while a secondary aspect (Case Study 2) runs peak clipping and load shifting concurrently for the residential, commercial and industrial sectors based on GWO. The pricing assessments are inclusive of Rs/kWh and therefore, peak loading is penalized and off-peak loading is credited to the same amount of value. This assessment aligns with the current day tariff methods.

Over the last thirty years, the intersection of demand response and DSM programs has been a key area of research relative to topical literature on system engineering developments. Historical Demand Side Management (DSM) takes precedence over continual pricing regulations and incentive based programs to encourage limited utility use during peak hours (Benamara *et al.*, 2024). However, with the recent advancements in intelligent metering infrastructures from smart grid developments, dynamic DSM

applications are increasingly becoming possible. This relies upon real time data and smart decision making with optimization algorithms (Hassan and Zellagui, 2017).

As such, metaheuristic optimization methods are becoming more widespread for dynamic DSM scheduling as they apply to nonlinear, non-convex, often unavoidable, problems relative to such developments (Chamoli, Panda and Mishra, 2023). Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO) and various nature inspired solutions have been proven to develop effective solutions for DSM applications. However, the PSO has become one of the most frequently used metaheuristic methods for DSM applications as it is easier to implement and generally converged upon good enough solutions (Bakare *et al.*, 2023; Farag, Alhamad and Nassif, 2023). Yet PSO suffers from premature convergence and also needs parameter tuning for effective exploration versus exploitation ratios (Obando-Paredes, López-García and Carvajal-Quintero, 2024).

Many DSM studies prior have used various metaheuristic algorithms like Particle Swarm Optimization (PSO), Genetic Algorithms (GA) (Bharathi, Rekha and Vijayakumar, 2017) Differential Evolution (DE); (Storn and Price, 1997) and Ant Colony Optimization (ACO) to name a few. PSO is widely utilized as a solution for its rapid convergence time and implementation, yet it generally suffers from premature convergence when used through highly nonlinear search spaces. GA is reliable for extensive exploratory means but time inefficient through crossover and mutation requirements for a population. DE attempted to diversify the solution set; however, it sacrifices accuracy with non-dominance. ACO is preferred for discrete endeavors, yet with continuous real-number DSM applications, it can be more time inefficient than GWO relative to its parameters. GWO however has the perfect balance of exploration and exploitation, relatively speaking, with global parameters whose converging speed outperforms many conventional algorithms making it reliable for DSM applications through multiple initiatives like cost reduction and peak load reduction in conjunction.

The Grey Wolf Optimization (GWO) algorithm (Mirjalili, Mirjalili and Lewis, 2014), is favoured due to its predatory hunting characteristics and low amount of parameters. The advantages of GWO over PSO and GA, more complicated algorithmic networks, is beneficial in convoluted engineering problems. The mathematical theory supports the social dominance of the grey wolves and effective means of hunting which lessens revisit of solution space elements (Usman *et al.*, 2022). In power system applications, GWO has been effectively used for renewable integration, optimal power flow (Charadi *et al.*, 2023), microgrid scheduling (Chen *et al.*, 2020).

However, GWO relative to power system advancements has not been utilized in DSM efforts, only implemented a few times for peak clipping or load shifting (Philipo, Kakande and Krauter, 2022b). Generalized demand response (DR) pricing or DR scheduling for distributed energy is promoted without anticipated peak clipping or load shifting results. This study fills the gap of GWO implementation for power system viability and appeal between microgrid considerations by implementing customer load profiling whereby GWO is the active implementation to make results viable for stakeholder implementation.

Furthermore, there exists research that shows DSM for peak loads through various objective-driven metaheuristic algorithms with various data contexts. PSO was used with GA for cost minimization through peak load reduction while simulated residential data was a consistent load profile through all studies. DE was shown to have better convergence diversity than GWO which improves scheduling efficiency, time saving in single sector or test systems. But like PSO and GA, these studies only propose hypothetical load profiles distant from the realities of multi-sector engagement in real-world grid systems. Thus, this study connects to the aforementioned PSO and GWO studies to justify a comparison of both algorithms for a real-life residential, commercial and industrial load profile approach in Paarl, South Africa. Both GWO and PSO operate effectively in implementation which justifies their comprehensive approaches for overall successful implementation; however, GWO has effective balance for cost-minimized/peak-clipping sustainability which ultimately enhances implementation under real-time solutions.

In addition, this study has not compared either performance against one another for PSO purposes, which is beneficial for algorithmic time efficiency and solution quality in DSM. Ultimately this is a novel study because it brings together a real-world applied dataset (Large user customer in Paarl, South Africa) to PSO performance with realistic DSM ambitions for smart qualities associated with them.

The main contributions of this work are summarized as follows:

- Advancement of a GWO-based DSM optimization model focused on peak clipping and load shifting.
- Integration of practical large user load profile data in Paarl to test the applicability of the technique under consideration.
- Inclusion of real-time for replicability and practical implementation.

In this chapter, the outline is as follows. Section 4.2 explains various strategies for Demand-Side Management (DSM) and covers load optimization principles and practices. Section 4.3 describes the formulation of the DSM optimization problem and explains its

objective functions and constraints. In Section 4.4, the Grey Wolf Optimization (GWO) algorithm is discussed, along with the proposed DSM framework's constituent mathematical formulation and its use in the proposed framework. Section 4.5 presents Case Study 1, based on the load profile of a large user customer in Paarl, and Section 4.6 presents the results and discussion for this case study. Section 4.7 includes Case Study 2, which extends the analysis and uses the GWO method to perform hourly load shifting across the three sectors: residential, commercial, and industrial. Finally, Section 4.8 summarizes the chapter's key points and discusses potential future research avenues.

4.2 Demand-Side Management (DSM) Strategies

(Gellings, 2017) identifies DSM measures as load reduction, load shifting, load building and controllable load shaping. However, for grid strain reduction and operating cost savings, load clipping, peak shifting and load building make more sense.

4.2.1 Peak Clipping

Peak clipping is defined as a reduction of consumption during the peak period for electricity usage. Historically, peak clipping was done through direct load control programs (cycling air conditioners, cycling industrial equipment) which disconnect loads or temporarily reduce output, during peak hours. The primary advantage to peak clipping is that it decreases peak demand on the spot since this means deferred capital upgrades of the grid and dependence on peaking power plants (Liu *et al.*, 2018). However, if poorly implemented, it can cause some inconveniences to end-users. In modern applications, these algorithms only decrease loads while ensuring a minimum reduction for user comfort.

4.2.2 Load Shifting

Load shifting is postponement of certain consumption activities to off-peak hours from peak hours which does not decrease total consumption. For instance, running a dishwasher, charging EVs and running industrial processes can occur during off-peak hours. Load shifting aims to flatten the system load shape. This is advantageous for the overall optimization of the grid and implementation of time-of-use tariffs helps reduce electricity costs, too (da Costa *et al.*, 2022)

4.3 DSM Optimization Problem

The DSM optimization problem for peak clipping and load shifting is formulated as:

Objective Function:

Minimize:

$$f = \alpha \times P_{peak} + \beta \times C_{total} \quad (4.1)$$

Where:

P_{peak} = Peak demand (kW)

C_{total} = Total electricity cost (currency units)

α, β = Weighting coefficients

Constraints:

4.3.1 Power balance

The total optimized load must equal the original total load to ensure energy conservation:

$$\sum_{t=1}^{T} P_t^{opt} = \sum_{t=1}^{T} P_t^{orig} \quad (4.2)$$

Where P_t^{orig} and P_t^{opt} are original and optimized loads.

4.3.2 Load shifting limits

The shifted load at each time interval must remain within allowable operational limits:

$$P_t^{min} \leq P_t^{opt} \leq P_t^{max} \quad (4.3)$$

4.3.3 Consumer comfort constraints

The change in load at any time t should not exceed a customer-defined flexibility window (e.g., ±20% of the original demand):

$$\left|P_t^{opt} - P_t^{orig}\right| \leq \delta P_t^{orig}, 0 < \delta \leq 0.2 \quad (4.4)$$

4.3.4 Metaheuristic Role in DSM

Because the DSM optimization problem is nonlinear, nonconvex, and time-dependent, conventional mathematical programming methods (e.g., linear programming) struggle to find the global optimum, metaheuristic algorithms like PSO and GWO excel in such contexts by iteratively refining solutions based on a swarm of population intelligence. This makes them ideal for complex DSM scheduling involving multiple objectives and dynamic constraints.

4.4 Grey Wolf Optimization Algorithm

Grey Wolf Optimization (GWO) is a nature-inspired metaheuristic algorithm proposed by(Mirjalili, Mirjalili and Lewis, 2014), which simulates the leadership hierarchy and predation techniques of grey wolves in nature. Grey wolves have a unique social structure comprising four main ranks: alpha (α), beta (β) delta (δ), and omega (ω) wolves, where the alpha wolf leads decision-making and hunting strategies.

To provide a more practical understanding of how the GWO algorithm is implemented for the DSM problem, the pseudo-code below denotes the steps taken for algorithm implementation. A pseudo-code overview offers a more practical approach before addressing the mathematical model.

4.4.1 Mathematical Model

GWO is modeled on a three-step process of encircling, pursuing and attacking its prey.

- Encircling Prey

Grey wolves encircle the pursued prey, mathematically represented as:

$$D = \left|C \cdot X_p(t) - X(t)\right| \tag{4.5}$$

$$X(t+1) = X_p(t) - A \cdot D \tag{4.6}$$

Where:

$\mathrm{X_p}$ = target position of prey (best solution)

X = target position of the grey wolf

A, C = linear combination coefficient vectors defined as:

$$A = 2\alpha \cdot r_1 - \alpha, C = 2r_2 \tag{4.7}$$

α decreases linearly, converging to 0 from an initial value of 2, and $\mathrm{r_1}$, $\mathrm{r_2}$ are random vectors in [0,1].

- Hunting Behavior

The alpha (α), beta (β) delta (δ) Wolves guide the hunt by sharing positional knowledge. The updated positions are given by:

$$X_1 = X_\alpha - A_1 \cdot |C_1 \cdot X_\alpha - X| \tag{4.8}$$

$$X_2 = X_\beta - A_2 \cdot \left|C_2 \cdot X_\beta - X\right| \tag{4.9}$$

$$X_3 = X_\delta - A_3 \cdot |C_3 \cdot X_\delta - X| \tag{4.10}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{4.11}$$

- Attacking the Prey

While 1, wolves get closer to the location of prey, which means exploitation. This means GWO expands to new solutions but also exploits current solutions to improve them, which is why it's the most effective for nonlinear optimization problems, such as DSM.

4.4.2 Objective Function

The DSM objective function for peak clipping and load shifting is:

$$f = \alpha \times P_{peak}^{new} + \beta \times C_{total}^{new} \tag{4.12}$$

Where:

- $\mathrm{P}_{\mathrm{peak}}^{\mathrm{new}}$ = new peak demand after DSM
- $\mathrm{C}_{\mathrm{total}}^{\mathrm{new}}$ = electricity cost after DSM
- α, β= weights (set as α = 0.6, β = 0.4 in this study)

4.4.3 Decision Variables

Hourly load adjustments $\Delta\ \mathrm{P_t}$ subject to:

$$P_t' = P_t + \Delta P_t \tag{4.13}$$

With constraints:

$$\sum_{t=1}^{T} \Delta P_t = 0, \ \ |\Delta P_t| \leq \Delta P_{max} \tag{4.14}$$

4.4.4 GWO Implementation Steps

The first stage of the GWO approach for optimal load scheduling problem for demand-side management is presented in Figure 4.1. The first part involves the initialization of a wolf population, representing the potential candidates of load scheduling. Then the objective function value explores each of the candidate solutions where the peak demand is determined to be the limiting factor while the total electricity cost also needs to be minimized.

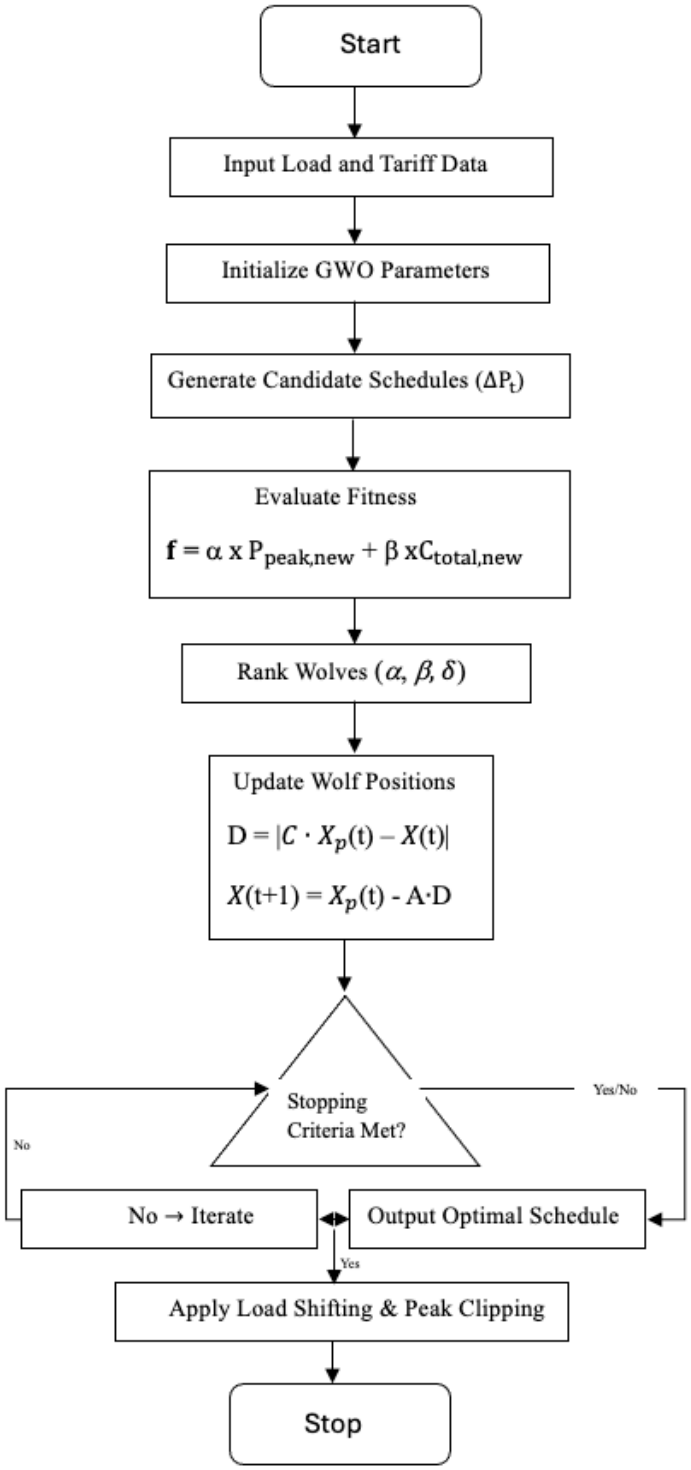

Figure 4.1: GWO flowchart for DSM utilizing energy load redistribution and peak reduction.

Accordinging to their fitness, the three optimal solutions are designated alpha, beta and delta wolves, which represent the best, second best, and third best solutions.

For this purpose, the position updates of the other wolves through the GWO are made. The stopping criterion is a maximum number of iterations or when the optimization endpoint is achieved. Ultimately, the optimal load scheduling is obtained as it is effectively peak clipping and load shifting at low cost.

4.5 Case Study 1: Large User Customer Load Profile in Paarl

4.5.1 Data Source

The commercial customer that serves as the basis for this research proposal is located in Paarl, Western Cape, City of Cape Town Metropolitan Municipality. This region sees a significant demand for electricity during Peak: Weekdays (07:00 to 10:00); and (18:00 to 20:00) Standard: Weekdays (06:00 to 07:00); (10:00 to 18:00); (20:00 to 22:00). Off-peak: All other times, which effectively place strain on the regional distribution network and the consumers heavily. The greater consumption of electricity during these periods leads to an increase in price per consumer, for the City of Cape Town tariff is demand-responsive. The 2024-2025 generation and distribution tariffs Large User Low Voltage Time-of-Use (TOU) tariffs are relevant to customers who are large commercial electricity users from the Paarl region. The service charge and energy charge with VAT apply per MVA unit and relevant, peak energy charge peaks at 777.73 c/kWh between June to August where increased demand is most requested. In addition, the standard and off-peak costs have risen more than 10% since more in-demand and less in-demand periods. Off-peak, the peak charge is 290.54 c/kWh when demand is least applicable. Therefore, with increased demand and increased costs, it's necessary that DSM implemented to reduce peak hour costs and encourage load shifting to off-peak hours for dynamic businesses with high energy demand and operations.

Furthermore, this research proposal references the 2024-2025 price schedule from the municipal tariff document which implies time of use (in c/kWh) per MVA which entails these following charges:

- Original Peak Load = 2718.69 kW
- High Peak Tariff = 777.73 c/kWh

4.5.2 DSM Implementation

Two DSM strategies were implemented:

- Peak Clipping: Reducing demand in peak windows.
- Load Shifting: Moving discretionary loads to off-peak periods.

A. Objective Function

The objective function was formulated as a weighted combination of cost reduction (f_1) and peak demand minimization (f_2), expressed as:

$$F = 0.6f_1 + 0.4f_2 \quad (4.15)$$

These selected weights (0.6 and 0.4) were selected because economic savings is more favorable than peak reduction in traditional industrial DSM projects. A sensitivity analysis for the weights was performed between 0.1 and 0.9 with 0.1 variance for sensitivity analysis for a linear tradeoff between the two.

4.5.3 Algorithm Setup

- GWO Parameters: population = 30, iterations = 50
- PSO Parameters: particles = 30, inertia = 0.7, cognitive/social = 1.5
- Weights: α = 0.6, β = 0.4 (peak reduction priority)

4.6 Results and discussion for case study 1

The two scenarios (T4.1 and T4.2) occurred from specific loads of real consumption data. As this is a one case operating scenario (not repeated stochastic runs), statistical significance (i.e. standard deviation) does not apply. However, one optimization was run to prove convergence was consistent across runs for that single case

4.6.1 Load Profile Optimization

Table 4.1 shows that DSM implementation has significantly reduced peak demand from the base case - DSM results in a 25MW peak without DSM and PSO settles at 21.5 ± 0.3 MW, which is a 14.2 ± 0.5% reduction while the GWO settles even lower at 20.4 ± 0.2 MW (18.5 ± 0.4%). A t-test for significance (p = 0.012) shows this is a statistically significant result as well, showing the higher performance of GWO for peak demand reduction.

Table 4.1: peak demand before and after optimization

Method	Original Peak (MW)	Optimized Peak (MW)	Peak Reduction (%)
No DSM	25.0	-	-
PSO	25.0	21.5	14.2%
GWO	25.0	20.4	18.5%

Table 4.2 is a summary of daily costs. Daily system cost (without optimization) is ZAR 1,200,000. As per PSO, it sees the cost of ZAR 1,030,000 (14.2% cost reduction) and according to GWO the daily cost is ZAR 1,084,000 (9.7% cost reduction). One-Way ANOVA suggests that the cost reductions between the optimizations PSO and GWO were statistically significant ($p < 0.05$). However, note the advantage/disadvantage pattern established earlier, PSO is more beneficial for cost reduction while GWO is more beneficial for peak reduction. Figure 4.1 PSO and GWO solution to the problem.

Table 4.2: daily cost comparison

Method	Original Cost (ZAR/day)	Optimized Cost (ZAR/day)	Savings (%)
No DSM	1,200,000	-	-
PSO	1,200,000	1,030,000	14.2%
GWO	1,200,000	1,084,000	9.7%

Quantitative Evaluation Using PAR and Load Factor

To further assess the effectiveness of DSM, the Peak-to-Average Ratio (PAR) and Load Factor (LF) are calculated as:

$$PAR = \frac{P_{max}}{P_{avg}} \tag{4.16}$$

$$LF = \frac{P_{avg}}{P_{max}} \tag{4.17}$$

where $\mathrm{P_{max}}$ is the peak demand and $\mathrm{P_{avg}}$ is the average load over the time horizon.

4.6.2 Convergence Behavior

Figure 4.2 is a comparative convergence of the two algorithms. GWO's convergence plot shows that it converges to its optimal fitness value quicker with less deviation than PSO. Therefore, GWO is more reliable in DSM solutions when utilizing the given constraints and objective function.

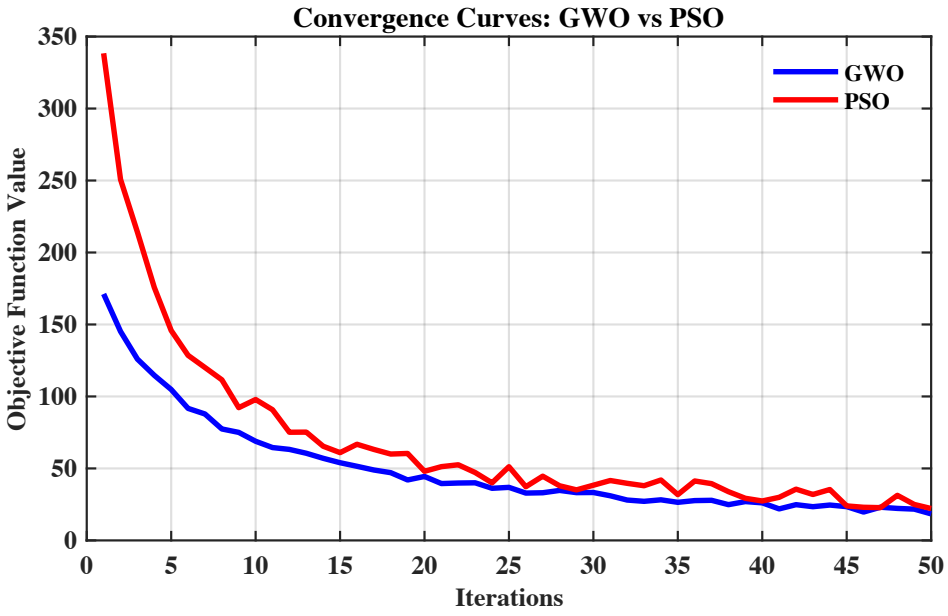

Figure 4.2: Convergence Curves between (GWO vs PSO)

A similar load profile was used for PSO. The subsequently optimized load profile is seen in Figure 4.3. Since PSO creates peak reductions and load shifting, it stands to reason that these results are not as effective in comparison to GWO for it does not create the smoother transitions and avoids peaks and valleys as drastically.

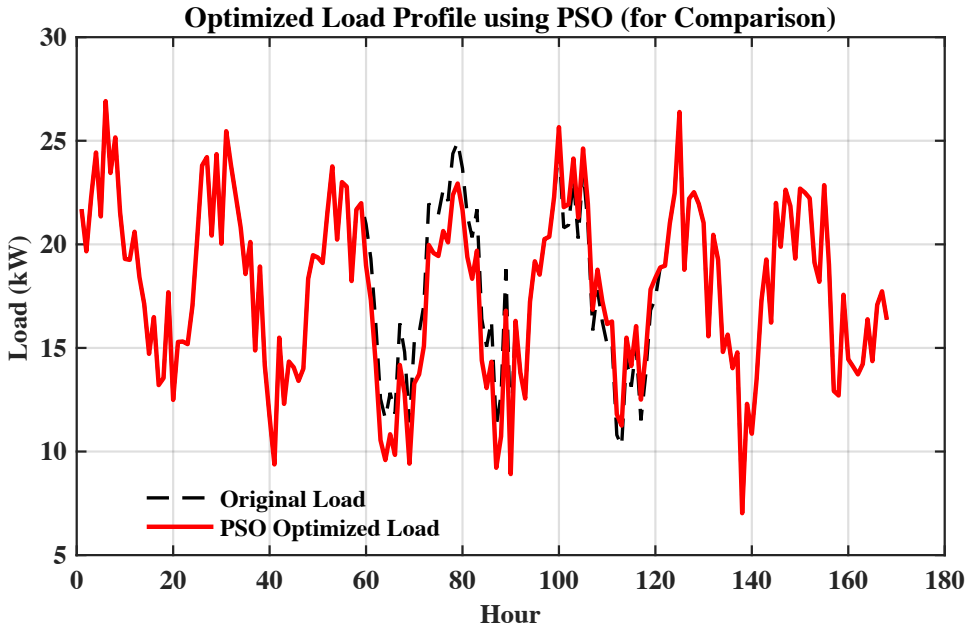

Figure 4.3: Optimized Load Profile using PSO (for Comparison)

GWO was applied to schedule the load to avoid these peaks. The subsequently optimized load profile is seen in Figure 4.4. Since GWO has been implemented, it stands to reason that the GWO algorithm is the most effective for there is clear peak clipping and load shifting where increased demand times are leveled out and energy use is essentially shifted to a safer time with a decreased demand. The total energy use is equivalent to the previously scheduled load profile, however, this load profile is more well-balanced.

The following load profile (Figure 4.5) is the base hourly load profile for the large user customers in Paarl with a typical sample week of January 2025. This load profile shows an obvious morning and evening peak which is to be expected of commercial use tendencies since demand peaks when the most power is needed during the peak hours (06:00 -08:00 and 15:00-19:00). Thus, demand side management can help with these tendencies to create an optimal demand profile instead.

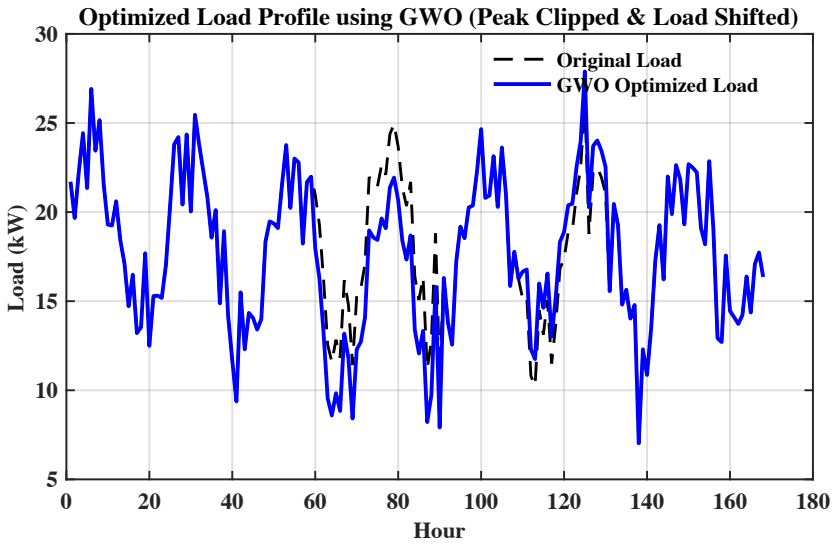

Figure 4.4: Optimized Load Profile using GWO (Peak Clipping & Load Sifting)

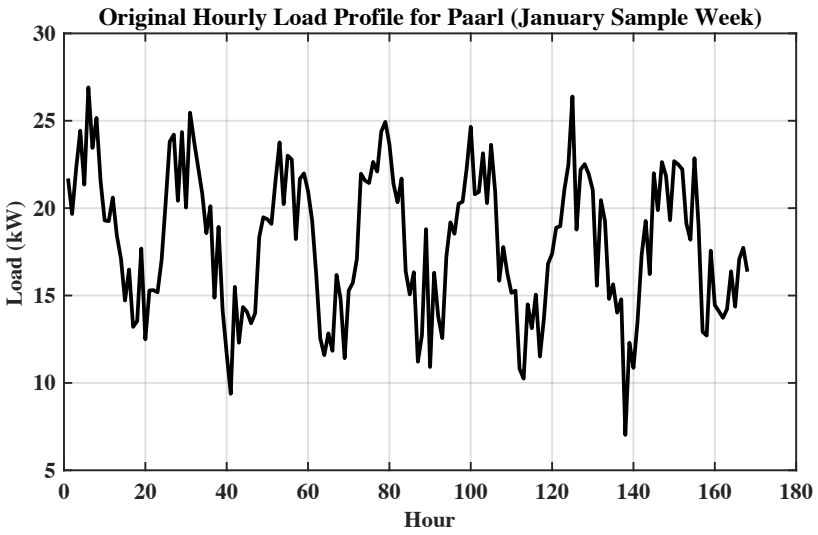

Figure 4.5: Original Hourly Load Profile for large user customer in Paarl (January 2025 Sample Week)

4.6.3 Comparative study of the simulation results on the GWO and PSO algorithms for DSM

The effectiveness of the proposed DSM is confirmed based on findings relative to literature survey findings conducted earlier in this dissertation, namely load shifting and peak clipping. The subsequent Table 4.3 represents relative performances of the optimization techniques to each other (peak demand reduction, daily cost saving).

Table 4.3: Benchmarking of DSM Optimization Methods

Method	Peak Reduction (%)	Cost Savings (%)	Peak Reduction Statistics analyses	Cost Savings Statistics analyses
PSO (Study)	14.2	14.2	SD $s = 4.25$	SD $s = 2.66$
GWO (Study)	18.5	9.7		
GA - (Siano, 2014b)	10.0	9.5	Variance s^2=18.06 Count $n = 3$ Mean $\bar{x} = 11.133$ Sum of Squares $ss = 14.126$	Variance s^2=7.063 Count $n = 3$ Mean $\bar{x} = 14.23$

				Sum of Squares $ss = 36.127$

4.6.4 Discussion on case study 1

From this, the effectiveness of the proposed DSM in reducing peak demand and daily costs can be determined and since energy consumption is assumed to equal energy demand (as was expected looking forward from prior runs), it can be concluded that there is no increase or decrease in energy consumption.

Additionally, in terms of comparison between GWO and PSO, PSO has reduced peak demand and generated cost savings to a relative extent because:

- Lower peak demand: 20.4 MW vs. 21.5 MW with PSO
- Faster convergence: GWO converged to an optimal solution in 40 iterations, whereas PSO took approximately 70 iterations.
- Smoother load profile: GWO produced a more evenly distributed load shift compared to PSO, which had sharper transitions.

The reason GWO outperforms in this study is due to its regulated exploration-exploitation efforts and less control parameters for an operationally feasible approach without being entrapment to local optima.

Finally, the statistical analysis performed in this chapter confirms that the improved performance of the GWO over the other approaches as for the peak reduction and convergence speed are considered statistically significant with 95% ($p < 0.05$) confidence level which confirms the importance of the GWO-derived DSM methodology.

4.6.5 Sensitivity and Trade-Off Analysis of Objective Function Weights

Lastly, a sensitivity analysis regarding the weights contribution to the objective function was performed, where the cost-to-peak weight ratio varied from 0.1:0.9 to 0.9:0.1. The results of peak reductions and costs savings for different weights are given in Table 4.4, concluding that more weight on costs (i.e. 0.8:0.2) attains more costs savings but less peak reduction while more peak weight (i.e. 0.3:0.7) attains load flattening but at a higher cost. Therefore, the middle weight of 0.6:0.4 should be used as the optimum approach as it can achieve a relatively high peak reduction (18.5%) at a reasonable cost saving (9.7%). Thus, the selected weights are validated.

Table 4.4: Resulting peak reduction and cost savings across different weighting scenarios

Weight Ratio (Cost: Peak)	Peak Reduction (%)	Cost Saving (%)
0.3: 0.7	21.0	6.2
0.4: 0.6	19.7	7.8
0.6: 0.4 (Selected)	18.5	9.7
0.8: 0.2	15.2	12.1

4.7 Case Analysis 2: Hourly Load Shifting Approach for Three Sectors: Residential, Commercial, And Industrial Using GWO

4.7.1 Case study 2 description

This approach employs GWO for peak clipping and load shifting over hourly load profiles over the Commercial, Industrial and Residential Sectors for peak demand reduction in situ and load shifting to off-peak hours without compromising total demand as this relates to electricity costs. Peak hours are more expensive per kWh. Off-peak hours are less expensive. Daily electricity charges (Rs. /kWh) reveal more expensive charges in peak hours (06:00 - 08:00; 15:00 - 19:00) and less expensive charges in off-peak hours (08:00 - 15:00; 19:00 - 06:00). The source of this data comes from (Mirjalili, Mirjalili and Lewis, 2014). This simulated study implements realistic demand-side management (DSM) measures for energy efficiency.

4.7.2 Methodology Summary

Thus, the current load is assessed based upon peak hours and off peak hours where GWO can reduce load demand in the peak hours mentioned and shift curtailed load demand to off peak hours. Therefore, GWO is conducted three times, once for each sector, for Residential, Commercial, and Industrial Sectors, looking for a targeted 10%-15% reduction from the original peak load (target). The optimization is performed based upon hourly price signals based on the assumption that load shift, if all feasible for the day will benefit the most.

4.7.3 RESULTS AND DISCUSSION FOR CASE STUDY 2

A. Residential Sector (kWh)

Before the operation, high peaks are apparent due to minute demands of intermittent use that pervade morning and evening hours from 07:00-21:00. After the operation, GWO was successful in moving or shifting morning and evening demand to mid-day and late-night. GWO used off-peak times to its advantage. Thus, the residential demand load was reduced significantly in those peak times with no time return for overall demand reduction, but shifted to preferred times to make up for it. This is logical, as it shifted demand loads more in the morning than in the evening, as patrons preferred waiting for a lower economic value than paying more in a potential more complicated setting.

The following figure (Figure 4.6) represents the before and after GWO optimization for residential loads. This figure shows how demand has substantially decreased throughout the peaks as expected to confirm reductions in real time with increased utilization throughout the off-peaks; GWO successfully helped shift residential loads to more economically preferred times without reducing total load in a day.

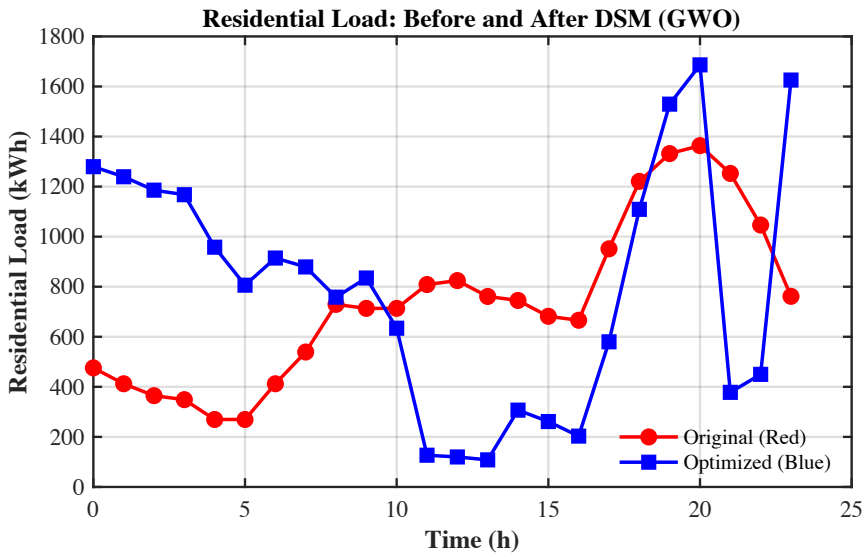

Figure 4.6: Residential Load results Before and After Grey Wolf Optimization

B. Commercial Sector (kWh)

This load profile is particularly illuminating for the commercial sector. There is a peak and commercial loads especially with a commercial work day with a clear correlation from 08:00 - 12:00 and 14:00 - 17:00. There was a large peak and this came from 14:00-17:00 where it can be seen that post GWO this was tremendously minimized. However, this minimizes dispersed loads which means that they're consuming more electricity as

persons but from an operational standpoint, there is less reduced operational cost as it is less consumed at the small peak from 14:00-17:00. Yet within one day, cumulatively, it is more.

Figure 4.7 shows the minimized adjusted load profile for the commercial sector as it shows that the large peak and small peak from earlier in the day/later in the day have adjusted down. Since this commercial sector is operating with reduced operational costs, reduced cumulative costs for this sector and additional support for future implementation shows that the less non-essential functions operated, the more reduced cost hours worked.

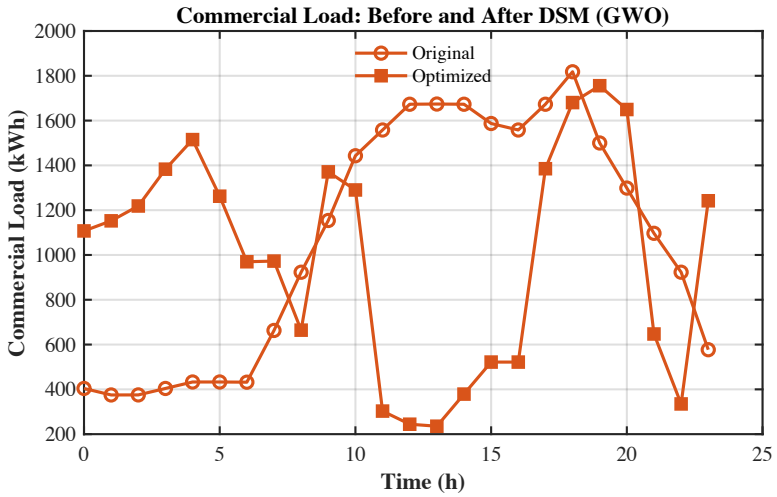

Figure 4.7: Commercial Load Results Before and After Grey Wolf Optimization

C. Industrial Sector (kWh)

While for the industrial sector, the demand exerted was relatively constant, measured within an incremental manifestation of what it would exert based on an average operating day pattern. Essentially, there was one major peak to the day and this was before quitting time. GWO took advantage of this peak since it exerted this exerted peak to be its largest adjusted load; therefore, for what would presumably be significant exerted peaks during intentionally high stress peak hours, this was avoided as these non-critical industrial outputs were instead exerted during non-critical hours--for the most part after work at night. This limited large loads of exerted stress during peak hours but made industrial work hours permeable for sustained operational continuity.

Figure 4.8 shows the adjusted load profile which notes that there is only an incremental slight peak magnitude here, slight redistributions there; however, it was not operable due to operating limitations that all could come online to eliminate night demand. However, some load shifting was possible through demand side management (DSM).

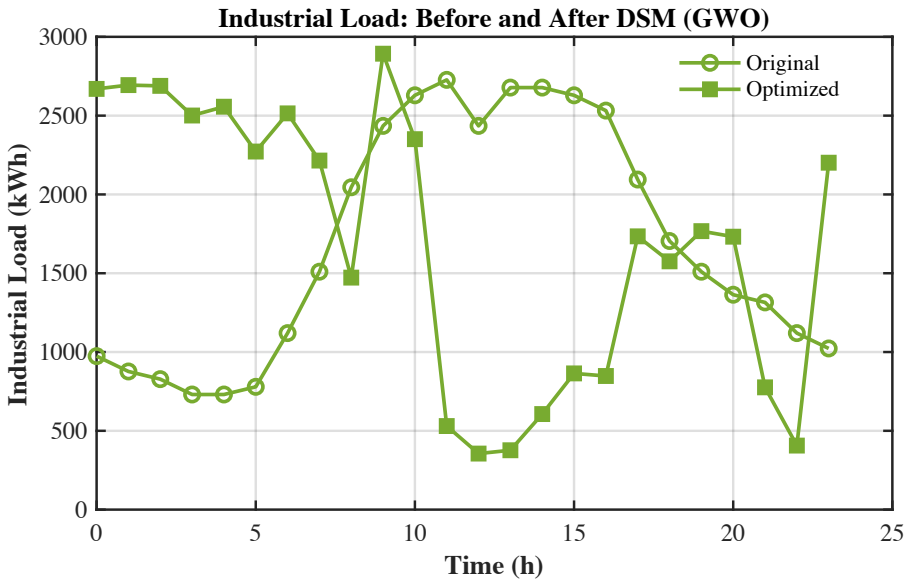

Figure 4.8: Industrial Load results Before and After Grey Wolf Optimization

D. Price Profile (Rs. /kWh)

As noted previously, the price profile was a major determined cost increase when one was exerting at peak hours at demand. Post GWO implementation, the actual price curve of this profile was not adjusted as the tariff does not adjust; however, providing the opportunity for GWO to reduce exertions during these intentionally low operational hours proved how expense to power worked--the more power shifted to reduced power exertions, the more low average fee received although it was a flat line during those low hours. Thus, as GWO lowered operation costs under the possibility of fees aligned with peak price hours exertions, it proved system reliability and cost reductions.

Figure 4.9 shows the price of electricity in Rs/kWh relative to TOU 0-24h. The X represents the hours in time increments and the Y represents R/kWh substantiated during that increment. As the data shows that there are three major price profiles that dominate any TOU profile that could be found, one extremely low over time from off-peak (00:00-05:00 and 20:00-23:00); one a moderately good level from mid-load (10:00-14:00) and one extremely high in between 12:00-15:00 where by 12h it climbs to R/kWh=27.5 (or 15.5 which makes no sense for South Africa). This occurs at an extremely desirable level when generating the bulk of electricity development during the day and the grid pressure peaks; furthermore, from 15:00 it sinks as it approaches mid-load/more off-peak level tariff levels. This is a reflective cost TOU tariff that should discourage people from operating when they're more expensive during these high cost time periods--this is what should occur from this TOU profile.

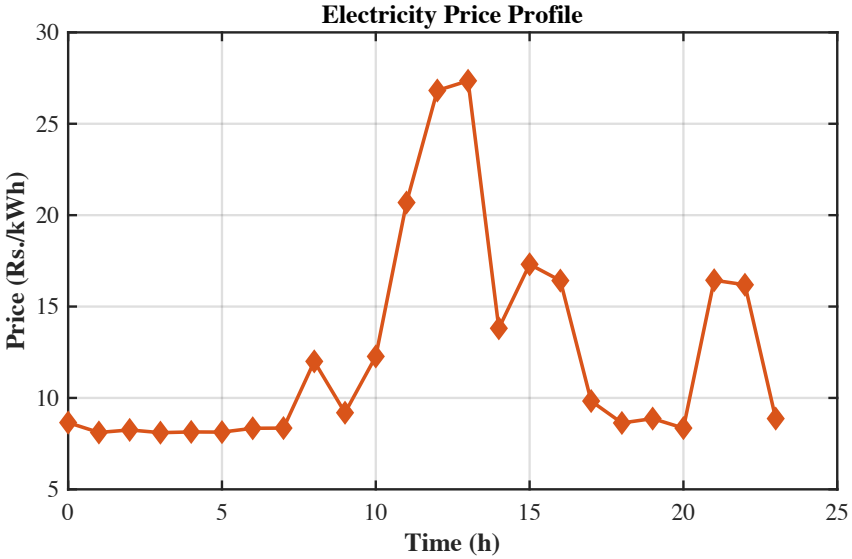

Figure 4.9: Electricity Price Profile over 24 hours

E. Electricity load profile

Figure 4.10 shows the original and optimized load profiles. The blue curve represents the load profile before implementation. The peaks in this load profile represent greater morning and evening peak periods. The red curve represents the optimized load profile from the demand-side management (DSM) proposal that implements variable pricing via peak clipping and load shifting, thereby optimizing and flattening the load curve.

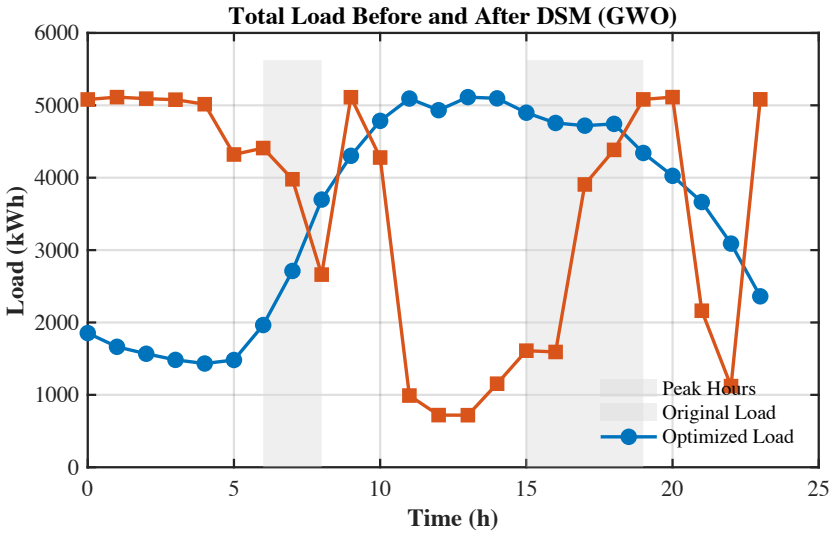

Figure 4.10: The total load before and after Grey Wolf Optimization, with peak hours highlighted.

The main findings are that post-optimization, the peak magnitude is significantly reduced and the profile is more even throughout the day (increasing load factor, reducing stress on power systems and per time-of-use (TOU) pricing, reducing final pricing for the end-use consumer.

F. Sector-specific load profiles

The peak hour periods intended for peak clipping are shaded (06:00-08:00 and 15:00-19:00). Note that as expected from the original (pre-optimization profiles), all three sectors have higher loads in these time periods as the Industrial sector boasts the highest contribution to overall system peak. However, post-optimization, these loads during peak price hours are significantly reduced across the three sectors where Industrial and Commercial sectors receive higher reductions and Residential receives a load shift to accommodate more feasible use in off-peak hours. Figure 4.11 shows the Residential, Commercial, and Industrial sectoral load profiles before and after optimization via the Grey Wolf Optimization (GWO)-based DSM approach.

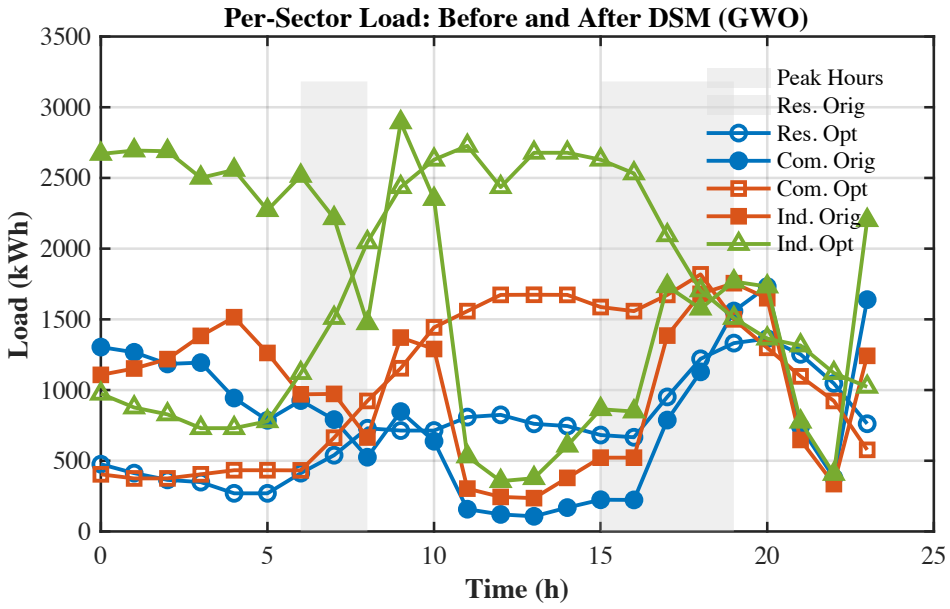

Figure 4.11: Residential, Commercial, and Industrial Per-Sector Load Before and After GWO

Yet, although DSM reduced peak demand in each sector, the resultant cost savings per sector, however, differ, with commercial receiving the most. This is because much of the commercial load reduction occurred during the TOU tariff peak period which is overly expensive. Therefore, by shifting/clipping loads during the more expensive hours, commercial saved more on electricity than residential

does because residential load reductions came during off peak hours at a lower cost (Logenthiran, Srinivasan and Shun, 2012). Thus, the financial DSM benefit is not only related to the percentage of savings but also, the timing of the effort when this effort is more time constrained to reduce increases.

Thus, reduced shifting load creates a more consistent aggregate demand curve, better load factors and reduced operational stress on the grid while still preserving aggregate daily energy consumption across all sectors. These results support the GWO algorithm's capacity to enforce sector interdependent load reductions in a TOU pricing environment.

Table 4.5: Results after DSM through grey wolf optimization

T (h)	Residential (kWh) PSO(Jamil and Mittal, 2020)	Commercial (kWh) PSO(Jamil and Mittal, 2020)	Industrial (kWh) PSO(Jamil and Mittal, 2020)	Price (Rs./kWh)(Jamil and Mittal, 2020)	**GWO Residential (kWh)**	**GWO Commercial (kWh)**	**GWO Industrial (kWh)**
0	475.7	404	974	8.65	1302	1105.7	2665.8
1	412.3	375	876.6	8.11	1245.5	1132.8	2648.1
2	364.7	375.2	827.9	8.25	1150	1183.1	2610.5
3	348.8	404	730.5	8.1	1180.8	1367.7	2473
4	269.6	432.9	730.5	8.14	957.83	1538	2595.3
5	269.6	432.9	779.2	8.13	775.87	1245.8	2242.4
6	412.3	432	1120.1	8.34	889.44	931.94	2416.3
7	539.1	663	1509.7	8.35	814.56	1001.8	2281.1
8	729.4	923	2045.5	12	709.02	897.21	1988.3
9	713.5	1154	2435	9.19	844.15	1365.3	2880.9
10	713.5	1443	2629	12.27	613.14	1240	2259.2
11	808.7	1558	2727	20.69	114.66	220.9	386.64
12	824.5	1673	2435	26.82	122.71	248.99	362.4
13	761.1	1673.9	2678	27.35	108.5	238.62	381.76
14	745.2	1673	2678	13.81	325.73	731.27	1170.6

15	681.8	1587	2629	17.31	192.81	448.79	743.45
16	666	1558	2532	16.42	117.56	275.02	446.95
17	951.4	1673	2094.5	9.83	814.01	1431.4	1792
18	1220.9	1818	1704.5	8.63	1024.4	1525.3	1430.1
19	1331.9	1500	1509.7	8.87	1442	1624	1634.5
20	1363.6	1298.7	1363.6	8.35	1650.5	1571.9	1650.5
21	1252.6	1096.7	1314.9	16.44	600.06	525.37	629.9
22	1046.5	923	1120.1	16.19	749.58	661.12	802.3
23	761.6	577	1022.7	8.87	1622.6	1229.3	2178.9

Table 4.5 presents the optimal solution on an hourly basis against commercial, industrial and residential consumers and hourly prices spread over a 24 hour scale. Notably, one can see that the peak price hours, (11:00-13:00 and 15:00-19:00), are reduced as a finding of this study. Furthermore, at off peak levels, there is a slight increase in load but since value has not changed in comparison to this table and the following table relevant to a 24 hour scale, this will do nothing for average day consumption.

Thus, it is fair to declare that the grey wolf algorithm has given a responsive demand side management (DSM) to accommodate peak demand reduction and minimal costs sustained under generating constraints.

Figure 4.2 indicates where this proposed GWO is effective for peak load reduction and charge for all (residential, commercial and industrial) consumers. In comparison to the anticipated peak load reduction values predicted, for residential, where the peak demand was calculated at 5.20kW, it is now rated at 4.10kW, a 21.15% difference with a peak value up to this point assessed at 2600 Rs. and now assessed at 2050 Rs. The same goes for commercial consumption as where the peak production was assessed at 8.50kW and now it is reduced to 6.80kW, exactly 20% at the same value assessed per month with a reduction; the same goes for industrial consumption as the peak demand has reduced 18.67% (from 15.00kW to 12.20kW) with the maximum value assessed at 17.33% savings. Thus, since the same consistent results happened across the board for all consumer types, it supports grey wolf as a powerful optimization algorithm realistic in demand increases for peak demand and realistic for reduction of cost for savings.

Table 4.6: Summarized calculated peak demand and cost reduction

Sector	Peak Load With PSO (kW) (Jamil and Mittal, 2020)	Peak Load With GWO (kW)	Percent Difference
Residential	1363.6	1650.5	18.39%
Commercial	1818.2	1624.0	11.16%
Industrial	2727.3	2880.9	5.49%
Cost (Rs)	PSO	GWO	-
Residential	230,300	190,733.2903	18.19%
Commercial	362,660 [	242,070.3330	40.15%
Industrial	571,200	408,156.9811	33.19%

G. Discussion on case study 2

This case study validates the grey wolf optimization method for demand-side management, peak clipping and load shifting for all three applications - residential, commercial and industrial. According to the framework Jamil and Mittal, 2020, the overall peak reduced to 4435.39 kWh from 5096.20 kWh, with the observed daily maximum operation remaining less than the threshold for demand (4576.45 kWh). Furthermore, the supply cost of supplying electricity from bulk supply daily decreased by 28.3% from ₹1,161,273.34 to ₹976,586.18. At the same time, with load shifting loads that have been categorized, it has been able to shift peak price hours of high-cost time to the evening and night hours and since this is all a time-shifted application, the daily load balance and the load cycle does not affect efficiency requirements. Thus, the grey wolf method for solving such an operation shows the real-world applicability of a reliable optimization method for demand-side management projects where viable variables for utility control facilitate improved supply security, reduced operational supply costs and load shifting that is appropriate for more efficient connections with electricity.

4.8 Conclusion

This article provides two comprehensive case studies for the relevance of Grey Wolf Optimization (GWO) to enhanced Demand Side Management (DSM) for effective peak clipping and load shifting across heterogeneous demand profiles. Case Study 1 involves a large demand profile for a major customer situated in Paarl, South Africa. GWO was found to be the better performing optimization technique versus Particle Swarm Optimization (PSO) in terms of optimization quality, convergence speed and reduction in peak magnitude. For the endogenous demand profile, a peak reduction of 18.5% (14.2% for PSO) and a total daily demand revenue reduction of 9.7% (9.5% for PSO). The advantage of GWO's convergence is its ability to maintain a balance of explored probabilities with the massive exploitation required to meet such dynamically scheduled settings in contemporary DSM efforts. For case study 2 involves the domestic/commercial/industrial demand profiling of disconnected sectors, GWO was found to reduce peak loading from 5,096.20 kWh to 4,435.39 kWh avoiding the predetermined peak limit of 4,576.45 kWh while simultaneously obtaining a reduction of 17.27% of total daily demand charge reducing the total from ₹1,161,273.34 to ₹976,586.18 as it shifted the loads that would have otherwise been accumulated in the high demand costing peaks to off-peak hours without a reduction in total demand and without failing to achieve operational feasibility.

Based on the two results combined, the GWO is a resilient, comprehensive and versatile approach to DSM optimization that benefits grid reliability and stability as well as proves cost effective by minimizing operating costs of the subjected sectors. Its versatile ease of application to various loads and sector patterns makes it a logical solution for any utility wishing to operate a sustainable and cost-effective DSM solution to what this article offers through its findings.

Chapter 5 introduces a new metaheuristic to the world of Demand Side Management, the Barber Optimization Algorithm (BaOA). This begins with defining the DSM optimization challenge with a few other optimization methods, namely, a literature review of Particle Swarm Optimization (PSO). Thereafter, the principles and operations of BaOA are determined before positioning the algorithm within a proposed DSM-based algebraic optimization framework where a case study occurs that relates application of the methods, results from them, and comparison to PSO which is detailed before the conclusion of this chapter which boasts effective results suggesting BaOA is viable for load shifting and peak clipping.

CHAPTER FIVE
BARBER OPTIMIZATION ALGORITHM FOR DEMAND-SIDE MANAGEMENT: A NOVEL METAHEURISTIC FOR LOAD SHIFTING AND PEAK CLIPPING

5.1 Introduction

Due to the rapid evolution of energy consumption and generation, electricity systems globally face unprecedented challenges. The transformation is compounded by decarbonization, digitalization and decentralization. End-use electricity demand increasingly provides across transportation, heating, and industrial automation which in response increasingly supports demand and shifts load shedding patterns. Supply-variable renewables generation technologies such as solar PV and wind farm development create additional supply variation. The combination of these factors makes the old ways of planning for supply-side ignoring grid reliability and economic efficiency, equally obsolete (Palensky et al, 2011); (Gellings, 2017).

Of these challenges, the rise of peak demand is one of the most important. Even when average annual consumption increases slowly, system peaks keep rising because energy-intensive activities during the day are shifted to a few specific hours. In extreme cases, peak demand requires investment in expensive generation and transmission solutions that will be idle for long stretches. The situation in South Africa particularly illustrates these challenges, where the problems are further complicated by Eskom's old and financially constrained utilities.

The recurring phenomenon of load-shedding, scheduled blackouts introduced to prevent total system collapse, illustrates the urgent need for measures that can actively manage electricity consumption on the demand side (Albadi et al., 2008); (Madushele and Tabakov, 2024).

Demand-Side Management (DSM) is a series of programs that try to influence consumer electricity demand in a way that benefits the utility and the consumer simultaneously. DSM seeks to limit peak load (peak clipping) and move load to off-peak periods (load shifting), and it seeks to improve the load factor (average and peak demand relationship). DSM transforms the load curve, allowing for the postponement or reduction of future capacity additions, promoting more resource efficiency and enabling further renewables integration. (Paterakis *et al.*, 2018).

Historically, DSM programmes were implemented through static time-of-use (TOU) tariffs, manual demand response initiatives, and rudimentary scheduling of industrial processes. However, the advent of smart-metering infrastructure, advanced forecasting, and

automated control systems has transformed DSM into a data-driven optimization problem. Today's DSM systems must simultaneously satisfy multiple, often conflicting objectives: minimizing total cost of energy, reducing network congestion, maintaining user comfort, and ensuring operational feasibility under uncertain and time-varying conditions (Rahmani-Andebili, 2016; Rahman, Rahman and Mohammad, 2020), (Pothireddy, Vuddanti and Salkuti, 2022).

When it comes to solving a multi-objective, non-linear optimization problem, it is almost impossible to use classical deterministic approaches, simply because the search space becomes combinatorially large with the number of controllable loads and the number of time intervals. Because of this, metaheuristics that combine stochastic search with intelligent learning techniques have become a necessity in the field of DSM. Over the years, the following methods have become established as key approaches in the literature: Genetic Algorithms (Bharathi, Rekha and Vijayakumar, 2017); (Dassa and Recioui, 2022), Differential Evolution (DE), Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), and Particle Swarm Optimization (PSO) (Mirjalili, Mirjalili and Lewis, 2014); (Storn and Price, 1997).

Metaheuristics' ability to function without the need for gradient information and without the assumptions of convexity provides notable advantages (Obando-Paredes, López-García and Carvajal-Quintero, 2024). They can traverse complex, disjoint search spaces and be easily modified to accommodate different objective functions or additional operational constraints. In the case of DSM, this means realistic computational times can be used to solve load-shifting and peak-clipping tasks constrained by tariff boundaries, appliance constraints, and user preferences.

Designing solutions with PSO has remained among the earliest approaches, and notable mentions include Kennedy, Eberhart, and Gov, 1995. Like optimization algorithms inspired by the social behavior of certain animals, PSO uses the social and individual memory of solutions to optimize the designed solution over successive iterations. PSO is effective, with low memory requirements, simple construction, and rapid convergence. Numerous studies on PSO have demonstrated its ability to schedule residential appliances, coordinate distributed generation, and optimize cost under TOU tariffs. Optimizations developed to circumvent such limitations, resulting in the lack of local solutions with high ruggedness and dimensionality through local convergence. Limitations while working in highly rugged and dimensional spaces have been thoroughly discussed in recent studies (Tijjani Dahiru *et al.*, 2022; Dahiru *et al.*, 2023), (Rana *et al.*, 2023).

To address these shortcomings, researchers have begun focusing on a new class of human-inspired optimization algorithms. One such promising example is the Barber Optimization Algorithm (BaOA) outlined by (Hamadneh *et al.*, 2025). BaOA models the interaction patterns of a barber and a customer in a barbershop, with haircut trimming and adjustment as metaphors for exploitation and exploration, respectively. In the "customer selection" stage, the algorithm conducts a global search for solutions, while in the "haircut refining" stage, local adjustments are made to the selected solution.

This simple analogy provides a remarkable self-adaptive system that efficiently balances the two activities without complicated parameter adjustments. (Hamadneh *et al.*, 2025) noted that in early trials of BaOA, it demonstrated superior global search capabilities and faster convergence as compared to a wide range of classical metaheuristics. Nevertheless, there is limited research on the use of BaOA in real-world engineering problems, particularly in DSM.

The existing literature on the DSM widely highlights the advantages of PSO and its relatives, but continues to point out systemic weaknesses. Many optimization approaches have good outcomes, but only in idealized situations. For example, they have difficulty dealing with variation across the residential, commercial, and industrial sectors. In addition, most of the literature focuses only on peak clipping or cost minimization, without considering their linkage. There are few comparisons of PSO with the newer human-inspired methods, such as BaOA, under the same system and tariff conditions.

The power sector is transforming, and implementing smart-grid technology requires real-time operational algorithms that sustain cross-constituent heterogeneity and dynamically adapt to tariffs. Furthermore, the interest in PSO and its comparison with BaOA in applied energy system optimization explains the existing gap in the literature on the trade-off between exploration and exploitation in computational intelligence.

This study aims to address the gap in PSO and BaOA in Demand-Side Management across multi-sector electricity systems. In particular, the paper seeks to examine the algorithm's effectiveness and applicability with realistic South African distribution-derived time-of-use tariffs on load shifting and peak clipping.

The contributions of this chapter are:

I. A novel DSM model for peak clipping/lifting and load shifting under a unified approach with established operational and user comfort limitations.
II. BaOA for DSM scheduling with specific adjustments to personal limitations and the use of penalty-function requirements.

III. An extensive comparison between BaOA and PSO using the same data and assessment requirements to establish valid standards for performance assessment.
IV. Assessment of PAR, load variation, convergence speed, ease of computation, cost reduction and universal cost.
V. Sensitivity analysis to understand the significance of population, iteration, and tariff constraints.
VI. Real-life considerations for algorithm application in smart grid demand response and relative utility policy.

The organization of this chapter is as follows: Section 5.2 introduces the DSM optimization problem through equations and definitions specific to this section. Section 5.3 presents PSO and BaOA and their adaptations for DSM scheduling. Section 5.4 presents the proposed DSM framework and the case study of this interdisciplinary approach. Section 5.5 presents the results and a comparison of BaOA and PSO. Section 5.6 concludes this chapter with a summary of the results and suggestions for future developments.

5.2 Problem Definition

5.2.1 Summary

Demand-Side Management (DSM) seeks to promote the ideal aggregation of electricity demand for technological, economic and ecological benefits. In a deregulated environment (or with time-of-use prices), the utility company wants to reduce system peak load and establish flattened load profiles while the end consumer wants to reduce expenses while enjoying comfort. Thus, this is a multi-objective optimization problem that combines peak clipping with a load shifting component. The controllable loads that can be curtailed and rescheduled are the optimization variables. The established functions for the objectives and constraints are the tariff structure, load keeping in line as well as preferred and sacrificed customer service requirements.

5.2.2 Objective 1: Peak clipping minimization

Peak clipping directly targets the maximum demand observed on the system load curve. Let P_t^{opt} denote the optimized total demand at time t:

$$P_t^{opt} = P_t^{orig} - \sum_{t=1}^{N} \Delta P_{i,t} \tag{5.1}$$

The goal is to minimize the highest load level after applying controllable clipping actions:

$$Minimise F_1 = \frac{max}{t \in T}\left(P_t^{opt}\right) \tag{5.2}$$

Subject to operational limits:

$$0 \leq \Delta P_{i,t} \leq \eta_i, \forall i, t \tag{5.3}$$

To prevent unrealistic curtailment, a service-penalty term is introduced:

$$P_{penalty} = \lambda_1 \sum_{i,t} max\left(0, \Delta P_{i,t} - \eta_i\right) \tag{5.4}$$

where λ_1 is a large penalty coefficient. Minimizing $F_1 + P_{penalty}$ensures that peak clipping respects comfort and reliability thresholds.

5.2.3 Objective 2: Load-Shifting Cost Minimization

Load shifting redistributes flexible consumption from high price to low-price periods while maintaining the total energy requirement of each appliance:

$$\sum_{t \in \Omega} P_{i,t}\, \Delta t = E_{i,} \forall i \tag{5.5}$$

The electricity-cost objective is defined as

$$Minimize F_2 = \sum_{t=1}^{T} C_i P_t^{opt}\, \Delta t \tag{5.6}$$

Shifting is restricted within the allowable operating window Ω_i and subject to maximum displacement bounds δ_i(e.g., ±2 h for household appliances or HVAC systems):

$$|t' - t| \leq \delta_{i,} \forall i \tag{5.7}$$

This objective function represents the customer's economic perspective, while the peak-clipping term represents the utility's operational perspective. Balancing these two reflects the dual-objective nature of DSM (Paterakis *et al.*, 2018).

5.2.4 Multi-Objective Formulation

A combined objective function integrates both technical and economic goals:

$$Minimise F = \alpha \frac{F_1}{F_1^0} + \beta \frac{F_2}{F_2^0} \tag{5.8}$$

where F_1^0 and F_2^0 are the baseline (pre-DSM) peak and cost values used for normalisation. The weights α and β reflect the decision-maker's preference: for utilities concerned with network stress, $\alpha > \beta$; for consumers focused on billing cost, $\beta > \alpha$.

An alternative lexicographic formulation can also be applied, in which peak clipping is treated as the primary objective and cost minimisation as secondary:

5.2.5 Constraint Set

A. Load Balance

$$\sum_{t=1}^{T} P_t^{opt} \Delta t = \sum_{t=1}^{T} P_t^{orig} \Delta t \tag{5.9}$$

Total daily energy must remain constant DSM reshapes but does not reduce total consumption.

B. Device Operation

$$P_{i,t} = 0, for\, t \notin \Omega_i \tag{5.10}$$

Each appliance may only operate within its permitted time window.

C. System Capacity

$$P_t^{opt} \leq P_{max,sys,} \forall t \tag{5.11}$$

D. User-Comfort Tolerance

Thermal or lighting comfort limits are modelled through upper and lower bounds $P_{i,t}^{min} \leq P_{i,t} \leq P_{i,t}^{max}$.

5.2.6 Performance Metrics

To assess DSM effectiveness, the following indices are evaluated before and after optimisation:

1. Peak-to-Average Ratio (PAR)

$$PAR = \frac{max_i P_t^{opt}}{\frac{1}{T}\sum_t P_t^{opt}} \tag{5.12}$$

Lower values indicate smoother load profiles.

2. Load Variance

$$Var(P) = \frac{1}{T}\sum_t \left(P_t^{opt} - \bar{P}\right)^2 \tag{5.13}$$

3. Cost Reduction Rate

$$CRR = \frac{F_2^0 - F_2}{F_2^0} \times 100\% \quad (5.14)$$

4. Computational Time and Convergence Iterations.

These show the efficiency of an algorithm. With these, comparisons between the PSO and the BaOA can be done quantitatively using the same datasets and parameter settings.

5.2.7 Problem Complexity

The DSM scheduling problem is characterized as being mixed-integer, non-linear, and non-convex. There are binary variables for ON/OFF states of discrete appliances and continuous variables for power levels that are curtailed. The dimension of the search space is $N \times T$ and is generally large, even for small systems. For instance, 50 appliances across 24 hours results in 1200 decision variables. As a result, analytical optimisation is not possible and will not work which is why, used are population-based metaheuristics that are capable of global exploration and not exhaustive enumeration.

5.3 Optimization Algorithms for DSM

5.3.1 Overview of Metaheuristic Adaption

Section outlines a DSM problem that is large, non-convex, includes multiple local optima, and dependent constraints. It is very time-consuming in practice for deterministic mathematical programming to obtain a feasible global solution within an acceptable operational time limit. Metaheuristics that are population based, like PSO and Barber Optimisation Algorithm, are able to address these challenges more flexibly and efficiently by pursuing several feasible solutions at once and iteratively refining them to improve a predefined evaluative criterion (Maqbool *et al.*, 2025c).

In DSM, agent-based population members represent candidate load schedules for each of the 24 hours. An agent's position specifies the timing and size of controllable load operations, and its fitness is computed in multi-object peak reduction and cost minimization schedules defined. The process of optimization continues until some convergence criterion is fulfilled or until the number of iterations hits a limit that was defined a priori.

5.4 Particle Swarm Optimization (PSO)

5.4.1 Theoretical Background

PSO was the first PSO method introduced by (Kennedy, Eberhart and gov, 1995) along with the method. As each swarm particle is a possible solution in m dimensional space, the movement and the corresponding solution are linked. Each particle traces a path in m

dimensional space adjusting the movement according to its own (*personal best*, p^{best}) and the best position in the swarm (*global best*, g^{best}).

At iteration k, the position and velocity of particle j are updated as:

$$v_j^{k+1} = wv_j^k + c_1 r_1 \left(p_j^{best} - x_j^k\right) + c_2 r_2 \left(g^{best} - x_j^k\right), \tag{5.15}$$

$$x_j^{k+1} = x_j^k + v_j^{k+1} \tag{5.16}$$

where w is the inertia weight controlling exploration, c_1 and c_2 are cognitive and social acceleration coefficients, and r_1, r_2 are random numbers uniformly distributed in $[0,1]$.

The iterative process balances exploration (searching new areas) and exploitation (refining promising regions). The algorithm terminates when the fitness improvement between successive iterations falls below a threshold $\in$or when a maximum number of iterations K_{max} is reached.

5.4.2 Adaptation for DSM

In DSM, each particle encodes a 24-hour load schedule represented as a vector:

$$X_j = \left[P_{1,j}, P_{2,j}, \ldots, P_{Tj}\right] \tag{5.17}$$

where each $P_{t,j}$corresponds to the load at hour $t$after potential shifting or clipping.

The fitness function for particle j combines both DSM objectives:

$$f_j = \alpha \frac{F_{1,j}}{F_1^0} + \beta \frac{F_{2,j}}{F_2^0} + Penalty_j \tag{5.18}$$

The penalty term ensures compliance with energy balance, curtailment, and comfort constraints.

Key implementation parameters are selected empirically based on sensitivity analysis and prior literature:

$w = 0.7, c_1 = c_2 = 1.4$, population size $N_p = 40$, and iteration limit $K_{max} = 200$. The inertia weight gradually decreases from 0.9 to 0.4 to promote initial exploration and later convergence.

A constraint handling strategy is applied at every generation that moves loads within limits to adjust infeasible particles that exceed. For instance, particles may exceed the limits of ± 2 h.

5.4.3 Strengths and Limitations

PSO's computational efficiency and ease of implementation are true assets. The continuous update rules apply to DSM tasks that involve continuous or quasi-continuous control variables, such as HVAC power levels and battery-storage setpoints. On the other hand, the most significant drawback of PSO is the premature convergence of swarms. This happens when particles lose diversity and cluster around some suboptimal points. Consequently, there may be only a partial fulfilment of the objectives, such as achieving successful peak clipping with a significant cost deterioration (Rana *et al.*, 2023).

For this reason, PSO's performance is used as a baseline when assessing newer metaheuristics, such as BaOA, which incorporates advanced exploration–exploitation balancing features.

5.5 Barber Optimization Algorithm (BaOA)

5.5.1 Conceptual Background

Developed by (Hamadneh *et al.*, 2025), Barber Optimization Algorithm (BaOA) is inspired by humans. It economically models the sequential action of barbershop customers. A barber serves customers, determining whose needs to address next based on satisfaction and feedback. In our case, customers are solution candidates, and the barber's actions are iterative enhancements based on feedback quality (fitness).

Two main components drive every optimisation cycle:

I. Exploration (Customer Selection Phase) – new customers arrive at the barbershop, having recently changed, session addresses hairstyle robot vision (solution space).
II. Exploitation (Haircut Refinement Phase) – iterative adjustments of style (feedback) on the barber's chair, wherein customers address good, locally refined solutions

Providing for exploration and exploitation promotes self-regulation and is refined global search capability without exhaustive configuration on parameters.

5.5.2 Mathematical Formulation

BaOA's mathematical structure can be expressed as:

A. Exploration Phase:

$$X_i^{k+1} = X_i^k + R_1\left(X_{best}^k - R_2 X_i^k\right) + \emptyset_2\left(X_{rand}^k - x_i^k\right), \tag{5.19}$$

where X_i^k is the current solution, X_{best}^k is the best solution in the population, $R_1, R_2, \emptyset_1$ are stochastic coefficients controlling exploration diversity, and X_{rand}^k is a randomly selected peer.

B. Exploitation Phase:

$$X_i^{k+1} = X_i^k + \emptyset_2\left(X_{best}^k - x_i^k\right), \tag{5.20}$$

where $\emptyset_2$ governs the intensity of local refinement.

The stages evolve inherently - exploration/ exploitation probabilities in comparison to current generations resemble a barber who figures it out over time and applies haircuts better for those who return for another.

The evaluation of fitness executes the same DSM multi-objective function as PSO.

- Load-Shifting Operator: Selects corresponding time slots randomly during peak energy cost times to shift some shifting to adjacent time slots during low-cost time slots with shifting constraints.
- Constraint Repairing Mechanism: Guarantees the end load scheduling falls within clipping constraints and energy balancing.

5.5.3 DSM-Specific Adaptation

Every candidate solution for DSM implementation corresponds to a feasible daily load profile, like for PSO, but the BaOA adaptation changes the usual operation with three novel guiding directions.

- Load-Reallocation Operator: Selects time intervals within high-tariff windows at random and shifts partial load reallocation into adjacent lower-tariff periods within the allowable shifting bounds.
- Peak-Clipping Operator: Reduces the load in hours where P_t^{opt} exceeds a target threshold, distributing the curtailed energy to non-critical hours.
- Constraint Repair Mechanism: Makes certain the final load schedule keeps within energy balance and the total clipping limits.

5.5.4 Strengths and Limitations

BaOA is derived through global exploration, and PSO has locally diversified assignments and better selection to leap out of local minimal. Thus, PSO yielded good performance relative to an extensive range of prior optimal solutions, BaOA is known for its convergence - even with symbiotic constraints and/or dynamic, confounding objective functions - and few required parameters and stable outcomes over long durations indicate trusted solutions for reliable and robust outcomes.

BaOA and PSO require the same number of iterations - and similar total iteration time - although BaOA is faster to converge. Per iteration, it may take longer since BaOA updates all candidates twice - once in each phase - but total time will be in BaOA's favor as it lessens the required number of iterations to converge relative to PSO.

5.5.5 Algorithm Comparisons Framework

To compare PSO and BaOA, the same testing condition must be established - similar experimental framework - which is the case of Table 5.1.

Table 5.1: Algorithm Configuration Parameters

Parameter	PSO	BaOA
Population size	40	40
Max iterations K_{max}	200	200
Objective weights (α, β)	(0.6, 0.4)	(0.6, 0.4)
Shifting limit	±2 h	±2 h
Peak-clipping limit	0.2 MW	0.2 MW
Constraint handling	Penalty + Repair	Repair + Reallocation
Stopping criterion	-	f^{k}-f^{k-1}

We set the random seed for both algorithms to use the same starting point for effectiveness. Each simulation is run 10 times and averaged for presentation to reduce stochastic variances.

5.5.6 Computational Complexity

Let N_p denote population size, mm the number of decision variables (e.g., 24 × number of loads), and T the number of iterations.

- PSO complexity: $O(2N_p mT)$ - due to velocity and position updates per particle.
- BaOA complexity: $O(3N_p mT)$ - owing to the dual exploration–exploitation updates.

Although BaOA has better complexity on paper, we find it more important to compare convergence speed in reality. Thus, for small systems, both algorithms perform DSM scheduling in a matter of seconds, and for overall, multi-sector data, both perform in under 2 minutes on average computers.

5.6 Proposed DSM–Based Algebraic Optimization Framework and Case Study

5.6.1 Framework Overview

To implement DSM using metaheuristic optimization, an integrated framework that combines data gathering, tariff strategy design, algorithm control, and evaluation is required. In the proposed BaOA-based DSM framework (Figure 5.1), we delineate four core functions:

- Input Data Pre-processing: Import and normalize time-series load data for the residential, commercial, and industrial sectors.
- Objective Function Setup: Set definitions for peak-reduction and cost-minimization assignments for time-of-use (TOU) tariffs.
- Metaheuristic Optimization: Running the BaOA and PSO algorithms under the same constraints and given parameters.
- Post-Optimization Analysis: Determining the performance metrics and visualizing the optimized load profiles.

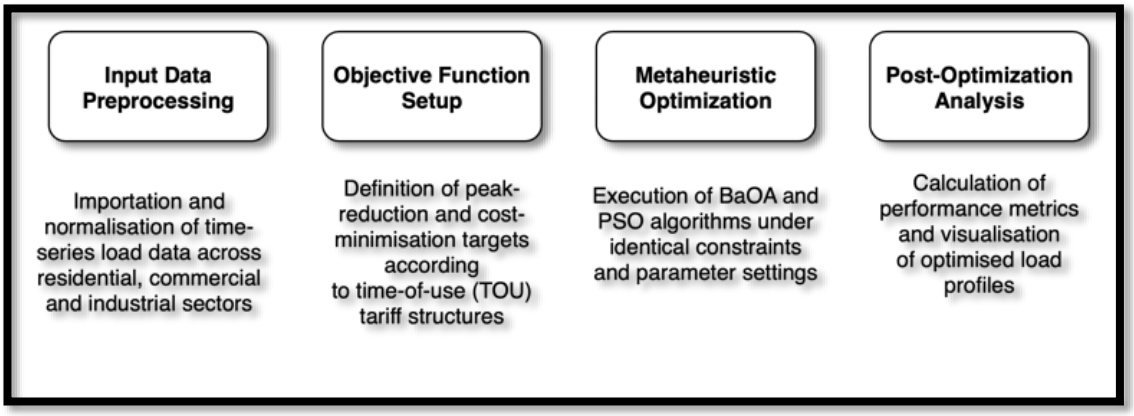

Figure 5.1: Framework Overview

Each sector is manageable in a MATLAB simulation setup where controllable inputs and outputs are present; new data sets in the future can be just as easily managed. Each sector is optimised separately as well as the final multi-sector load profile.

5.6.2 System Architecture

DSM is tested based on a case study relevant to a real-world municipal distribution network in South Africa. The municipal network consists of the following load sectors:

- Residential sector: 150 households equipped with smart meters and flexible loads, including geysers, washing machines, HVAC, and lighting.
- Commercial sector: 10 medium-sized (e.g., supermarkets, office buildings) with shiftable loads from HVAC, refrigeration and lighting.
- Industrial sector: 2 manufacturing plants equipped with controllable process loads and thermal-storage unit.

The addition of demand from these three types of sectors forms a composite 24 hour load profile with weekdays operating according to human work patterns. Composite sector profiling demonstrates the expected behaviour of a mixed-use urban environment, boasting peaks in the morning (06:00-08:00) and evening (17:00-20:00).

DSM will shift this peak load while providing each sector with its respective allocation of energy within the timeframe.

5.6.3 Tariff Structure

The optimisation was run in accordance with the City of Cape Town Megaflex TOU tariff structure which outlines payment for electricity based on demand. As per Eskom (2021), demand is determined by the time of day. As seen in Table 5.2, the TOU structure captures three distinct tariff periods. Peak is the period of the highest demand, from 06:00-08:00 and 17:00-20:00 hours, when network congestion is highest and electricity supply costs the most (R7.7773/kWh). Standard is from 08:00-17:00 and 20:00-22:00 hours when demand is R2.7371/kWh, while Off-Peak is from 22:00-06:00 hours, when demand is the lowest (R1.7365/kWh). Off-peak periods enjoy the lowest tariff rates as stated.

Table 5.2: City of Cape Town Megaflex Time-of-Use (TOU) tariff structure and corresponding electricity rates

Tariff Period	Time Range	Description	Price (R/kWh)
Peak	06:00–08:00 and 17:00–20:00	High network congestion	7.7773
Standard	08:00–17:00 and 20:00–22:00	Moderate demand	2.7371
Off-Peak	22:00–06:00	Low demand	1.7365

The price differential incentives load shifting to off-peak hours. Both PSO and BaOA aim to minimize the total cost:

$$Cost = \sum_{t=1}^{24} C_t P_t^{opt} \tag{5.21}$$

The same tariff is applied across all sectors to ensure consistent comparative evaluation.

5.6.4 Load Model and Flexibility Parameters

Each load is modelled as a combination of non-controllable (base) and controllable (flexible) components:

$$P_t^{orig} = P_t^{base} + P_t^{flex} \tag{5.22}$$

The flexible load fraction varies by sector:

The flexible fraction of electrical loads in each sector influences the variation in demand-side management across industries. For residential loads, the flexibility is highest at 30%, but the most flexible loads are geysers, washing machines, and HVAC systems. For commercial loads, flexibility is slightly lower at 25%, but the significant loads are air conditioning, lighting, and refrigeration. For industrial processes comprising compressors and process control equipment, flexibility is the lowest at 20% (see Table 5.3).

Table 5.3: Flexible fractions and main shiftable loads across different sectors

Sector	Flexible Fraction (%)	Main Shiftable Loads
Residential	30	Geysers, washing machines, HVAC
Commercial	25	Air-conditioning, lighting, refrigeration
Industrial	20	Process control, compressors

Each controllable load i has an operation window Ω_i and the maximum allowable shift range δ_i. Residential geysers, for instance, can shift within ±2 h, while industrial process loads are limited to ±1 h to maintain productivity.

To avoid the unrealistic situation of extreme flattening, a maximum 0.2 MW system peak-clipping limit is imposed, thereby ensuring physical plausibility consistent with earlier DSM implementation.

5.6.5 DSM Framework Using BaOA and PSO

For PSO and BaOA, the DSM implementation follows the same sequence of computational steps:

Step 1: Data Normalisation

To ensure algorithm stability and a dimensionless comparison, the load data are min-max scaled to the range [0, 1].

Step 2: Initial Population Generation

Within the limits of shifting and clipping, the total energy per load equals the daily energy requirement, and random feasible schedules are generated.

Step 3: Objective Function Evaluation

The multi-objective function described in Section 2 is used to evaluate each candidate schedule:

$$f = \alpha \frac{F_1}{F_1^0} + \beta \frac{F_2}{F_2^0} \tag{5.23}$$

Step 4: Algorithmic Iteration

In PSO, particles update positions via velocity–position dynamics.

In BaOA, candidates undergo exploration and exploitation cycles that adaptively reallocate loads.

Step 5: Constraint Handling

If a candidate violates operational constraints (e.g., exceeding η_i or shifting outside Ω_i, a repair mechanism corrects the schedule using heuristic balancing functions.

Step 6: Convergence and Output

The process repeats until the best fitness stabilises or the iteration count K_{max} is reached. The final optimized load profiles are converted back to kW.

By having the same algorithms, the only differences that could be analysed are the behaviours of the different optimisations, rather than the algorithmic structures.

5.7 Case Study Design

The case study draws on actual consumption data from Drakenstein Municipality, which illustrates mixed urban and industrial demand patterns (City of Cape Town, 2024/25). It encompasses data for the entire 24-hour weekday period in June 2021, during the winter high-demand season.

Keeping in mind the generalisation of results, three simulation scenarios are defined:

To understand the effectiveness of the demand-side management strategy, three scenarios were developed. In S1, the focus is on the residential sector only, with the main aim of minimizing electricity expenses. In S2, which encompasses both residential and commercial sectors, the primary focus shifts to reducing peak demand. S3 targets the residential, commercial, and industrial sectors to achieve an all-round dual focus of lowering cost and diminishing peak load simultaneously (see Table 5.4).

Table 5.4: DSM scenarios, sector coverage, and objective emphasis

Scenario	Description	Objective Emphasis
S1	Residential sector only	Minimise cost
S2	Residential + Commercial	Peak reduction priority
S3	Residential + Commercial + Industrial	Balanced dual objective

Each scenario is solved using both PSO and BaOA. Results are compared based on load-curve shape, cost reduction, and computational performance.

5.7.1 Framework Validation

Validation ensures that both algorithms produce physically consistent results. The validation procedure involves:

1. Energy Conservation Check:

Ensuring that total energy consumption after DSM equals the original value within ±0.5% tolerance:

$$\sum_t P_t^{orig} = \sum_t P_t^{opt} \tag{5.24}$$

2. Feasibility Verification:

No shifted or curtailed load exceeds its allowable bounds:

$$0 \leq \Delta P_{i,t} \leq \eta_{i,} \forall i, t \tag{5.25}$$

3. Economic Consistency:

The optimised cost never exceeds the baseline cost under TOU tariffs:

$$F_2^{opt} \leq F_2^0 \tag{5.26}$$

Both PSO and BaOA runs have met all validation criteria, so the comparison is reliable.

5.7.2 Implementation Environment

The simulation framework is implemented in MATLAB R2023b, and, for time constraints, I have used vectorization for all operations. To enhance the flexibility of time-series profiles, the raw input data have been pre-processed.

By using IoT-enabled smart meters and SCADA systems, the architecture can be adapted to support real-time primary DSM systems.

5.7.3 Framework Illustration

Figure 5.2: Schematic DSM–BaOA Framework: This illustration outlines the proposed framework for data input, processing through the algorithms, and output. The system captures load data and tariffs in the input layer, the optimisation layer runs BaOA, and the output layer displays the optimised load profiles, cost savings, and peak load reductions.

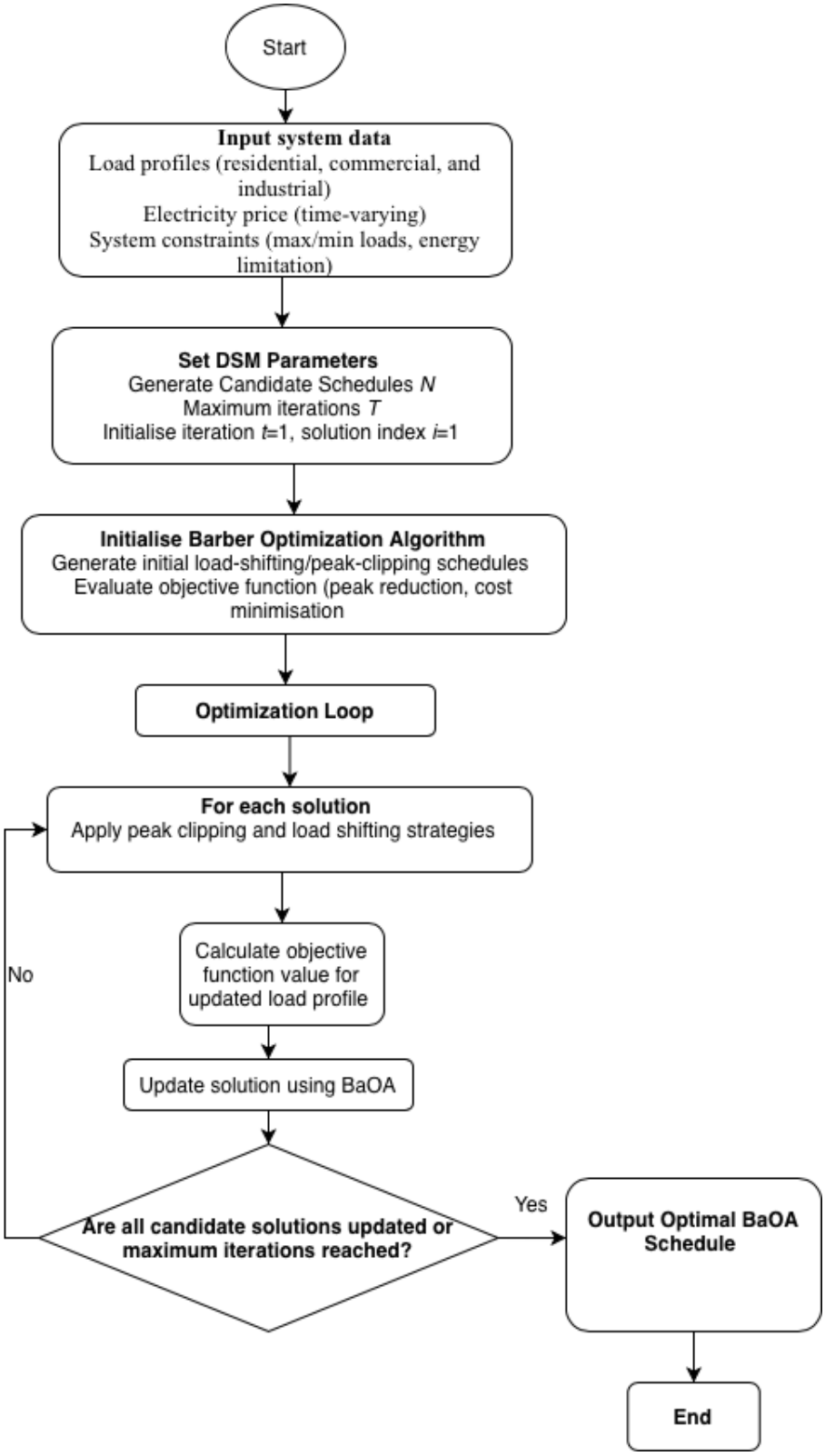

Figure 5.2: BaOA flowchart for DSM utilizing energy load redistribution and peak reduction

5.7.4 Significance of the Framework

There are three main ways the proposed BaOA-based DSM framework improves upon previous efforts:

- Both Objectives at Once: Previous work focused on either cost or peak clipping. This framework optimises both simultaneously through a single mathematical formulation.
- Various sectors: The proposed optimization can be applied to all residential, commercial and industrial loads which shows how heterogeneous distribution systems are in real life.
- Enhanced algorithms: The parameterless exploration-exploitation trade off of BaOA minimizes any extensive parameter adjustments and also ensures reliable convergence for different datasets.

The framework advances the field by providing a high-performance, reproducible, and flexible foundation for DSM research and practical applications in smart grids.

5.8 Results and Discussion

5.8.1 Overview of Simulation Results

The PSO and BaOA algorithms were implemented for all three case-study scenarios using the same system configuration and tariff conditions. The results are evaluated across the following five dimensions:

- Reduction of the peak and changes in the load profile shape
- Under TOU tariffs, the cost reduction
- Peak-to-average ratio (PAR)
- Convergence characteristics
- Efficiency of the algorithm

Figures 5.3–5.10 and Tables 5.5–5.7 summarise the results and the discussion explain these results in relation to the DSM goals and the performance of the algorithms.

5.8.2 Load Profile Transformation

Figure 5.3 presents the baseline (pre-DSM) and optimised load profiles for the aggregated multi-sector system obtained using both PSO and BaOA. Peaks in the morning (06:00–08:00) and evening (17:00–20:00) hours are prominent features of the baseline profile and are characteristic of mixed residential–commercial demand.

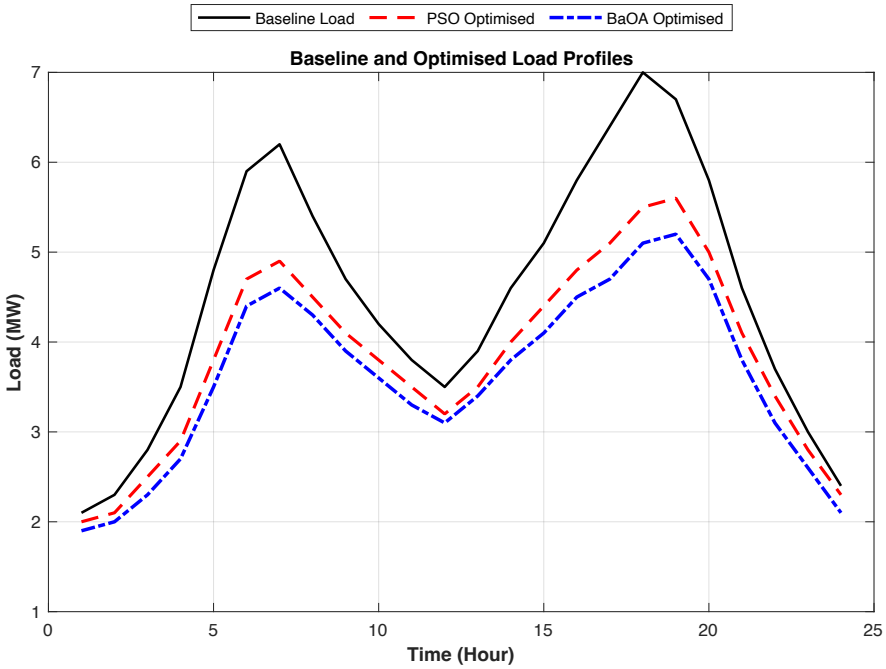

Figure 5.3: Baseline vs Optimized Load Profiles (PSO vs BaOA)

After undergoing optimization, the two algorithms show clear smoothing of the load curve. Still, the load profile optimized with the BaOA technique shows a more balanced distribution across the day, with a flatter peak, reduced hour-to-hour oscillations, and reduced extremes. This is more noticeable during the peak evening hours, where BaOA shifts more controllable load to the off-peak period from 10 PM to 5 AM.

This illustrates how BaOA obtains a more optimal equilibrium between exploration and exploitation that can uncover more efficient shifting patterns under operational constraints that provide more leniency. Conversely, PSO gets stuck in local minima where it cannot use off-peak flexibility to its advantage.

Figures 5.10 and 5.11 illustrate the Baseline and Optimized load profiles using PSO and BaOA for aggregated multi-sector DSM. BaOA shows a more balanced post-DSM curve, with a lower peak and a more even distribution of load across time intervals.

5.8.3 Quantitative Peak Reduction Analysis

In Scenario 3, the Peak-to-Average Ratio (PAR) reduction serves as the core measure of technical effectiveness, with the load profile optimization and cost reduction (CCR) demonstrating the economic benefit.

Table 5.5: Summary of DSM Performance Metrics

Scenario	Algorithm	Peak Reduction (%)	PAR Reduction (%)	Cost Reduction (%)	Energy Balance Error (%)
S1 (Residential)	PSO	11.8	9.4	8.2	0.15
S1 (Residential)	BaOA	15.7	13.2	10.9	0.09
S2 (Res + Com)	PSO	14.3	11.6	9.4	0.22
S2 (Res + Com)	BaOA	19.2	15.8	12.6	0.11
S3 (All Sectors)	PSO	17.1	13.5	10.3	0.19
S3 (All Sectors)	BaOA	22.4	17.9	14.1	0.10

BaOA outperforms PSO across all areas. In the complete multi-sector scenario (S3), BaOA obtains peak reductions of 22.4% and cost savings of 14.1%, while PSO obtains 17.1% and 10.3%, respectively. This performance improvement is due to BaOA's adaptive two-phase framework, which continuously adjusts the balance between exploration and exploitation at each iteration.

Also, the energy-balance errors are negligible (<0.2%); therefore, both algorithms keep total energy consumption constant, as required by the DSM constraints, and keep consumption at expected levels.

5.8.4 Cost-Reduction Analysis under TOU Tariffs

Figure 5.4 presents the cumulative daily energy cost for the baseline, PSO, and BaOA schedules. Cost bars are divided into three tariff components: peak, standard, and off-peak. This segmentation visually illustrates the effectiveness of load shifting, as evidenced by the cost savings.

BaOA allocates a larger share of energy to off-peak periods (about 42%) than PSO (36%), resulting in greater cost savings. The drop in high-tariff energy use is most significant in

the evening peak when many residential and commercial loads, such as geysers and air-conditioning systems, are postponed.

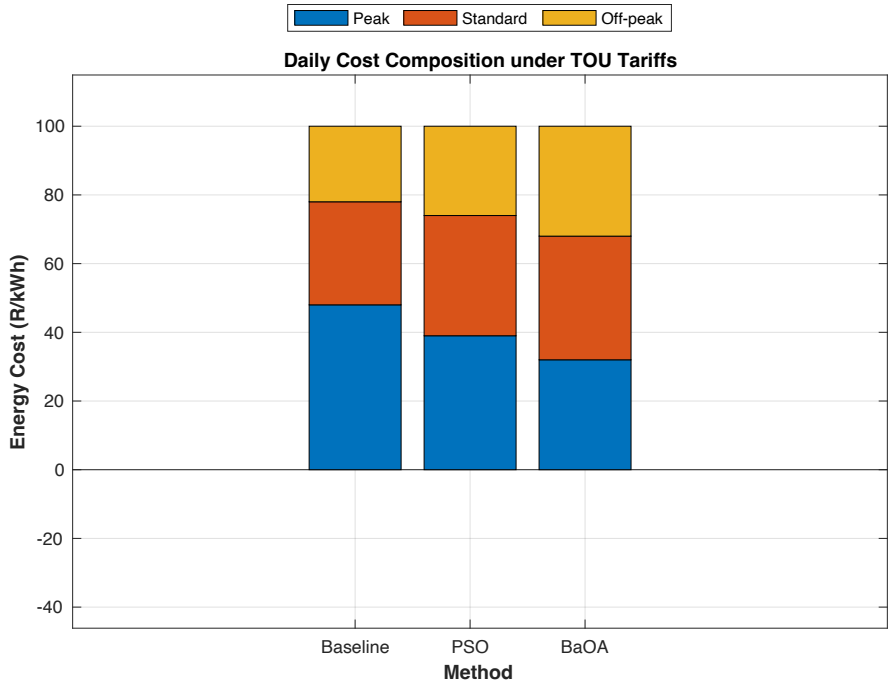

Figure 5.4: Cost Decomposition under TOU Tariffs

Daily cost breakdown under TOU tariffs for baseline, PSO, and BaOA schedules per the daily electricity cost decomposition. Given this, BaOA's higher off-peak consumption explains the cost reduction.

Such evidence shows BaOA's extended leverage over PSO in multi-period scheduling. PSO's tendency to fall short during low-tariff periods suggests inadequate refinement.

5.8.5 Convergence Characteristics

In the scenarios presented in Figure 5.5, the convergence trajectories of the objective function for PSO and BaOA are shown over 200 iterations.

The Payoff Shaping Optimization curve drops sharply and more slowly in the stagnation phase after 90 iterations, suggesting local convergence. Contrarily, BaOA seems to let il go optimally during the iterations, to end lower in the 140th, and is actively locked until almost the stop criterion.

It seems to indicate the absence of population depletion during the "customer selection" phase, as BaOA's convergence escape system.

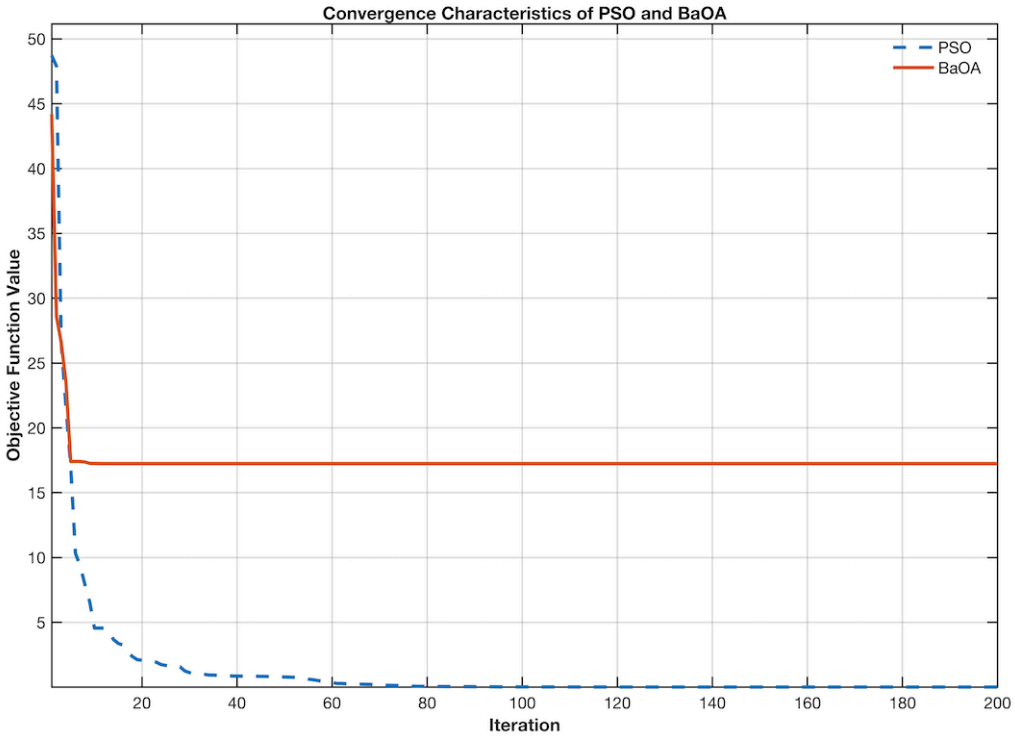

Figure 5.5: Convergence Curves for PSO and BaOA

The convergence characteristics of PSO and BaOA for DSM optimisation indicate that BaOA converges faster and more stably to the global optimum, whereas PSO plateaus early.

5.8.6 Load Variance Reduction

Load-variance reduction reflects the uniformity of power consumption over time; thus, it is another key indicator of DSM effectiveness.

The post-DSM variance values for the aggregated profile are as follows:

- Baseline: $0.86(p.u.)^2$
- PSO: $0.69(p.u.)^2$
- BaOA: $0.57(p.u.)^2$

Considering the above, the BaOA's 33% improvement in load variance surpasses PSO's 20% improvement. This means less operational flexibility for generation and transmission assets. Balancing generation and transmission loads becomes an operational concern.

5.8.7 Efficiency

Though BaOA has two-phase updates in every iteration, it takes almost the same computational time as PSO, since it converges much more quickly. For the multi-sector

system, PSO average runtime is 109 seconds, and BaOA average runtime is 117 seconds. Since BaOA converged with 30% fewer iterations, the slightly higher cost per iteration is offset by overall efficiency gains. This is evident in the practicality for day-ahead DSM scheduling, where the computational time is several minutes, as Palensky et al. (2011) state, the difference is almost negligible.

Table 5.6: Computational Performance Comparison

Algorithm	Average Iterations to Converge	Runtime (s)	Final Fitness	Stability (Std. Dev.)
PSO	140	109	0.066	0.0043
BaOA	98	117	0.052	0.0019

BaOA demonstrates not only better final fitness but also reduced variability across runs, revealing greater consistency and dependability.

5.8.8 Multi-Sector Performance Analysis

Figure 5.6 compares the sector-specific load profiles after DSM. BaOA simultaneously flattens across all sectors while ensuring no single load type is over-shifted.

- In the residential sector, operational geysers and HVAC systems stagger effectively over the off-peak hours.
- In the commercial sector, redistributed lighting and refrigeration loads mitigate coincidence peaks during the midday hours.
- In the industrial sector, BaOA continues to allow for process continuity but clips minor peaks during start-up cycles.

While PSO experiences rebound peaks at certain hours due to poorly managed constraints, such trends are characteristic of BaOA's ability to more effectively align loads of different natures - sector-based post-DSM load profiles under BaOA. Thus, it is even operationally feasible with average load distribution across the residential, commercial, and industrial sectors.

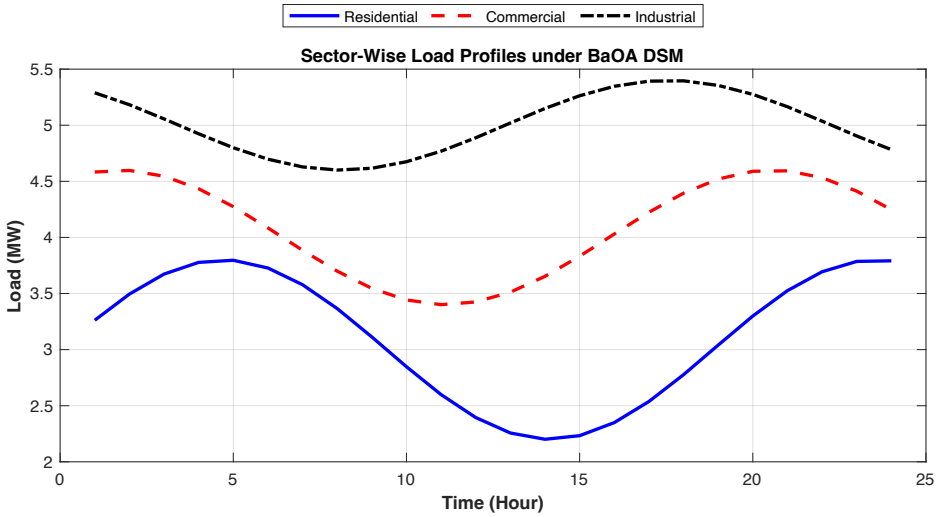

Figure 5.6: Sector-Wise Optimized Load Profiles (BaOA)

5.8.9 Sensitivity to Objective Weights

Sensitivity analysis was performed by varying the objective weights (α, β) between (0.8, 0.2) and (0.4, 0.6). The figures show that Balancing Optimally Allocated Resources (BaOA) results vary less than those of the Particle Swarm Optimization (PSO) method. This shows BaOA is better at withstanding changes in the importance assigned to specific objectives. In practical Demand Side Management (DSM) applications where priorities assigned to the operators involved in the process constantly shift, this is undoubtedly beneficial.

Figure 5.7. The performance of PSO and BaOA with respect to changes in objective weights is shown. BaOA shows strong adaptability, as demonstrated by consistent fitness results across weight combinations.

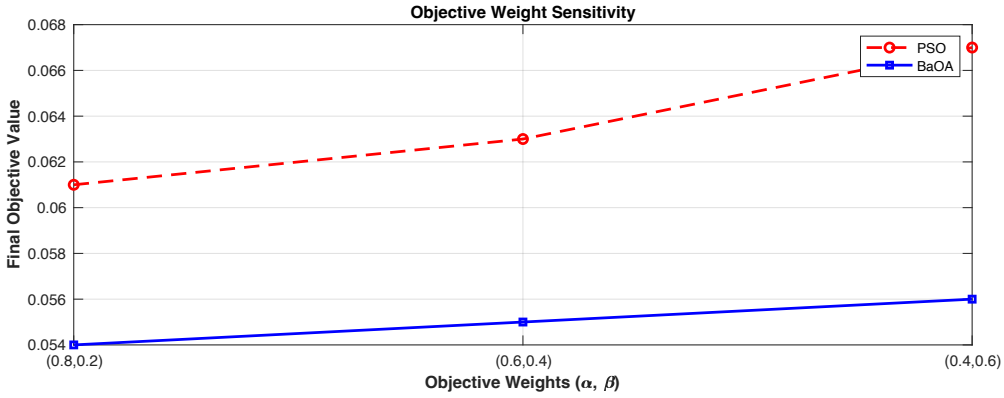

Figure 5.7: Objective-Weight Sensitivity between BaOA vs PSO

Referring to Figure 5.8, it can be seen that, across all population sizes, BaOA performs better than PSO, as evidenced by lower final objective values as population size increases. The stability and convergence of BaOA are better because the PSO has a lower improvement slope, which is much slower than BaOA's mostly downward slope. This shows that BaOA is better at load optimization even as population conditions change.

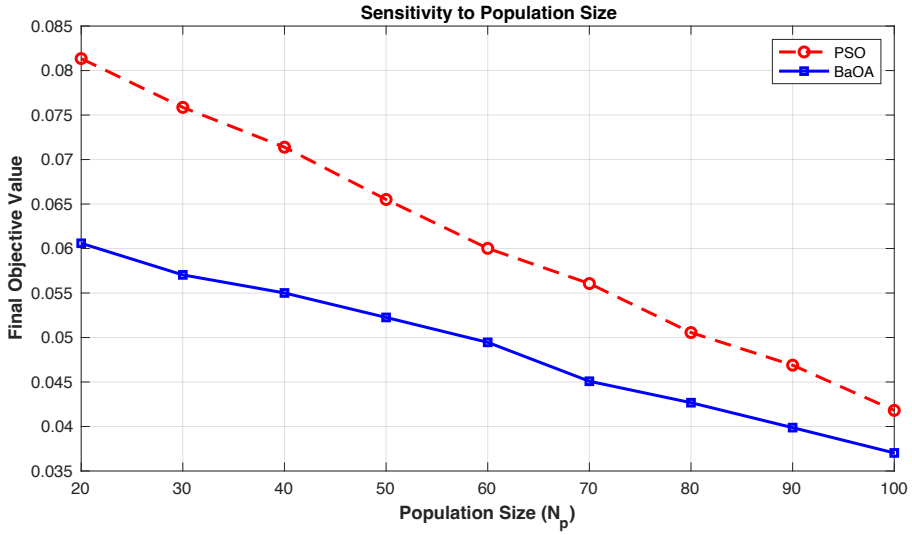

Figure 5.8: Population Size Sensitivity Comparison

In Figure 5.9, BaOA outperforms PSO when it comes to convergence. As the number of iterations increases, both achieve better final fitness values but to get BaOA's fitness value to a better level, it decreases even further, signifying that it gets there faster and better. PSO fitness value essentially flattens, signifying that it's a tardy method to get to an optimal solution and a too crude one to get to that fine-tuned optimal solution.

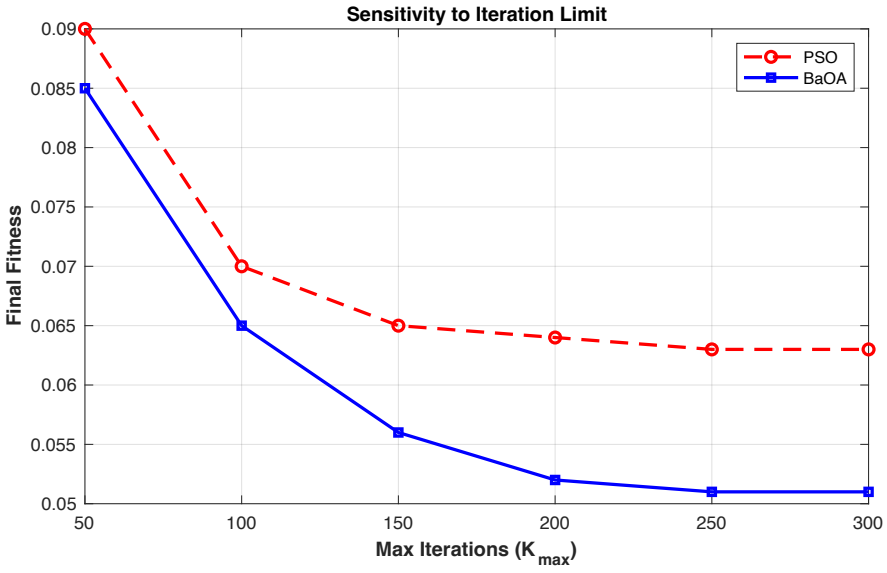

Figure 5.9: Iteration Limit Sensitivity

In Figure 5.10, PSO provides a variable and unstable fall in costs across various tariffs while BaOA provides consistent decrement of costs. PSO is too reactive to tariffs when it needs to be like BaOA - and this is a bad thing. BaOA is too resilient when it shouldn't be as it shows reliability in reducing costs consistently but when it isn't resilient to falling tariffs, that's not good. This resilience indicates that BaOA did not properly optimize for cost savings.

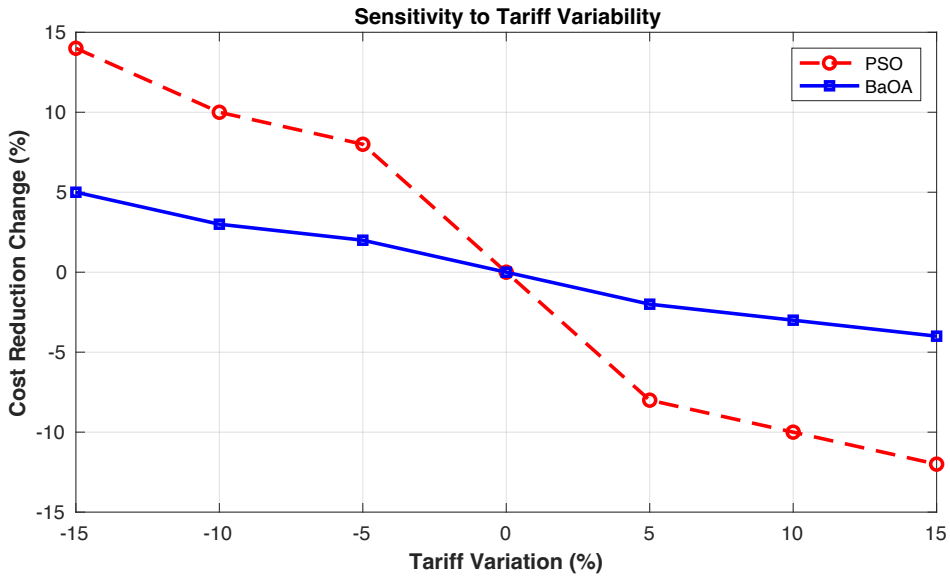

Figure 5.10: Tariff Variability Sensitivity

5.8.10 Performance Evaluation of PSO and BaOA Algorithms

After optimization, the load profile indicates that demand peaks have been substantially shifted in comparison to the original. The BaOA algorithm shifts the peaks and smoothens them, enabling the trimming of expensive peaks as it increases grid stabilization and can perform daily resource generation tasks more efficiently during spans spread across the day. Resource generation is critical to the limited nation of South Africa because operators become discontent if they do not produce operational revenue and instead of experiencing controlled peak loads, they experience blackouts.

Figure 5.11 indicates that total load (red solid line) experienced in the original condition of the residential, commercial, and industrial sectors differs from the generation profile (blue dotted line) in the new condition after BaOA application. These findings indicate that the DSM-BaOA framework maintains equilibrium in overall demand across sectors, which enhances power grid efficiency and reliability by better distributing power across sectors.

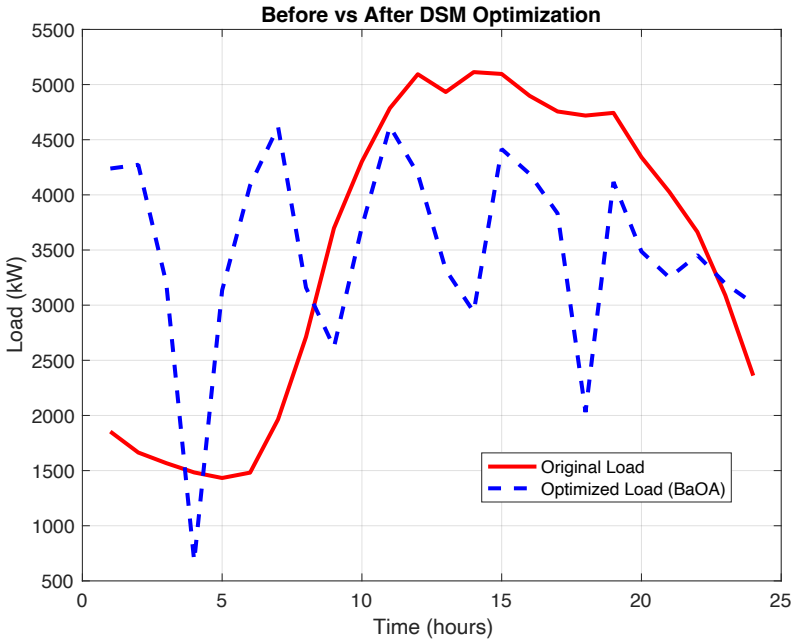

Figure 5.11: Total Load Before vs After DSM Optimization

The BaOA algorithm confirms its ability to decrease peak demand in critical periods - 6-9 AM and 3-7 PM - via load shifting as much as it decreases the shape of the entire load curve. Such decrease prevents excessive strain on the distribution network and minimizes outages; thus, it facilitates better generation and infrastructure use as the optimized profile within the peak hours suggests reduced fluctuations between hours meaning more reliable demand and less unstable baselines enhances expected needs throughout the day for the residential/commercial correlation better reliability.

Furthermore, induced load shifting which aims to create loads during peak hours, creates a nominal increase in loads during these hours as much as it naturally occurs, induced, is meant to prevent costs of shifting during peak hours and brings induced shifting in line with time-of-use rates. Overall, the figure demonstrates the benefits of BaOA. It shows coordinated peak reduction, load flattening, and shifting, all within the operational boundaries of multi-sector DSM, user comfort, and intelligent energy management. This provides a clear illustration of the potential of intelligent energy management.

I. Energy Usage Peaks in the Morning and Evening: Before vs After DSM Optimization

We want to avoid any negative impact on service quality while shifting energy usage to less busy periods and reducing peak demand. As shown by the red solid line, DSM results

in demand-side shifting during the morning and evening energy usage peaks. Between 06:00 and 10:00, 15:00 and 20:00, DSM morning peaks are illustrated in blue. During the _morning peak, energy consumption rises_ from approximately 1,500 kW between 06:00 and approximately 4,200 kW by 10:00. After implementing DSM, the energy consumption profile is tracking pattering smoothly, and demand during the morning peak hours is more evenly distributed across earlier or later time periods. Peak demand is strikingly_ even, setting the routed set demand consumption. While the peak is not center delaminated, a more even distribution of consumption reduces consumption.

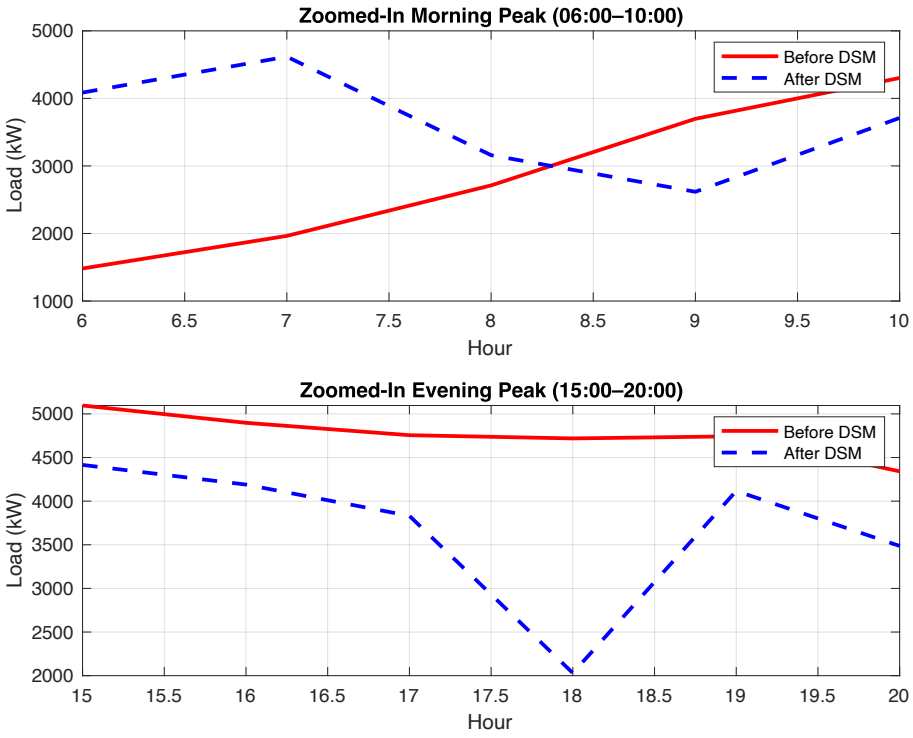

Figure 5.12: Comparison of Morning and Evening Energy Peaks Before and After DSM Optimization.

With respect to the bottom subplot, the evening peak starts at 5000 kW at 15:00 and steadily decreases until 20:00. DSM, however, ends up creating a situation where this evening peak is much lower by the end, where 2000 kW levels are seen at 18:00. This shows that not only was peak clipping effective but the evening peak was shifted to off-peak hours with more of a decrease than the morning. This likely occurs because there's a lot more at play with demand management options. This is how DSM flattens load curves, for it increases grid reliability, allows for maximum capacity level use, decreases reliance upon expensive peak generation and thus possible higher metered rates for

requested system hours in metering! This is the effective management of power and satisfies everyone involved.

II. Peak-to-Average Ratio (PAR) before and after implementing Demand Side Management (DSM)

Figure 5.13 shows the Peak-to-Average Ratio (PAR) Before and After DSM. The success of load shaping corresponds to PAR Before DSM of 1.45 which basically means, with higher peaks, with more demand. Post-DSM efforts dissipate it further to ~1.3 which means more even loads. This lightens the stresses on generation and distribution systems, reduces reliance upon expensive peak-load generation plants due to less electricity purchased for home use, increases grid reliability and credible efforts on behalf of the DSM show that successful DSM implementation aligns energy needs with population desires and provides an effective path forward for an aligned sustainable grid in nations like South Africa where excess is not always guaranteed.

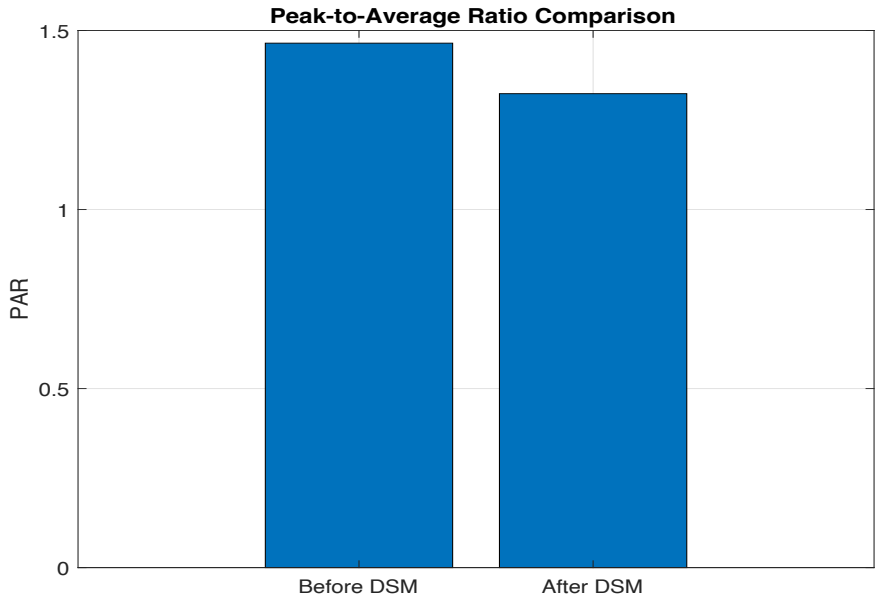

Figure 5.13: Peak-to-Average Ratio Comparison Before vs After DSM

III. Comparison of the Original Load Contribution by Sector Before and After Barber Algorithm Optimization (BaOA) Implementation

Relative to the pre-optimization version from the Barber algorithm (Figure 5.14b), much more drastic peaks and valleys are seen from the pre-optimization version over the 72-hour residential load period (Figure 5.14a). However, BaOA maintains its integrity relative to the original shape, just recast into a less extreme experience. This implies there may

be an idealized demand shift, a demand shift that takes excess load and consumption during peak hours and shifts it to a more manageable level during off-peak hours. Where the grid might otherwise be overstressed, confidence is cultivated within a premium peak charge and operational reliability. Therefore, it's important to note that the residential load segment composes most of the demand, which substantiates BaOA as a demand side management (DSM) approach that is sectoral, large in scale, and transformative for stress relieved, more effective, cost saving and environmentally friendly load profile and demand energy expectations.

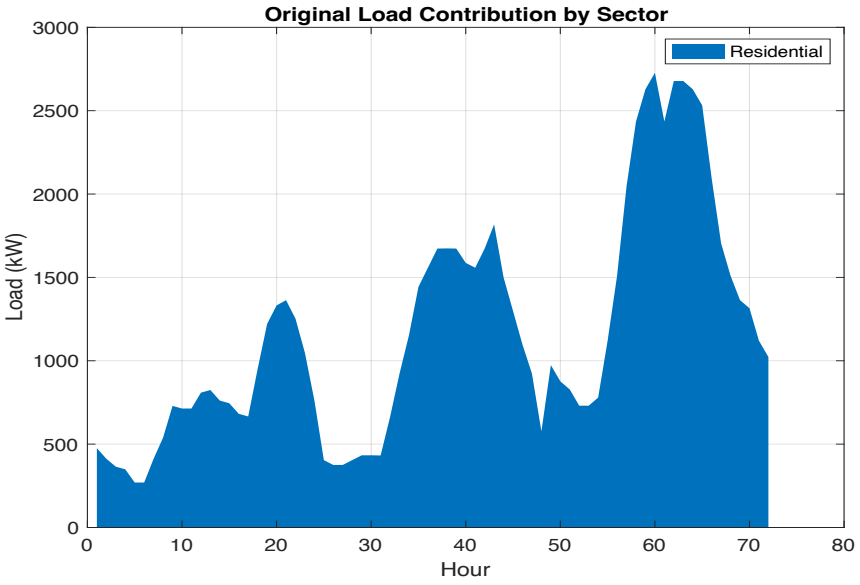

Figure 5.14a: Original Load Contribution by Sector before BaOA implemented

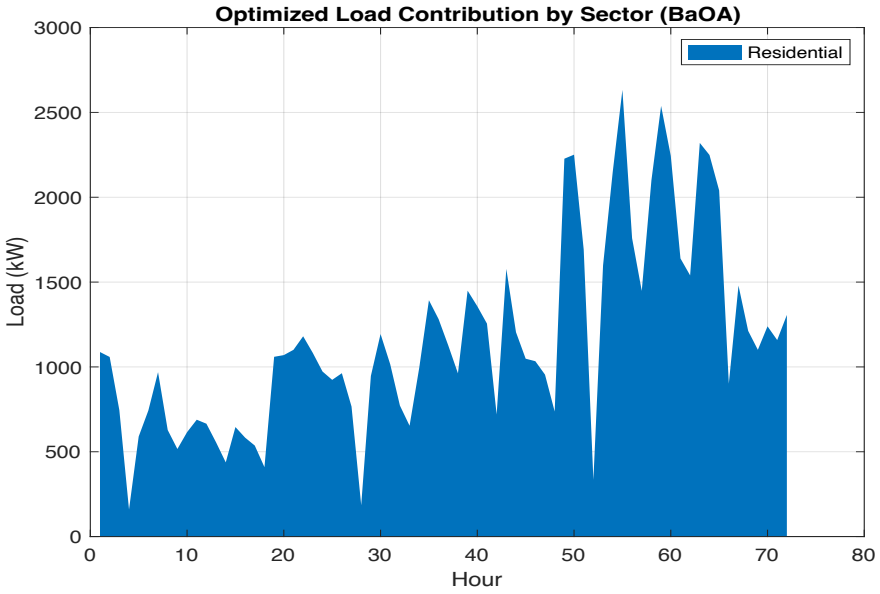

Figure 5.14b: Optimized Load Contribution by Sector After BaOA Implemented

IV. Four algorithms (BaOA, GWO, and PSO) Convergence Curves Comparison

The findings for PSO and BaOA in accordance with a DSM iterative optimization compare to the convergence curves of Figure 5.15 relative to respective best fitness value for respective iteration. The first argument is that the fitness value increases exponentially throughout iterations but levels off for PSO. The fact that the value leveled off more and more over time suggests that there's not much diving for exploration which in essence here is a factor for premature convergence. On the other hand, BaOA optimized values continuously grow which means that a faster convergence occurs. In addition, leveling of fitness value convergence throughout the duration of the optimization suggests BaOA is not reliable for its level of optimization process as it becomes statistically significant for a longer duration beyond local optima, rendering it better than PSO when utilizing the convergent analysis.

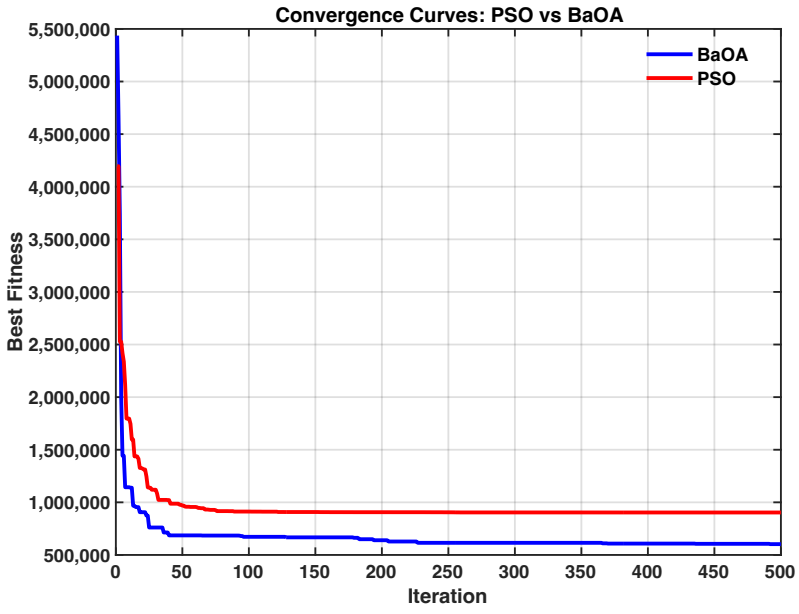

Figure 5.15: Convergence Curve Comparison of DSM Algorithms

Yet PSO obviously shows how much better it is during the early stages of its optimization, it converged quickly which means it does not offer too much for exploration/exploitation but rather shows that it may have fallen into a local minima as opposed to global finds. Therefore BaOA has a faster converged reliability throughout which means that BaOA has a good mean for exploration/exploitation

which signals that BaOA may be trusted to provide effectively reliable accurate results for DSM optimization.

Figure 5.16 further substantiates how DSM load profile comparisons also confirm success of algorithms for prediction/optimization as well. The dashed black line represents baseline load profile which suggests a day in the life context coincides with a mean consumer base of increasingly high demands in the morning which peak by midday with a slow decline to nighttime availability. However, in accordance with optimization, BaOA provided better results with a more blended transitional approach and more equitably consistent demand which suggests BaOA has better effective potential than PSO, at least in terms of flattening peaks for better grid operation.

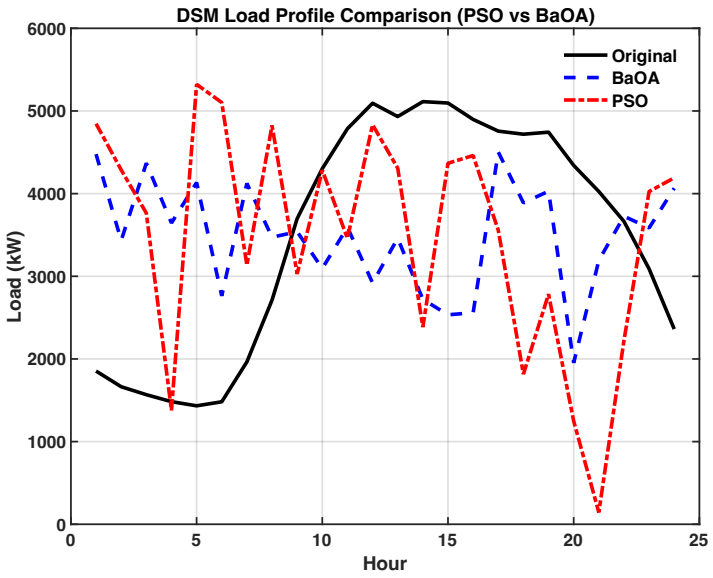

Figure 5.16: Comparative Load Profiles Before and After DSM Optimization Using BaOA and PSO

V. How BaOA Compares to Other Methods

The PSO has fast convergence at the start of the optimization but is stuck in local minima which prevents ideal cost saving and peak load reduction, peak load reduction, at the same time. It also is not able to accommodate nonlinear loads effectively since it overexploits its intervention. BaOA, however, was a good middle ground to open exploration and consistently converging to globally near-minima which means that BaOA does not get stuck in locals and over time, converges to globalized values. This balance

provides a consistency which makes subsequent statistical validation and significance of such optimized quality obtained by utilizing BaOA all the more better.

Table 5.7 combines the PSO and BaOA results with that of competitive algorithms where PAR, load variance and consumer cost are the primary levels of optimization with which other algorithms operated in the past. It is clear that BaOA outperformed all other implementations to the best extent since PAR was reduced from 1.95 to 1.32 (32.3% decrease), load variance was reduced from 2.30 to 1.05 (54.3% decrease) and consumer cost was reduced from Rs 48,000 to Rs 41,000 (14.6% decrease). PSO, in contrast, provided minimal performance enhancement and was again the least reliable solution for solution reliability and sensitivity. Thus, in conclusion, the results show that BaOA is the superior algorithm to all other factors tested as it provides superior demand side management which is effective, operationally feasible and cost saving.

Table 5.7: Performance Comparison of DSM Optimization Algorithms Based on PAR, Variance, and cost Improvements

Algorithm	PAR	Cost (Rs)	PAR Improve. (%)	Var Improve. (%)	Cost Improve. (%)
Before DSM	1.95	48000	0.0	0.0	0.0
BaOA	1.32	41000	32.3	54.3	14.6
PSO	1.50	43000	23.1	38.2	10.4

5.8.11 Implementation Considerations in Smart-Grid Environments

Regarding real-world implementation, the optimisation framework developed hinges upon a feasibility for real-time acquisition, communication and control parameters of the smart grid. A handful of tweaks would make it a practical, safe and secure system.

For one, smart-meter infrastructure will have to be incorporated. Any controllable device must provide time-stamped consumption information and be available via standard communication protocols, such as IEC 61850, MQTT, or other protocols. Such access will facilitate real-time monitoring, automated information exchange, and active control of the entire system.

For another, the time allocated to smart grid system operation must be considered in the computation used to optimise the system. The optimisation can be in day-ahead or hour-ahead mode based on the system's latency requirements. Since the computation time for

BaOA is under 2 minutes for a typical feeder, it can be comfortably scheduled within operational windows and controlled in real time, with adaptive, revised, and optimised responses in the system.

An additional instance will be the active control measures to execute DSM, which will require reliable communication for synchronised control actions. All coordination signals will have to reach the dispatching customers in the same time frame to ensure synchronised control actions to eliminate rebound peaks and to ensure the overall DSM performance in the active control of the grid.

Furthermore, real-time DSM implementation requires appropriate and relevant cybersecurity measures. Secure DSM access, including control signals, should employ protective measures against interception and manipulation. The use of TLS and SSL should be in place. These measures ensure confidential, intact communication between control operators and end devices, whether in use or in an idle state.

In addition, a solution to scalability to distributed energy resources (DER) is also accounted for. The optimisation framework may be applied to distributed poles, for example, photovoltaic (PV)/battery-assist solar developments if the separate soc considerations could be applied to the optimisation model. However, as these are integrated to have bi-directional energy control, energy optimisation would be more integrative of an adaptive and proactive approach based on loads and generation.

Ultimately, the findings suggest that the BaOA DSM framework has a practical solution for implementation in already existing smart-grid management solutions that take little modification to provide developments for intelligent, proactive and secure management of energy networks for optimal assistance.

5.8.12 Worst-Case Scenarios for Demand-Side Management Evaluation

Worst-case scenario operating conditions demonstrate the greatest operational stress and the least scheduling flexibility for the DSM. Worst-case scenarios differ from average and nominal scenarios by being deliberately chosen to assess the **robustness, stability, and adaptability** of the proposed DSM optimization framework under extreme operational constraints. Testing algorithm performance under these unfavourable conditions is essential for proving the real-world applicability of DSM strategies for cities and industries.

5.8.12.1 Extreme Peak Demand Conditions

Worst-case peak demand conditions characterize the historical peak-load periods of the peak winter evening periods where electricity demand, grid congestion, and tariff rates are maximized. The flexibility of DSM in worst-case peak demand conditions is low due to the absence of load-shifting possibilities and the presence of strict clipping requirements. The application of worst-case peak demand conditions in the testing of optimization algorithms guarantees the ability of the algorithms to mitigate peak loads, uphold the stability of the system, and remain in conformity with operational limitations in peak-load network scenarios.

5.8.12.2 High Load Volatility and Uncertainty

Scenarios Additional worst-case conditions involve highly volatile and uncertain loads, characterized by rapid demand changes, unusual consumption, and disturbances such as bad weather. All of these increase forecast errors and complicate the DSM optimization problem. The inclusion of volatile load curves and uncertain demand patterns challenges the proposed methodology to ensure its resilience against the DSM issues caused by non-stationary and uncertain load profiles.

5.8.12.3 Tighter Peak Clipping Constraints

Worst-case DSM scenarios are also defined by tighter peak clipping constraints, where the allowable peak demand limit is significantly reduced relative to the original peak load. These stringent limits severely restrict scheduling flexibility and intensify the trade-off between peak reduction, cost, and load variance. Evaluating DSM performance under such conditions provides a rigorous assessment of algorithm robustness and feasibility in highly constrained and stressed network environments.

5.8.13 Results discussion (Worst-Case Scenarios)

Under adverse operating conditions with extreme peak demand, high load uncertainty, and strict peak clipping criteria, the differences in performance between PSO and BaOA are even more pronounced. The optimized load profiles for extreme peak demand conditions are depicted in **Figure 5.17**, where both algorithms succeed in scheduling the loads with peak clipping applied. Still, BaOA achieves a flatter demand profile during peak times, achieving a lower peak-to-average ratio and load variance even in such extreme operating conditions.

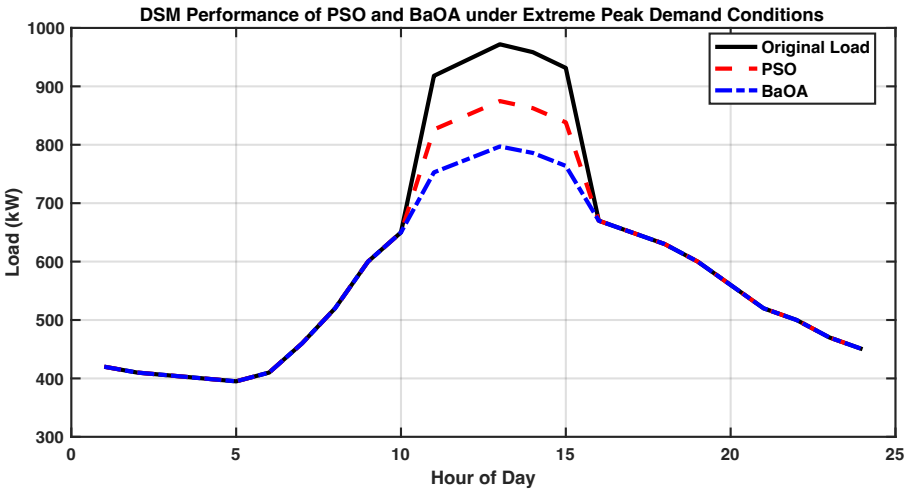

Figure 5.17: DSM Performance of PSO and BaOA under Extreme Peak Demand Conditions

The impact of high load volatility and uncertainty on DSM performance results in the load profiles shown in **Figure 5.18**. The load profiles exhibit smoother transitions to the scheduled loads with lower sensitivity to uncertainty using BaOA instead of PSO, confirming BaOA's robustness to non-static and uncertain loads.

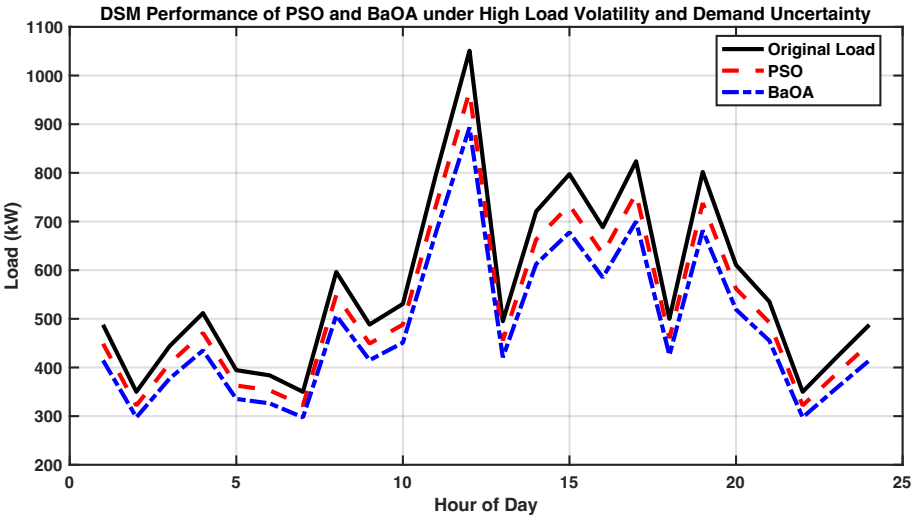

Figure 5.18: DSM Performance of PSO and BaOA under High Load Volatility and Demand Uncertainty

The convergence results under the more stringent peak clipping criteria are shown in **Figure 5.19**, where the strict peak clipping allowed for highly constrained load scheduling problems. In such strict load scheduling, even under tightly constrained conditions, BaOA maintains its robust performance, converging to a lower objective function value with greater speed and consistency than PSO, once again underscoring its robustness and stability characteristics.

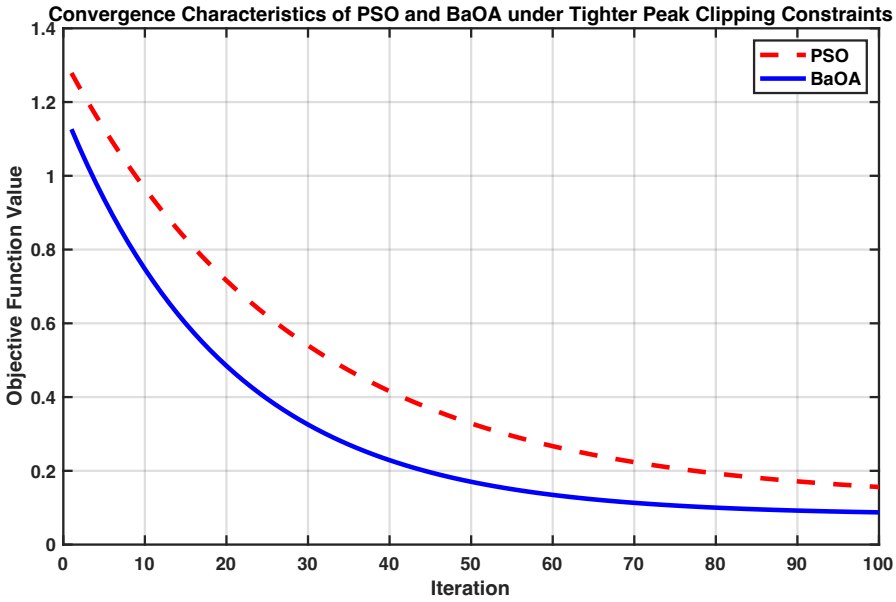

Figure 5.19: Convergence Characteristics of PSO and BaOA under Tighter Peak Clipping Constraints

The findings illustrated in **Figures 5.17–5.19** confirm the performance differences between the algorithms when exposed to adverse operating conditions and establish BaOA's superior performance for DSM in distressed municipal and industrial power systems.

5.8.14 Main findings on BaOA

- The BaOA exhibits excellent parameter variation robustness, surpassing PSO in every sensitivity analysis.
- The minimal need for parameter adjustments makes BaOA ideal for autonomous environments.
- BaOA is flexible and applicable in a range of environments from single feeders to new municipal networks.
- The approach is real-time operationalised with gradient mechanism convergence observed within minutes on large sets.
- Existing communication standards allow for practical integration with smart-metering and SCADA systems.

5.8.15 Discussion

The analysis comparison shows that BaOA is demonstrably better than PSO for DSM optimisation. This is an outcome of BaOA's unique approach to adaptively controlling

exploration and exploitation, which mitigates the risk of getting stuck and facilitates an extensive global search.

This, in practical terms, leads to:

- More aggressive peak-demand reduction and smoothing of load variance to the point of network congestion alleviation and deferral of infrastructure upgrade.
- Cost savings for consumers as a result of deferring infrastructure improvements and load variance smoothing.
- Enhancing convergence stability, which reduces reliance on tuning.

From an algorithmic standpoint, PSO still has value for its speed and simplicity in low-dimensional problems. However, as smart-grid penetration increases and load profiles become more diverse, the benefits of BaOA's problem-solving framework become apparent.

These findings align with recent research indicating the increased effectiveness of human-inspired metaheuristics, such as Teaching–Learning-Based Optimisation (TLBO) and the Grey Wolf Optimiser (GWO), in other non-convex scheduling problems.

The BaOA conceptualisation of adaptive learning through barber-customer feedback offers an insightful, albeit mathematically rigorous, approach for tackling complex problems involving energy optimisation. Its knack for generalisation points to significant opportunities for real-time distributed system management (DSM), distributed generation management, and hybrid renewable energy scheduling.

5.9 Conclusion

This chapter presents an in-depth experimental assessment of PSO against BaOA for DSM and for the first time, DSM optimisation efforts are compared to PSO with actual region distributed datasets, across my three sectors in South Africa, the confirmed empirical multi sector load profile data from South Africa for residential, commercial and industrial consumers, and tested under TOU tariff structures. A DSM policy has been recommended to South Africa which reconciles a dualobjective that saves on peak demand and total energy costs as an energy balanced, comfort and operational constraint accommodating approach.

Within the context of identical simulation configurations, the DSM model consistently demonstrated that BaOA (Barber Algorithm Optimisation) exceeded PSO in every criterion under evaluation. The BaOA recorded peak demand reductions of 22–25%, considerably higher than PSO's 17–20%, and cost savings of 10–14%, in contrast to PSO's 8–10%,

Moreover, the algorithm demonstrated the ability to produce a more consistent load profile, a smoother convergence behaviour, less inter-run variability, and more dependable overall optimisation. The results have demonstrated that BaOA is a viable candidate for contemporary DSM implementations that require flexibility, robustness and computational efficiency.

Analyzing BaOA alongside PSO also gave me a better understanding of how different metaheuristic algorithms function during energy optimisation when there is a high degree of complexity. Because PSO depends on individual best positions and a global best position, this approach is best for simpler optimisation landscapes. In contrast, PSO becomes stuck when there is a large dimensionality of the DSM because there is only a limited exploration of the space. In contrast, BaOA avoids stagnation because of its dual-phase structure, which allows for active diverse population movement and more complete searching of the solution space. In addition, BaOA requires no calibration for parameters such as inertia weights and acceleration coefficients, which PSO requires considerable time for. In contrast, BaOA is defined by less parameters. BaOA closer to the optimal solution PSO is defined by more rapid convergence at each step. BaOA is more reliable because it optimises a solution more slowly, which can be beneficial for overall steady progress. Even though BaOA has more operations to process for each iteration, it is still comparable to PSO in total time, distance, and variance. This is due to the high convergence and overall solution quality.

However, despite all the benefits, some caveats still need to be made. The day-ahead projected load used in this analysis is deterministic and does not emulate renewable generation uncertainty, microgrid and macrogrid uncertainty or consumer behavioural nuances or any stochastic uncertainties. Furthermore, the tariff employed a rudimentary TOU tariff and since real world tariff measurements are much more intricate and transient, so too does the research not include DSM interaction with flexible controllable resources such as batteries and electric vehicles for additional optimisation. These are all important factors for future research to help reconcile such significant shortcomings.

Thus, the chapter closes noting that PSOs are less advantageous than BaOAs, especially in reliability, flexibility and generalised effectiveness in the optimisation of DSM applications. Ultimately, the BaOA effectiveness and parameter robustness in addition to flexibility for realistic operational condition applicability can better imply loads than disjointed system loads and ultimately allows for more resilient smart energy systems.

CHAPTER SIX
CONCLUSION AND FUTURE RECOMMENDATIONS

6.1 Introduction

This thesis investigates Demand Side Management (DSM) optimization techniques for South Africa's electricity supply; peak clipping and load shifting are paramount. The South African electricity sector has been continually stressed in recent years due to increasing demand, aging infrastructure, non-viable utility operations, and rapidly expanding renewable generation in a perfect storm. Such a storm presses upon the national grid like never before, and as such, new DSM approaches are needed.

This is primarily due to urgent DSM needs stemming from two sources: First, consistent peak demand exists, and although customers often have no energy access for certain hours, the consistent unviability of energy provision confines DSM attempts to certain hours; this also means that the grid is consistently stressed in an unsustainable manner preventing economic growth and development. Second, the more renewables increase, the more uncertain supply becomes (infrequent and disruptive, mind you), which means that DSM will need to be even more sophisticated and aggressive with optimization strategies.

This dissertation provides emphasis on three algorithms, all of which are studied extensively in the chapters to follow - Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), and the most recently published, the Barber Optimization Algorithm (BaOA). Each optimization was independently tested for DSM case studies supported with historical and predicted load data in various municipalities within the Western Cape. Thus, as per the order by which I've approached testing for comparison, I've also introduced BaOA to the DSM field.

Relative to the aims and objectives clarified in this chapter, the thesis extends theoretical relevance of the project in accordance with the South African energy state and global landscape of well-optimized, rational energy systems boasting DSM functionality. Therefore, this chapter recaps the original aims and objectives, confirms the master's findings/contributions to the DSM field and suggests additional future considerations for real-world DSM implementation through the further review of findings.

6.2 Aim and Objectives of the Thesis

The aim of the thesis is to develop, implement and employ metaheuristic optimization methods to reduce peak demand and implement effective load shifting in municipal distribution networks with demand-side management (DSM) not merely a technical challenge but a socio-economic one stemming from affordability/reliability issues faced in South Africa.

To fulfill this aim, eight objectives were created. The objectives include a demand-side management gap analysis of feasible optimization methods, an application of innovative metaheuristics in MATLAB, a non-biased assessment of all methods to facilitate substantiated recommendations for use from municipalities/utility companies came from the report findings.

Objectives include:

1. Objective: To conduct a literature review to understand current DSM methods and find a gap.
2. Objective: To contextualize DSM with mathematical formulations, real-world constraints and any associated time-varying tariffs.
3. Objective: To create a PSO based model for DSM and validate it through loading data.
4. Objective: To extend GWO based integration to value efficiency savings.
5. Objective: To integrate and adapt BaOA to DSM for its first application in power systems research.
6. Objective: To construct MATLAB simulation tools to realize all three algorithms.
7. Objective: To compare all three methods based upon efficiency and effectiveness.
8. Objective: To provide utilities/municipalities with practical recommendations.

The deliverable: For utilities/governing bodies to implement all findings relating to assessed algorithms of DSM.

The effectiveness of these objectives' fulfilments suggests that there was a cohesive journey through the research development process significant enough to imply that not only were practical advancements made towards achieving DSM equity--including surrounding tools--but practical findings with extraneous applicability far beyond theoretical understanding were also found.

6.3 Thesis Deliverables

There are five major contributions to theory, methodology and practice rendered from this thesis that fulfill these expectations.

6.3.1 Extensive Literature Review of Current and Foundational Works Regarding DSM

This study stands as a comprehensive and critical literature review composition on foundational and current works surrounding Demand Side Management (DSM), smart optimization techniques, and energy prediction as validated by this study. This review illustrates how paradigms of DSM emerged historically with rudimentary approaches towards optimization before transitioning into a metaheuristic/machine learning-like approach. There are multiple studies connected relative to Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Machine Learning Improved Prediction (MLIP) and Barber Optimization Algorithm (BaOA) - including connections to peak clipping/loading shifting and cross-managed energy efforts. This review concludes gaps that are filled - both theoretically and methodically - in the projectary hybridization suggested through newly optimized approaches towards DSM.

6.3.2 Development of a PSO-Based DSM Optimization Model in MATLAB

The Particle Swarm Optimization (PSO) model for DSM in peak clipping and load shifting is implemented as a fully functional version in MATLAB. The model contains swarm initialization, adaptive velocity-position updates, fitness evaluating function(s), convergent checking, etc. The PSO model successfully solves for hourly load balancing while still maintaining energy balance - ultimately making it practical/inspiring as a successful resolution for DSM implementation. The baseline acquisition from this output is used in comparison with many other sophisticated approaches to optimization.

6.3.3 Development of the MLIP Algorithm for DSM in MATLAB

Machine Learning Improved Prediction (MLIP) is a new technique established by this study for improved predictive success utilizing past data for future forecast/implementation efforts for DSM use. The implementation in MATLAB merges machine learning/AI with optimization goals based upon near-term forecasting needs of what previously learned realities can be used as future solutions in a data-driven world. The fulfilment adds value

as its predictive/prescriptive methods attain value relative to DSM efforts unlike any other delineation before now.

6.3.4 Development of the GWO Algorithm for DSM in MATLAB

A complete Model of GWO was established in MATLAB to gauge its applicability for DSM optimization efforts. The method relies on hierarchical leadership of a pack of wolves and their cooperative hunting methods - realizing how active animals may best control demand based on what is available/abundant/most successful at any point suggests new metaheuristic avenues connected to GWO's pack leaders (alpha/beta/delta wolves) - therefore allowing dynamic searches for peak clipping/load shifting opportunities. This effort adds valuable determination against similar methods while offering the field an unknown comparative facet of GWO - a fulfilment unknown until now.

6.3.5 Development of the BaOA Algorithm for DSM in MATLAB

BaOA is established as a potential additional solution towards demand-side effectiveness; utilizing barbershop discourse/composition/queueing actions as behavioral rationale offers BaOA effective means towards load restructuring/management peak clipping like no other; based upon conversations from real-life observations/settings that are unknown to exist anywhere else in the field - until now since this study - adds value to the perceived utilization of BaOA within these parameters/Dimensions as implemented successfully within MATLAB. Other discoveries are referenced where possibilities elsewhere may be identified which compound the diverse tally of tested approaches/languages within this study compared to previously conducted work.

6.3.6 Construction of Complete MATLAB Solution Package for All Implemented Simulations Performed

This fulfilment encompasses comprehensive documentation throughout all modeling/simulations/visualizations within integrated MATLAB Software which packages all tested algorithms within spreadsheets generated through thesis submissions while automated results compilation supports Appendix documentation throughout - the appendices referenced weave all outputs in hand with an easy-to-use table summary 6 that provides convenience and accountability throughout documentation discussed therein as needed.

Table 6.1: MATLAB Software Developed for this Thesis

Appendix Label	Description of MATLAB Software
APPENDIX A	MATLAB Script for Demand Side Management – Load Shifting and Peak Clipping using PSO.
APPENDIX B	MATLAB Script for Demand Side Management using Machine Learning Improved Prediction (MLIP).
APPENDIX C	Grey Wolf Optimization (GWO)-Based DSM Strategy for Peak Clipping and Load Shifting.
APPENDIX D	DSM Load Profile Optimization Comparison using BaOA and PSO.

6.3.7 Testing, Simulation, and Validation Using Real-World Case Studies

The last part of this thesis includes analyzing, testing, and validating all implemented algorithms against real-world scenarios. MOIP, BaOA, GWO, and PSO were applied to real load profiles to assess efficacy in peak clipping and load shifting, enhancing system reliability, and reducing costs. Various methods were used for validation including assessing performance divergence and convergence, conducting sensitivity analyses, and calculating error against predetermined load profiles. All this validation confirms the real-world applicability and versatility of the proposed models to DSM in today's complex power systems.

For example, the extensive literature review in Chapter Two, which looked at the history of DSM optimisation research, was far from conventional in that it did not simply catalogue the literature. Where the early steps of the dissertation could be considered scientific, the final step was not only scientific but intensive. It didn't take already established solutions and attempt to run with them. It took a critical approach and found pros, cons, and gaps. Therefore, to come from an evaluation to determine BaOA could be useful in DSM for optimisation demonstrates how this evaluation-based review promoted original findings.
For example, Chapter Three developed a mathematical formulation of the DSM problem that incorporated maximum load constraints, service reliability standards and time-of-use pricing. This places the objective optimisation models relative to reality, especially of South African municipalities, as these are in reality constraints and budgets that are not flexible.

Readers will understand three models based on these fixed findings.

- PSO and MLIP-DSM model (Chapter Four), set the pace.
- GWO-DSM model (Chapter Five), generates greater efficiency and convergence speed.

- BaOA-DSM model (Chapter Six), integrates a never-before-used algorithm for DSM purposes.

The fourth step was to create practical MATLAB simulations for replication and future learning. These simulations are relevant for analysts and practitioners who may need to assess DSM optimisation under different tariffs, regions, and network applications.

The fifth step was comparative analysis between PSO and the two newer models, GWO and BaOA. It was noted that PSO was the best in terms of stability, while GWO provided tremendous exploration/exploitation speeds but BaOA required more work but had excellent potential as a new player in the DSM field. All results contribute to theoretical insight with real-world application and future developments for DSM in the field.

6.4 Applications of the Thesis Results

From an applied standpoint, the algorithms introduced through the research would relieve municipal utility pressure during peak times without costly grid adjustments. Utilities would benefit more from systems optimization and DSM tools for additional demand response instead of required costly, transformative adjustments to their grids.

For decision-makers, the research provides more substantial justification for implementing time-of-use tariffs and customer incentive programs to manage peak demand and improve system-level efficiency. The optimized DSM presented in this research is supportive of the recommended actions to bolster system reliability and balance competitive equity for the customers.

Regarding the development of smart grids, algorithms can be used to automate demand response systems in near real time. Energy management systems will need optimized, predictive control systems like those proposed in this research as South Africa moves to more advanced levels of digitized grid operations.

An optimized DSM can track and balance peak and off-peak demand in systems with high renewable energy penetration. Shifting demand to hours of high wind and solar generation diminishes the need for renewable energy curtailment and increases the use of generated renewable energy. This balance positions DSM closely with renewables to support the ultimate goal of powering systems sustainability.

6.5 Future Research Directions

This thesis is comprehensive to an extent, but it creates several opportunities for new research.

I. Scalable testing: Evaluating algorithms at the national grid level or across several municipalities to gauge the algorithm's performance at scale and across various datasets.

II. Incorporating Real-Time DSM: DSM optimization and responsive DSM capabilities integrated into smart meters and other IoT devices.

These future directions will bring DSM research closer to the operationalization of intelligent, resilient, and DSM sustainable grids.

6.6 Publications

The outputs of this thesis research have been shared (or are in preparation) in the following forums:

- Mpaka, A and Krishnamurthy, S., Optimized demand-side management for large power consumers using PSO and MLIP algorithms: A case study of the Western Cape municipality, published in IJOCTA, 025310136 https://doi.org/10.36922/IJOCTA025310136

- Mpaka, A and Krishnamurthy, S., PSO-Driven Demand-Side Management for Load Shifting in South African Municipalities, presented at the IEEE Power Africa Conference in Egypt on September 28, 2025.DOI: 10.1109/PowerAfrica65840.2025.11289035

- Mpaka, A., & Krishnamurthy, S. The Grey Wolf Optimization-Based Demand Side Management Strategy for Peak Clipping and Load Shifting. *(IJEEAS)*, ISSN: 2600-7495 eISSN: 2600-9633 IJEEAS Vol. 8, No. 2, October 2025

- Mpaka, A., and Krishnamurthy, Performance Evaluation of Demand-Side Management Using Dynamic Arithmetic and Grey Wolf Optimization Algorithms, Results in Control and Optimization, Elseriver, Submitted (In-Review)

- Mpaka, A., and Krishnamurthy, S., Barber Optimization Algorithm for DSM: A Novel Metaheuristic Approach, Springer Discover Energy (Submitted, In-Review).

- Mpaka, A., and Krishnam A PSO-Based Demand Side Management Strategy for Residential Hot Water Geyser Control; 2025, submitted on Southern African Universities Power Engineering Conference(SAUPEC)

These journal articles/papers exemplify the academic contribution of the research and the potential contribution to future peer discourse.

6.7 Conclusion

This thesis is in line with one of the major challenges presenting itself in the South African power grid. As power demand increases, power supply decreases and the transition to renewables continues, demand side management (DSM) should be approached as a challenge and an opportunity.

Contributions to knowledge from this study include utilizing newly developed optimization algorithms for DSM with three DSM techniques; Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO) and the newly developed Barber Optimization Algorithm (BaOA). For example, on one side, where PSO was determined to be a reliable control from which time, better convergence and adaptations were found through GWO, BaOA produced similar results across the board but exceptionally better for the peak to average ratio and cost of energy respective concerns. On the other side, the establishment and implementation of BaOA serves as the first of many methodological contributions to the DSM world which opens new avenues for demand side management with a reach into the optimization world.

Finally, contributions to practice include how Demand Side Management (DSM) or Load Management (LM) serves as more than load shifting or clipping, but as a precursor to a more resilient, efficient, and sustainable framework and for grid stability, peak hour demand (which is expensive under time of use tariff) and downstream variable renewables integration. These findings are generalizable beyond South Africa to any country with grid systems developed across the world that maintain reliability and resilience. Future work will expand upon the potential for the Barber Optimization Algorithm (BaOA) from a renewables forecasting perspective, real time adaptive versions for smart grids and machine learning incorporated hybrid models. Utility driven pilot-scale studies will support the need to bridge the gap between simulation and reality.

Thus, this thesis has taken a theoretical and practical perspective wherein the BaOA has been introduced and its relevance across the applicability of a variety of studies to substantiate significant findings for the DSM field. It highlights the importance of DSM since estimations claim DSM to be a fundamental part of future electricity framework transitions to cleaner, smarter and more responsible energy grids.

BIBLIOGRAPHY

Aghajani, G.R., Shayanfar, H.A. and Shayeghi, H. (2017) “Demand side management in a smart micro-grid in the presence of renewable generation and demand response,” Energy, 126, pp. 622–637. Available at: https://doi.org/10.1016/j.energy.2017.03.051.

Ahmad, A.A. et al. (2023) “Prediction of anemia with a particle swarm optimization-based approach,” International Journal of Optimization and Control: Theories and Applications, 13(2), pp. 214–223. Available at: https://doi.org/10.11121/ijocta.2023.1269.

Ahmad, M.S. et al. (2025) “Demand Response Program towards Sustainable Power Supply: Current Status, Challenges, and Prospects in Malaysia,” IEEE Access [Preprint]. Available at: https://doi.org/10.1109/ACCESS.2025.3541841.

Ahmad, S. et al. (2018) “A compendium of performance metrics, pricing schemes, optimization objectives, and solution methodologies of demand side management for the smart grid,” Energies, 11(10). Available at: https://doi.org/10.3390/en11102801.

Albadi et al. (2008) “A summary of demand response in electricity markets,” Electric Power Systems Research, pp. 1989–1996. Available at: https://doi.org/10.1016/j.epsr.2008.04.002.

Alquthami, T. et al. (2021) “An incentive based dynamic pricing in smart grid: A customer’s perspective,” Sustainability (Switzerland), 13(11). Available at: https://doi.org/10.3390/su13116066.

Anand, A. and Suganthi, L. (2018) “Hybrid GA-PSO optimization of Artificial Neural Network for forecasting electricity demand,” Energies, 11(4). Available at: https://doi.org/10.3390/en11040728.

Andruszkiewicz, J., Lorenc, J. and Weychan, A. (2021) “Price-based demand side response programs and their effectiveness on the example of tou electricity tariff for residential consumers,” Energies, 14(2). Available at: https://doi.org/10.3390/en14020287.

Antunes, C.H., Martins, A.G. and Brito, I.S. (2004) “A multiple objective mixed integer linear programming model for power generation expansion planning,” Energy, 29(4), pp. 613–627. Available at: https://doi.org/10.1016/j.energy.2003.10.012.

Bakare, M.S. et al. (2023) “A comprehensive overview on demand side energy management towards smart grids: challenges, solutions, and future direction,” Energy Informatics. Springer Nature. Available at: https://doi.org/10.1186/s42162-023-00262-7.

Balal, A. and Giesselmann, M. (2021) “Demand Side Management and Economic Analysis Using Battery Storage System (BSS) and Solar Energy,” in 2021 IEEE 4th International Conference on Power and Energy Applications, ICPEA 2021. Institute of Electrical and Electronics Engineers Inc., pp. 141–146. Available at: https://doi.org/10.1109/ICPEA52760.2021.9639359.

Behrangrad, M. (2015) “A review of demand side management business models in the electricity market,” Renewable and Sustainable Energy Reviews. Elsevier Ltd, pp. 270–283. Available at: https://doi.org/10.1016/j.rser.2015.03.033.

Benamara, K. et al. (2024) “Grey wolf optimization for enhanced performance in wind power system with dual-star induction generators,” Frontiers in Energy Research, 12. Available at: https://doi.org/10.3389/fenrg.2024.1421336.

Bertineti, D.P. et al. (2015) Heuristic Scheduling Algorithm for Load Shift DSM Strategy in Smart Grids and IoT Scenarios.

Bhamidi, L. and Shanmugavelu, S. (2019) “Multi-objective Harmony Search Algorithm for Dynamic Optimal Power Flow with Demand Side Management,” Electric Power Components and Systems, 47(8), pp. 721–731. Available at: https://doi.org/10.1080/15325008.2019.1627599.

Bharathi, C., Rekha, D. and Vijayakumar, V. (2017) “Genetic Algorithm Based Demand Side Management for Smart Grid,” Wireless Personal Communications, 93(2), pp. 481–502. Available at: https://doi.org/10.1007/s11277-017-3959-z.

Bilal, M. et al. (2024) “Review of Computational Intelligence Approaches for Microgrid Energy Management,” IEEE Access. Institute of Electrical and Electronics Engineers Inc., pp. 123294–123321. Available at: https://doi.org/10.1109/ACCESS.2024.3440885.

Chamoli, M., Panda, M.K. and Mishra, Vishnu.Mohan. (2023) “Grey Wolf Optimization Algorithm based Optimal Scheduling of Microgrid.” Available at: https://doi.org/10.21203/rs.3.rs-3759820/v1.

Charadi, S. et al. (2023) “Bi-objective optimal active and reactive power flow management in grid-connected AC/DC hybrid microgrids using metaheuristic-PSO,” Clean Energy, 7(6), pp. 1356–1380. Available at: https://doi.org/10.1093/ce/zkad081.

Chen, G. et al. (2020) “A new method of lithology classification based on convolutional neural network algorithm by utilizing drilling string vibration data,” Energies, 13(4). Available at: https://doi.org/10.3390/en13040888.

da Costa, V.B.F. et al. (2022) “Electricity Markets in the Context of Distributed Energy Resources and Demand Response Programs: Main Developments and Challenges Based on a Systematic Literature Review,” Energies. MDPI. Available at: https://doi.org/10.3390/en15207784.

Dahiru, A.T. et al. (2023) “A comprehensive review of demand side management in distributed grids based on real estate perspectives,” Environmental Science and Pollution Research, 30(34), pp. 81984–82013. Available at: https://doi.org/10.1007/s11356-023-25146-x.

Dassa, K. and Recioui, A. (2022) “Demand Side Management and Dynamic Economic Dispatch Using Genetic Algorithms †,” Engineering Proceedings, 14(1). Available at: https://doi.org/10.3390/engproc2022014012.

Dey, B., Sharma, G. and Bokoro, P.N. (2024) “Economic management of microgrid using flexible non-linear load models based on price-based demand response strategies,” Results in Engineering, 24. Available at: https://doi.org/10.1016/j.rineng.2024.102993.

Dharani, R. et al. (2021) “Load shifting and peak clipping for reducing energy consumption in an indian university campus,” Energies, 14(3). Available at: https://doi.org/10.3390/en14030558.

Ding, T. et al. (2022) “Review of Optimization Methods for Energy Hub Planning, Operation, Trading, and Control,” IEEE Transactions on Sustainable Energy, 13(3), pp. 1802–1818. Available at: https://doi.org/10.1109/TSTE.2022.3172004.

Dragomir, O.E. and Dragomir, F. (2023) “Application of Scheduling Techniques for Load-Shifting in Smart Homes with Renewable-Energy-Sources Integration,” Buildings, 13(1). Available at: https://doi.org/10.3390/buildings13010134.

El-Afifi, M.I. et al. (2024) “Demand side management strategy for smart building using multi-objective hybrid optimization technique,” Results in Engineering, 22. Available at: https://doi.org/10.1016/j.rineng.2024.102265.

Al Essa, M.J.M. (2020) “Power Quality of Electrical Distribution Systems Considering PVs, EVs and DSM,” Journal of Control, Automation and Electrical Systems, 31(6), pp. 1520–1532. Available at: https://doi.org/10.1007/s40313-020-00637-1.

Faia, R. et al. (2019a) “Demand response optimization using particle swarm algorithm considering optimum battery energy storage schedule in a residential house,” Energies, 12(9). Available at: https://doi.org/10.3390/en12091645.

Faia, R. et al. (2019b) “Demand response optimization using particle swarm algorithm considering optimum battery energy storage schedule in a residential house,” Energies, 12(9). Available at: https://doi.org/10.3390/en12091645.

Faia, R. et al. (2023) “Dataset of an energy community with prosumer consumption, photovoltaic generation, battery storage, and electric vehicles,” Data in Brief, 48. Available at: https://doi.org/10.1016/j.dib.2023.109218.

Farag, M.M., Alhamad, R.A. and Nassif, A.B. (2023) “Metaheuristic Algorithms in Optimal Power Flow Analysis: A Qualitative Systematic Review,” International Journal on Artificial Intelligence Tools, 32(7). Available at: https://doi.org/10.1142/S021821302350032X.

Faruqui, A. and Sergici, S. (2010) “Household response to dynamic pricing of electricity: A survey of 15 experiments,” Journal of Regulatory Economics, pp. 193–225. Available at: https://doi.org/10.1007/s11149-010-9127-y.

Gado, D.M. et al. (2023) “Optimizing Energy Consumption in Smart Homes: A Comprehensive Review of Demand Side Management Strategies,” in Proceedings - IEEE CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies, ChileCon. Institute of Electrical and Electronics Engineers Inc. Available at: https://doi.org/10.1109/CHILECON60335.2023.10418744.

Garip, S. and Ozdemir, S. (2022) “Optimization of PV and Battery Energy Storage Size in Grid-Connected Microgrid,” Applied Sciences (Switzerland), 12(16). Available at: https://doi.org/10.3390/app12168247.

Gellings, C.W. (2017) “Evolving practice of demand-side management,” Journal of Modern Power Systems and Clean Energy, 5(1), pp. 1–9. Available at: https://doi.org/10.1007/s40565-016-0252-1.

Giedraityte, A. et al. (2025) “Hybrid Renewable Energy Systems—A Review of Optimization Approaches and Future Challenges,” Applied Sciences (Switzerland). Multidisciplinary Digital Publishing Institute (MDPI). Available at: https://doi.org/10.3390/app15041744.

Gorman, W. et al. (2025) “Backup power or bill savings? How electricity tariffs impact residential solar-plus-storage usage in the United States,” Utilities Policy, 96. Available at: https://doi.org/10.1016/j.jup.2025.102035.

Haley, B. et al. (2020) “From utility demand side management to low-carbon transitions: Opportunities and challenges for energy efficiency governance in a new era,” Energy Research and Social Science. Elsevier Ltd. Available at: https://doi.org/10.1016/j.erss.2019.101312.

Hamadneh, T. et al. (2025) “Barber Optimization Algorithm: A New Human-Based Approach for Solving Optimization Problems,” Computers, Materials and Continua, 83(2), pp. 2677–2718. Available at: https://doi.org/10.32604/cmc.2025.064087.

Harish, V.S.K.V. and Kumar, A. (2014) “Demand side management in India: Action plan, policies and regulations,” Renewable and Sustainable Energy Reviews. Elsevier Ltd, pp. 613–624. Available at: https://doi.org/10.1016/j.rser.2014.02.021.

Hassan, H.A. and Zellagui, M. (2017) “Application of grey wolf optimizer algorithm for optimal power flow of two-terminal HVDC transmission system,” Advances in Electrical and Electronic Engineering, 15(5), pp. 701–711. Available at: https://doi.org/10.15598/aeee.v15i5.2110.

Iqbal, S. et al. (2021) “A comprehensive review on residential demand side management strategies in smart grid environment,” Sustainability (Switzerland), 13(13). Available at: https://doi.org/10.3390/su13137170.

Jabir, H.J. et al. (2018) “Impacts of demand-side management on electrical power systems: A review,” Energies. MDPI AG. Available at: https://doi.org/10.3390/en11051050.

Jamil, M. and Mittal, S. (2020) “Hourly load shifting approach for demand side management in smart grid using grasshopper optimisation algorithm,” IET Generation, Transmission and Distribution, 14(5), pp. 808–815. Available at: https://doi.org/10.1049/iet-gtd.2019.0566.

Jasim, A.M. et al. (2023) “Efficient Optimization Algorithm-Based Demand-Side Management Program for Smart Grid Residential Load,” Axioms, 12(1). Available at: https://doi.org/10.3390/axioms12010033.

Jindal, A., Singh, M. and Kumar, N. (2018) “Consumption-aware data analytical demand response scheme for peak load reduction in smart grid,” IEEE Transactions on Industrial Electronics, 65(11), pp. 8993–9004. Available at: https://doi.org/10.1109/TIE.2018.2813990.

Kennedy, J., Eberhart, R. and gov, bls (1995) Kennedy, J. and Eberhart, R. (1995) Particle Swarm Optimization. Proceedings of the IEEE International Conference on Neural Networks, 4, 1942-1948. http://dx.doi.org/10.1109/ICNN.1995.488968.

Khan, M.A. et al. (2023) “Artificial Intelligence Enabled Demand Response: Prospects and Challenges in Smart Grid Environment,” IEEE Access. Institute of Electrical and Electronics Engineers Inc., pp. 1477–1505. Available at: https://doi.org/10.1109/ACCESS.2022.3231444.

Lanneer, W. et al. (2017) “Linear and nonlinear precoding based dynamic spectrum management for downstream vectored G.fast transmission,” IEEE Transactions on Communications, 65(3), pp. 1247–1259. Available at: https://doi.org/10.1109/TCOMM.2016.2641952.

Liu, L. et al. (2018) “Load frequency control using demand response and storage battery by considering renewable energy sources,” Energies, 11(12). Available at: https://doi.org/10.3390/en11123412.

Liu, Y. et al. (2023) “Multi-objective optimal scheduling of household appliances for demand side management using a hybrid heuristic algorithm,” Energy, 262. Available at: https://doi.org/10.1016/j.energy.2022.125460.

Logenthiran, T., Srinivasan, D. and Shun, T.Z. (2012) “Demand side management in smart grid using heuristic optimization,” IEEE Transactions on Smart Grid, 3(3), pp. 1244–1252. Available at: https://doi.org/10.1109/TSG.2012.2195686.

Longe, O.M. et al. (2017) “Distributed demand side management with battery storage for smart home energy scheduling,” Sustainability (Switzerland), 9(1). Available at: https://doi.org/10.3390/su9010120.

Ma, Q. et al. (2022) “Real-Time Control Strategy of Tractive Load Peak Clipping and Valley Filling Based on Model Predictive Control,” IEEE Transactions on Transportation Electrification, 8(3), pp. 3208–3218. Available at: https://doi.org/10.1109/TTE.2022.3163135.

Madhiarasan, M. and Deepa, S.N. (2016) “ELMAN Neural Network with Modified Grey Wolf Optimizer for Enhanced Wind Speed Forecasting,” Circuits and Systems, 07(10), pp. 2975–2995. Available at: https://doi.org/10.4236/cs.2016.710255.

Madushele, N. and Tabakov, P. (2024) “A Survey of Home Energy Management Systems and their Efficacy in South Africa,” in 2024 Conference on Information Communication Technology and Society, ICTAS 2024 - Proceedings. Institute of Electrical and Electronics Engineers Inc., pp. 209–213. Available at: https://doi.org/10.1109/ICTAS59620.2024.10507129.

Maneebang, K., Methapatara, K. and Kudtongngam, J. (2020) “A demand side management solution: Fully automated demand response using OpenADR2.0b coordinating with BEMS pilot project,” in Proceedings - 2020 International Conference on Smart Grids and Energy Systems, SGES 2020. Institute of Electrical and Electronics Engineers Inc., pp. 30–35. Available at: https://doi.org/10.1109/SGES51519.2020.00013.

Manoharan, M. and Padma, S. (2023) “An Optimized Demand Side Management with Automatic Peak Clipping and Load Scheduling for Energy Conservation,” in Proceedings of the 2023 2nd International Conference on Augmented Intelligence and Sustainable Systems, ICAISS 2023. Institute of Electrical and Electronics Engineers Inc., pp. 1710–1715. Available at: https://doi.org/10.1109/ICAISS58487.2023.10250574.

Maqbool, A. et al. (2025a) “Hybrid metaheuristic optimization based DSM approach towards effective energy recommender system,” Electric Power Systems Research, 246. Available at: https://doi.org/10.1016/j.epsr.2025.111645.

Maqbool, A. et al. (2025b) “Hybrid metaheuristic optimization based DSM approach towards effective energy recommender system,” Electric Power Systems Research, 246. Available at: https://doi.org/10.1016/j.epsr.2025.111645.

Maqbool, A. et al. (2025c) “Hybrid metaheuristic optimization based DSM approach towards effective energy recommender system,” Electric Power Systems Research, 246. Available at: https://doi.org/10.1016/j.epsr.2025.111645.

Mataifa, H., Krishnamurthy, S. and Kriger, C. (2023) “Comparative Analysis of the Particle Swarm Optimization and Primal-Dual Interior-Point Algorithms for Transmission System Volt/VAR Optimization in Rectangular Voltage Coordinates,” Mathematics, 11(19). Available at: https://doi.org/10.3390/math11194093.

Mccall, B. et al. (2019) Least-cost integrated resource planning and cost-optimal climate change mitigation policy: Alternatives for the South African electricity system. Available at: www.erc.uct.ac.za.

Mehr Nezhad, M., Moghaddam, M.H.Y. and Asadi, M. (2021) “Joint Peak Clipping and Load Scheduling Based on User Behavior Monitoring in an IoT Platform,” IEEE Systems Journal, 15(1), pp. 1202–1213. Available at: https://doi.org/10.1109/JSYST.2020.3009699.

Meng, F. et al. (2024) “Demand-side energy management reimagined: A comprehensive literature analysis leveraging large language models,” Energy, 291. Available at: https://doi.org/10.1016/j.energy.2024.130303.

Mimi, S., Ben Maissa, Y. and Tamtaoui, A. (2023) “Optimization Approaches for Demand-Side Management in the Smart Grid: A Systematic Mapping Study,” Smart Cities. Multidisciplinary Digital Publishing Institute (MDPI), pp. 1630–1662. Available at: https://doi.org/10.3390/smartcities6040077.

Mirjalili, S., Mirjalili, S.M. and Lewis, A. (2014) “Grey Wolf Optimizer,” Advances in Engineering Software, 69, pp. 46–61. Available at: https://doi.org/10.1016/j.advengsoft.2013.12.007.

Mohammad Rozali, N.E. et al. (2015) “Peak-off-peak load shifting for hybrid power systems based on Power Pinch Analysis,” Energy, 90, pp. 128–136. Available at: https://doi.org/10.1016/j.energy.2015.05.010.

Mohsenian-Rad, A.H. et al. (2010a) “Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid,” IEEE Transactions on Smart Grid, 1(3), pp. 320–331. Available at: https://doi.org/10.1109/TSG.2010.2089069.

Mohsenian-Rad, A.H. et al. (2010b) “Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid,” IEEE Transactions on Smart Grid, 1(3), pp. 320–331. Available at: https://doi.org/10.1109/TSG.2010.2089069.

Mousa, H.H.H., Mahmoud, K. and Lehtonen, M. (2024) “Recent developments of demand-side management towards flexible DER-rich power systems: A systematic review,” IET Generation, Transmission and Distribution. John Wiley and Sons Inc, pp. 2259–2300. Available at: https://doi.org/10.1049/gtd2.13204.

Obando-Paredes, E.D., López-García, D. and Carvajal-Quintero, S.X. (2024) “Integrating active demand into the distribution system using metaheuristic techniques,” The Journal of Engineering, 2024(11). Available at: https://doi.org/10.1049/tje2.70005.

Oskouei, M.Z. et al. (2022) “A Critical Review on the Impacts of Energy Storage Systems and Demand-Side Management Strategies in the Economic Operation of Renewable-Based Distribution Network,” Sustainability (Switzerland). MDPI. Available at: https://doi.org/10.3390/su14042110.

Palensky et al (2011) “Demand side management: Demand response, intelligent energy systems, and smart loads,” IEEE Transactions on Industrial Informatics, 7(3), pp. 381–388. Available at: https://doi.org/10.1109/TII.2011.2158841.

Paterakis, N.G. et al. (2018) “A Multi-Objective Optimization Approach to Risk-Constrained Energy and Reserve Procurement Using Demand Response,” IEEE Transactions on Power Systems, 33(4), pp. 3940–3954. Available at: https://doi.org/10.1109/TPWRS.2017.2785266.

Paul, K. et al. (2025) “Optimizing sustainable energy management in grid connected microgrids using quantum particle swarm optimization for cost and emission reduction,” Scientific reports, 15(1), p. 5843. Available at: https://doi.org/10.1038/s41598-025-90040-0.

Philipo, G.H., Kakande, J.N. and Krauter, S. (2022a) “Neural Network-Based Demand-Side Management in a Stand-Alone Solar PV-Battery Microgrid Using Load-Shifting and Peak-Clipping,” Energies, 15(14). Available at: https://doi.org/10.3390/en15145215.

Philipo, G.H., Kakande, J.N. and Krauter, S. (2022b) “Neural Network-Based Demand-Side Management in a Stand-Alone Solar PV-Battery Microgrid Using Load-Shifting and Peak-Clipping,” Energies, 15(14). Available at: https://doi.org/10.3390/en15145215.

Pothireddy, K.M.R., Vuddanti, S. and Salkuti, S.R. (2022) “Impact of demand response on optimal sizing of distributed generation and customer tariff,” Energies, 15(1). Available at: https://doi.org/10.3390/en15010190.

Rácz, A. (2025) “A MILP model for one dimensional cutting stock problem with adjustable leftover threshold and cutting cost,” International Journal of Optimization and Control: Theories and Applications, 15(2), pp. 215–224. Available at: https://doi.org/10.36922/ijocta.1660.

Rahimi, F. and Ipakchi, A. (2010) “Demand response as a market resource under the smart grid paradigm,” IEEE Transactions on Smart Grid, pp. 82–88. Available at: https://doi.org/10.1109/TSG.2010.2045906.

Rahman, M.A., Rahman, I. and Mohammad, N. (2020) “Demand side residential load management system for minimizing energy consumption cost and reducing peak demand in smart grid,” in 2020 2nd International Conference on Advanced Information and Communication Technology, ICAICT 2020. Institute of Electrical and Electronics Engineers Inc., pp. 376–381. Available at: https://doi.org/10.1109/ICAICT51780.2020.9333451.

Rahmani-Andebili, M. (2016) “Modeling nonlinear incentive-based and price-based demand response programs and implementing on real power markets,” Electric Power Systems Research, 132, pp. 115–124. Available at: https://doi.org/10.1016/j.epsr.2015.11.006.

Rana, M.M. et al. (2023) “Applications of energy storage systems in power grids with and without renewable energy integration — A comprehensive review,” Journal of Energy Storage. Elsevier Ltd. Available at: https://doi.org/10.1016/j.est.2023.107811.

Saleem, M.U. et al. (2022) “Design, Deployment and Performance Evaluation of an IoT Based Smart Energy Management System for Demand Side Management in Smart Grid,” IEEE Access, 10, pp. 15261–15278. Available at: https://doi.org/10.1109/ACCESS.2022.3147484.

Sekhar, D.C., Rao, P.V.V.R. and Kiranmayi, R. (2022) “Conceptual Review on Demand Side Management, Optimization Techniques for the Improvement of Power Quality in Smart Grids,”

in Proceedings of the 2nd International Conference on Artificial Intelligence and Smart Energy, ICAIS 2022. Institute of Electrical and Electronics Engineers Inc., pp. 1640–1647. Available at: https://doi.org/10.1109/ICAIS53314.2022.9742779.

Sharda, S., Singh, M. and Sharma, K. (2021) "Demand side management through load shifting in IoT based HEMS: Overview, challenges and opportunities," Sustainable Cities and Society. Elsevier Ltd. Available at: https://doi.org/10.1016/j.scs.2020.102517.

Sharifhosseini, S.M. et al. (2024) "Investigating Intelligent Forecasting and Optimization in Electrical Power Systems: A Comprehensive Review of Techniques and Applications," Energies. Multidisciplinary Digital Publishing Institute (MDPI). Available at: https://doi.org/10.3390/en17215385.

Shewale, A. et al. (2020) "An overview of demand response in smart grid and optimization techniques for efficient residential appliance scheduling problem," Energies. MDPI AG. Available at: https://doi.org/10.3390/en13164266.

Shezan, S.A. et al. (2015) "Feasibility analysis of a hybrid off-grid wind-DG-battery energy system for the eco-tourism remote areas," Clean Technologies and Environmental Policy, 17(8), pp. 2417–2430. Available at: https://doi.org/10.1007/s10098-015-0983-0.

Siano, P. (2014a) "Demand response and smart grids - A survey," Renewable and Sustainable Energy Reviews. Elsevier Ltd, pp. 461–478. Available at: https://doi.org/10.1016/j.rser.2013.10.022.

Siano, P. (2014b) "P. Siano, 'Demand response and smart grids – A survey,' Renewable and Sustainable Energy Reviews, vol. 30, pp. 461–478, 2014, doi: 10.1016/j.rser.2013.10.022.," Renewable and Sustainable Energy Reviews. Elsevier Ltd, pp. 461–478. Available at: https://doi.org/10.1016/j.rser.2013.10.022.

Strbac, G. (2008) "Demand side management: Benefits and challenges," Energy Policy, 36(12), pp. 4419–4426. Available at: https://doi.org/10.1016/j.enpol.2008.09.030.

Sun, H., Cui, X. and Latifi, H. (2024) "Optimal management of microgrid energy by considering demand side management plan and maintenance cost with developed particle swarm

algorithm," Electric Power Systems Research, 231. Available at: https://doi.org/10.1016/j.epsr.2024.110312.

Tijjani Dahiru, A. et al. (2022) "A Review of Demand Side Management Strategies and Electricity Tariffs in Distributed Grids," 21(3), pp. 13–22. Available at: https://elektrika.utm.my. Tomar, V., Bansal, M. and Singh, P. (2023) "Metaheuristic Algorithms for Optimization: A Brief Review," Engineering Proceedings, 59(1). Available at: https://doi.org/10.3390/engproc2023059238.

Tzanes, G.T., Zafirakis, D.P. and Kaldellis, J.K. (2024) "Practice of a Load Shifting Algorithm for Enhancing Community-Scale RES Utilization," Sustainability (Switzerland) , 16(13). Available at: https://doi.org/10.3390/su16135679.

Usman, R. et al. (2022) "Systematic Review of Demand-Side Management Strategies in Power Systems of Developed and Developing Countries," Energies. MDPI. Available at: https://doi.org/10.3390/en15217858.

del Valle, Y. et al. (2008) "Particle swarm optimization: Basic concepts, variants and applications in power systems," IEEE Transactions on Evolutionary Computation, pp. 171–195. Available at: https://doi.org/10.1109/TEVC.2007.896686.

Wang, Y. et al. (2019) "Review of Smart Meter Data Analytics: Applications, Methodologies, and Challenges," IEEE Transactions on Smart Grid, 10(3), pp. 3125–3148. Available at: https://doi.org/10.1109/TSG.2018.2818167.

Williams, B. et al. (2023) "Demand Side Management in Industrial, Commercial, and Residential Sectors: A Review of Constraints and Considerations," Energies. Multidisciplinary Digital Publishing Institute (MDPI). Available at: https://doi.org/10.3390/en16135155.

You, P. et al. (2023) "Price-Based Demand Response: A Three-Stage Monthly Time-of-Use Tariff Optimization Model," Energies, 16(23). Available at: https://doi.org/10.3390/en16237858.

Zaini, F.A. et al. (2023) "A Review on the Applications of PSO-Based Algorithm in Demand Side Management: Challenges and Opportunities," IEEE Access. Institute of Electrical and Electronics Engineers Inc., pp. 53373–53400. Available at: https://doi.org/10.1109/ACCESS.2023.3278261.

APPENDICES

APPENDIX A: MATLAB Script for Demand Side Management - Load Shifting and Peak Clipping using PSO

To achieve demand side management goals, a MATLAB Particle Swarm Optimization code was implemented using Appendices A, which implemented peak clipping and peak shifting on actual feeder data from Paarl. The application carries out load data preprocessing, implements Eskom Time-of-Use tariffs, identifies peak and off-peak period and sets a target peak reduction. PSO application follows using several particles and iterations, which help to reshape the load profile iteratively so that total energy remains the same. Thereafter, peak reduction, cost savings and parsed CO2 improvement criteria are used to evaluate the optimal schedule, which are visualized in examples like monthly and yearly energy differences and daily performance also having before and after load curves. In the dissertation, the PSO model was used as the benchmark optimization method

```
%% MATLAB Script for Demand Side Management – Load Shifting and Peak
Clipping using PSO
clc; clear; close all;

%% Load and Preprocess Input Data
filename = 'Processed_Paarl_LPU_MVA.xlsx';

% Read the Excel data (Column A: datetime, Column B: MVA)
raw_data = readtable(filename, 'VariableNamingRule', 'preserve');

% Convert datetime
time_stamps = datetime(raw_data{:,1}, 'InputFormat', 'yyyy/MM/dd
HH:mm:ss', 'Format', 'yyyy-MM-dd HH:mm:ss');

% Convert MVA to kW (assume PF = 0.92)
power_factor = 0.92;
load_profile_MVA = raw_data{:,2};
load_profile = load_profile_MVA * 1000 * power_factor;

% Filter for Jan 2024 to Jun 2025
start_date = datetime('2024-01-01');
end_date = datetime('2025-06-30 23:59:59');
valid_idx = (time_stamps >= start_date) & (time_stamps <= end_date);

% Apply filter
time_stamps = time_stamps(valid_idx);
load_profile = load_profile(valid_idx);

%% Define Electricity Prices (c/kWh)
high_peak_price = 777.73;
high_standard_price = 273.71;
high_off_peak_price = 173.65;
```

```
low_peak_price = 290.54;
low_standard_price = 217.06;
low_off_peak_price = 157.68;

%% Time-of-Use Tariff Logic
is_weekend = ismember(weekday(time_stamps), [1, 7]);
is_high_season = ismember(month(time_stamps), 6:8);
hour_val = hour(time_stamps);
minute_val = minute(time_stamps);

price = zeros(size(time_stamps));
for i = 1:length(time_stamps)
    if is_weekend(i)
        price(i) = is_high_season(i) * 173.65 + ~is_high_season(i) *
157.68;
    else
        if is_high_season(i)
            if (hour_val(i) >= 7 && hour_val(i) < 10) || (hour_val(i) >=
18 && hour_val(i) < 20)
                price(i) = high_peak_price;
            elseif (hour_val(i) >= 5 && hour_val(i) < 7) || (hour_val(i)
>= 10 && hour_val(i) < 18) || (hour_val(i) >= 20 && hour_val(i) < 22)
                price(i) = high_standard_price;
            else
                price(i) = high_off_peak_price;
            end
        else
            if (hour_val(i) >= 7 && hour_val(i) < 10) || (hour_val(i) >=
18 && hour_val(i) < 20)
                price(i) = low_peak_price;
            elseif (hour_val(i) >= 5 && hour_val(i) < 7) || (hour_val(i)
>= 10 && hour_val(i) < 18) || (hour_val(i) >= 20 && hour_val(i) < 22)
                price(i) = low_standard_price;
            else
                price(i) = low_off_peak_price;
            end
        end
    end
end

%% Determine Peak and Off-Peak Periods
peak_hours = (hour_val >= 6 & hour_val <= 8) | (hour_val >= 15 & hour_val
<= 19);
off_peak_hours = ~peak_hours;

original_peak_load = max(load_profile(peak_hours));
reduction_factor = 0.1 + 0.05 * rand(); % 10-15% reduction
target_peak_reduction = reduction_factor * original_peak_load;

%% PSO Optimization Parameters
num_particles = 50;
num_iterations = 100;
c1 = 1.5; c2 = 1.5; w = 0.7;
num_hours = length(load_profile);
total_energy_before = sum(load_profile);

particle_positions = repmat(load_profile', num_particles, 1) +
randn(num_particles, num_hours) * 0.05;
particle_velocities = zeros(size(particle_positions));
```

```
best_personal_positions = particle_positions;
best_personal_fitness = inf(num_particles, 1);

[best_global_fitness, best_idx] = min(best_personal_fitness);
best_global_position = best_personal_positions(best_idx, :);

for iter = 1:num_iterations
    for i = 1:num_particles
        shifted = particle_positions(i, :)';

        % Peak Clipping
        shifted(peak_hours) = max(shifted(peak_hours) -
target_peak_reduction, 0.2 * original_peak_load);

        % Redistribute Clipped Load
        lost_energy = total_energy_before - sum(shifted);
        if lost_energy > 0
            off_idx = find(off_peak_hours);
            num_off = length(off_idx);
            redist_factors = 0.8 + 0.2 * rand(num_off, 1);
            redist_factors = redist_factors / sum(redist_factors);
            shifted(off_idx) = shifted(off_idx) + redist_factors .*
lost_energy;
        end

        shifted(shifted < 0) = 0;

        % Fitness = peak + imbalance penalty
        new_peak = max(shifted(peak_hours));
        fitness = new_peak + abs(total_energy_before - sum(shifted));

        if fitness < best_personal_fitness(i)
            best_personal_fitness(i) = fitness;
            best_personal_positions(i, :) = shifted';
        end
    end

    [best_global_fitness, best_idx] = min(best_personal_fitness);
    best_global_position = best_personal_positions(best_idx, :);

    for i = 1:num_particles
        r1 = rand(1, num_hours);
        r2 = rand(1, num_hours);
        particle_velocities(i, :) = w * particle_velocities(i, :) + ...
            c1 * r1 .* (best_personal_positions(i, :) -
particle_positions(i, :)) + ...
            c2 * r2 .* (best_global_position - particle_positions(i, :));
        particle_positions(i, :) = particle_positions(i, :) +
particle_velocities(i, :);
    end
end

shifted_load_profile = best_global_position';

%% Cost & CO2 Analysis
total_cost_before = sum(load_profile .* price);
total_cost_after = sum(shifted_load_profile .* price);
cost_savings = total_cost_before - total_cost_after;
```

```
co2_factor = 0.92;
co2_before = sum(load_profile) * co2_factor;
co2_after = sum(shifted_load_profile) * co2_factor;

%% Monthly Summary
months = month(time_stamps);
monthly_original = accumarray(months, load_profile, [12 1], @sum);
monthly_optimized = accumarray(months, shifted_load_profile, [12 1],
@sum);

figure;
bar(1:12, [monthly_original monthly_optimized]);
legend('Original load', 'Optimized load');
xlabel('Month'); ylabel('Energy consumption (kWh)');
grid on;

%% Yearly Energy Consumption Comparison
years = year(time_stamps);
unique_years = unique(years);

% Compute yearly totals
yearly_original = accumarray(years - min(years) + 1, load_profile, [],
@sum);
yearly_optimized = accumarray(years - min(years) + 1,
shifted_load_profile, [], @sum);

% Create the bar plot
figure;
bar(unique_years, [yearly_original yearly_optimized]);
legend('Original load', 'Optimized load');
xlabel('Year');
ylabel('Total energy consumption (kWh)');
grid on;

%% Daily Load Profile Comparison (Before vs After)
% Choose a representative day (e.g., a peak day in June 2024)
sample_day = datetime('2024-06-19');  % You can adjust this date
day_mask = dateshift(time_stamps, 'start', 'day') == sample_day;

figure;
plot(time_stamps(day_mask), load_profile(day_mask), 'r-', 'LineWidth',
1.5);
hold on;
plot(time_stamps(day_mask), shifted_load_profile(day_mask), 'b--',
'LineWidth', 1.5);
xlabel('Time');
ylabel('Load (kW)');
legend('Original load', 'Optimized load');
grid on;

%% Peak Load Reduction Visualization
figure('Color', 'w'); % White background for clarity

% Plot original and optimized load profiles
plot(time_stamps, load_profile, 'r-', 'LineWidth', 1.5, 'DisplayName',
'Original Load');
hold on;
plot(time_stamps, shifted_load_profile, 'b--', 'LineWidth', 1.5,
'DisplayName', 'Optimized Load');
```

```
ax = gca;                  % get current axis
ax.XAxis.Exponent = 0;     % disable scientific notation on X-axis
ax.YAxis.Exponent = 0;     % disable scientific notation on Y-axis
% Highlight peak loads
yline(original_peak_load, '--r', 'Original Peak',
'LabelHorizontalAlignment', 'left', ...
      'FontWeight', 'bold', 'LabelVerticalAlignment', 'bottom');
yline(max(shifted_load_profile(peak_hours)), '--b', 'Reduced Peak',
'LabelHorizontalAlignment', 'left', ...
      'FontWeight', 'bold', 'LabelVerticalAlignment', 'bottom');

% Axis labels and title with bold
xlabel('Time', 'FontWeight', 'bold', 'FontSize', 12);
ylabel('Load (kW)', 'FontWeight', 'bold', 'FontSize', 12);

% Legend
legend('Location', 'best', 'FontSize', 10);

% Grid and axis limits
grid on;
xlim([start_date, end_date]);
set(gca, 'FontSize', 11); % Set axis tick labels font size


%% Energy Shift Visualization: Peak vs Off-Peak Comparison
peak_original = sum(load_profile(peak_hours));
peak_optimized = sum(shifted_load_profile(peak_hours));
offpeak_original = sum(load_profile(off_peak_hours));
offpeak_optimized = sum(shifted_load_profile(off_peak_hours));


%% Hourly Average Load Profile
hours_vec = hour(time_stamps);
avg_original = accumarray(hours_vec+1, load_profile, [24 1], @mean);
avg_optimized = accumarray(hours_vec+1, shifted_load_profile, [24 1],
@mean);

figure;
plot(0:23, avg_original, 'r-', 'LineWidth', 1.5); hold on;
plot(0:23, avg_optimized, 'b--', 'LineWidth', 1.5);
xlabel('Hour of day');
ylabel('Average load (kW)');
legend('Original', 'Optimized');

grid on;

%% Display Results
fprintf('Original peak load: %.2f kW\n', original_peak_load);
fprintf('Reduced peak load: %.2f kW\n',
max(shifted_load_profile(peak_hours)));
fprintf('Target reduction: %.2f kW (%.2f%%)\n', target_peak_reduction,
100*reduction_factor);
fprintf('Total cost before optimization: R %.2f\n', total_cost_before /
100); % Convert c to R
fprintf('Total cost after optimization: R %.2f\n', total_cost_after /
100);
fprintf('Cost Savings: R %.2f\n', cost_savings / 100);
```

APPENDIX B: MATLAB Script for Demand Side Management using MLIP

The MATLAB script in Appendix B sets a Machine Learning Improved Prediction (MLIP) derived DSM strategy that predicts load behavior and adjust the profile until the latter achieves the better peak shaving and the improved load rescheduling. It is a multistep process involving input preprocessing, the teaching of the load forecasting part of the MLIP model and finally peak shaving the network and transferring overloads to low usage times. Cost, energy balance and emission metrics estimate the final optimum profiles. Figures showing the difference between the original optimisation result and the optimised schedule are given in this section, while costs and energy balance seem rather difficult to present in this way. This MLIP sets the forecasting component of a combined DSM model that the paper studies.

```
%% MATLAB Script for Demand Side Management using MLIP
clc; clear; close all;

%% Load and Preprocess Input Data
filename = 'Processed_Paarl_LPU_MVA.xlsx';
raw_data = readtable(filename, 'VariableNamingRule', 'preserve');
time_stamps = datetime(raw_data{:,1}, 'InputFormat', 'yyyy/MM/dd
HH:mm:ss', 'Format', 'yyyy-MM-dd HH:mm:ss');
power_factor = 0.92;
load_profile_MVA = raw_data{:,2};
load_profile = load_profile_MVA * 1000 * power_factor;

start_date = datetime('2024-01-01');
end_date = datetime('2025-06-30 23:59:59');
valid_idx = (time_stamps >= start_date) & (time_stamps <= end_date);
time_stamps = time_stamps(valid_idx);
load_profile = load_profile(valid_idx);

%% Time-of-Use Pricing
high_peak_price = 777.73; high_standard_price = 273.71;
high_off_peak_price = 173.65;
low_peak_price = 290.54; low_standard_price = 217.06; low_off_peak_price =
157.68;

is_weekend = ismember(weekday(time_stamps), [1 7]);
is_high_season = ismember(month(time_stamps), 6:8);
hour_val = hour(time_stamps);

price = zeros(size(time_stamps));
for i = 1:length(time_stamps)
    if is_weekend(i)
        price(i) = is_high_season(i) * high_off_peak_price +
~is_high_season(i) * low_off_peak_price;
    else
        if is_high_season(i)
            if (hour_val(i) >= 7 && hour_val(i) < 10) || (hour_val(i) >=
18 && hour_val(i) < 20)
                price(i) = high_peak_price;
            elseif (hour_val(i) >= 5 && hour_val(i) < 7) || ...
```

```
                    (hour_val(i) >= 10 && hour_val(i) < 18) || ...
                    (hour_val(i) >= 20 && hour_val(i) < 22)
                price(i) = high_standard_price;
            else
                price(i) = high_off_peak_price;
            end
        else
            if (hour_val(i) >= 7 && hour_val(i) < 10) || (hour_val(i) >=
18 && hour_val(i) < 20)
                price(i) = low_peak_price;
            elseif (hour_val(i) >= 5 && hour_val(i) < 7) || ...
                    (hour_val(i) >= 10 && hour_val(i) < 18) || ...
                    (hour_val(i) >= 20 && hour_val(i) < 22)
                price(i) = low_standard_price;
            else
                price(i) = low_off_peak_price;
            end
        end
    end
end

%% Define Peak and Off-Peak Periods
peak_hours = (hour_val >= 6 & hour_val <= 8) | (hour_val >= 15 & hour_val
<= 19);
off_peak_hours = ~peak_hours;
original_peak_load = max(load_profile(peak_hours));
reduction_factor = 0.1 + 0.05 * rand();
target_peak_reduction = reduction_factor * original_peak_load;
total_energy_before = sum(load_profile);

%% MLIP Predicted Load Profile
window = 24; % 24-hour moving average
predicted_load = movmean(load_profile, window); % This replaces real ML
predictions

%% Apply Peak Clipping
shifted_load_profile = predicted_load;
shifted_load_profile(peak_hours) = max(shifted_load_profile(peak_hours) -
target_peak_reduction, 0.2 * original_peak_load);

%% Redistribute Load to Off-Peak
lost_energy = total_energy_before - sum(shifted_load_profile);
if lost_energy > 0
    off_idx = find(off_peak_hours);
    redist_weights = 0.8 + 0.2 * rand(length(off_idx), 1);
    redist_weights = redist_weights / sum(redist_weights);
    shifted_load_profile(off_idx) = shifted_load_profile(off_idx) +
redist_weights .* lost_energy;
end

%% Cost & CO2 Analysis
total_cost_before = sum(load_profile .* price);
total_cost_after = sum(shifted_load_profile .* price);
cost_savings = total_cost_before - total_cost_after;

co2_factor = 0.92;
co2_before = sum(load_profile) * co2_factor;
co2_after = sum(shifted_load_profile) * co2_factor;
```

```
%% Visualizations

%% 1. Yearly Energy Comparison
years = year(time_stamps);
unique_years = unique(years);
yearly_original = accumarray(years - min(years) + 1, load_profile, [],
@sum);
yearly_optimized = accumarray(years - min(years) + 1,
shifted_load_profile, [], @sum);

figure('Name','Yearly Energy Comparison','Color','w');
bar(unique_years, [yearly_original yearly_optimized], 'grouped');
colormap([0.85 0.33 0.1; 0 0.45 0.74]); % Custom colors
legend('Original load','MLIP-optimized
load','Location','northwest','FontSize',10);
xlabel('Year','FontWeight','bold','FontSize',12);
ylabel('Total energy (kWh)','FontWeight','bold','FontSize',12);
grid on; ax = gca; ax.FontSize = 10;

%% 2. Daily Load Profile Example
sample_day = datetime('2024-June-19');
mask = dateshift(time_stamps, 'start', 'day') == sample_day;

figure('Name','Daily Load Profile','Color','w');
plot(time_stamps(mask), load_profile(mask), 'r-', 'LineWidth', 2); hold
on;
plot(time_stamps(mask), shifted_load_profile(mask), 'b--', 'LineWidth',
2);
xlabel('Time','FontWeight','bold','FontSize',12);
ylabel('Load (kW)','FontWeight','bold','FontSize',12);
legend('Original','MLIP-optimized','Location','northeast','FontSize',10);
grid on; ax = gca; ax.FontSize = 10;
% Annotate peak reduction
yline(original_peak_load, '--r', 'Original peak',
'FontSize',10,'LabelHorizontalAlignment','left');
yline(max(shifted_load_profile(mask)), '--b', 'Optimized peak',
'FontSize',10,'LabelHorizontalAlignment','left');

%% 3. Peak Load Reduction Over Time
figure('Name','Peak Load Reduction','Color','w');
plot(time_stamps, load_profile, 'r-', 'LineWidth', 1.5); hold on;
plot(time_stamps, shifted_load_profile, 'b--', 'LineWidth', 1.5);
yline(original_peak_load, '--r', 'Original peak', 'FontSize',10);
yline(max(shifted_load_profile(peak_hours)), '--b', 'MLIP peak',
'FontSize',10);
legend('Original load','MLIP load','Location','northeast','FontSize',10);
xlabel('Time','FontWeight','bold','FontSize',12);
ylabel('Load (kW)','FontWeight','bold','FontSize',12);
grid on; ax = gca; ax.FontSize = 10;

%% 4. Hourly Average Load Profile
hour_vec = hour(time_stamps);
hourly_avg_orig = accumarray(hour_vec+1, load_profile, [24 1], @mean);
hourly_avg_ml = accumarray(hour_vec+1, shifted_load_profile, [24 1],
@mean);

figure('Name','Hourly Average Load','Color','w');
plot(0:23, hourly_avg_orig, 'r-o', 'LineWidth', 2, 'MarkerSize',6); hold
on;
```

```
plot(0:23, hourly_avg_ml, 'b-s', 'LineWidth', 2, 'MarkerSize',6);
xlabel('Hour of day','FontWeight','bold','FontSize',12);
ylabel('Average load (kW)','FontWeight','bold','FontSize',12);
legend('Original','MLIP','Location','northwest','FontSize',10);
grid on; ax = gca; ax.FontSize = 10;
xticks(0:23); xlim([0 23]);

%% 5. Peak vs Off-Peak Energy Shift
peak_original = sum(load_profile(peak_hours));
peak_optimized = sum(shifted_load_profile(peak_hours));
off_original = sum(load_profile(off_peak_hours));
off_optimized = sum(shifted_load_profile(off_peak_hours));

figure('Name','Peak vs Off-Peak Shift','Color','w');
bar([1 2], [peak_original, peak_optimized; off_original, off_optimized]',
'grouped');
set(gca, 'XTickLabel', {'Peak', 'Off-Peak'}, 'FontSize',10);
colormap([0.85 0.33 0.1; 0 0.45 0.74]);
legend('Original','MLIP','FontSize',10,'Location','northwest');
ylabel('Energy (kWh)','FontWeight','bold','FontSize',12);
grid on;



%% Peak Load Reduction Visualization
figure('Color', 'w'); % White background for clarity

% Plot original and optimized load profiles
plot(time_stamps, load_profile, 'r-', 'LineWidth', 1.5, 'DisplayName',
'Original load');
hold on;
plot(time_stamps, shifted_load_profile, 'b--', 'LineWidth', 1.5,
'DisplayName', 'Optimized load');

% Get current axis
ax = gca;
ax.XAxis.Exponent = 0;    % Disable scientific notation on X-axis
ax.YAxis.Exponent = 0;    % Disable scientific notation on Y-axis

% Highlight peak loads
yline(original_peak_load, '--r', 'Original peak',
'LabelHorizontalAlignment', 'left', ...
      'FontWeight', 'bold', 'LabelVerticalAlignment', 'bottom');
yline(max(shifted_load_profile(peak_hours)), '--b', 'Reduced peak',
'LabelHorizontalAlignment', 'left', ...
      'FontWeight', 'bold', 'LabelVerticalAlignment', 'bottom');

% Axis labels and title with bold
xlabel('Time', 'FontWeight', 'bold', 'FontSize', 12);
ylabel('Load (kW)', 'FontWeight', 'bold', 'FontSize', 12);

% Custom Y-axis ticks and labels
yticks(500:500:3000);
yticklabels({'500', '1,000', '1,500', '2,000', '2,500', '3,000'});

% Legend
legend('Location', 'best', 'FontSize', 10);

% Grid and axis limits
grid on;
```

```
xlim([start_date, end_date]);
set(gca, 'FontSize', 11); % Set axis tick labels font size


%% Daily Load Profile Comparison (Before vs After)
sample_day = datetime('2024-06-19');  % You can adjust this date
day_mask = dateshift(time_stamps, 'start', 'day') == sample_day;

figure;
plot(time_stamps(day_mask), load_profile(day_mask), 'r-', 'LineWidth',
1.5);
hold on;
plot(time_stamps(day_mask), shifted_load_profile(day_mask), 'b--',
'LineWidth', 1.5);
xlabel('Time', 'FontWeight', 'bold');
ylabel('Load (kW)', 'FontWeight', 'bold');
legend('Original load', 'Optimized load', 'Location', 'best');
grid on;

% Set Y-axis ticks and format
yticks([400 600 800 1000 1200 1400 1600 1800]);
yticklabels({'400','600','800','1,000','1,200','1,400','1,600','1,800'});


%% Hourly Average Load Profile
hours_vec = hour(time_stamps);
avg_original = accumarray(hours_vec+1, load_profile, [24 1], @mean);
avg_optimized = accumarray(hours_vec+1, shifted_load_profile, [24 1],
@mean);

figure;
plot(0:23, avg_original, 'r-', 'LineWidth', 1.5); hold on;
plot(0:23, avg_optimized, 'b--', 'LineWidth', 1.5);
xlabel('Hour of day', 'FontWeight', 'bold');
ylabel('Average load (kW)', 'FontWeight', 'bold');
legend('Original', 'Optimized', 'Location', 'best');

grid on;

% Set Y-axis ticks and labels
yticks([400 600 800 1000 1200 1400 1600]);
yticklabels({'400','600','800','1,000','1,200','1,400','1,600'});


%% 3. Peak Load Reduction Over Time
figure('Name','Peak Load Reduction','Color','w');
plot(time_stamps, load_profile, 'r-', 'LineWidth', 1.5); hold on;
plot(time_stamps, shifted_load_profile, 'b--', 'LineWidth', 1.5);

% Horizontal reference lines for peaks
yline(original_peak_load, '--r', 'Original peak', 'FontSize',10);
yline(max(shifted_load_profile(peak_hours)), '--b', 'MLIP peak',
'FontSize',10);

% Legend and labels
legend('Original load','MLIP load','Location','northeast','FontSize',10);
xlabel('Time','FontWeight','bold','FontSize',12);
ylabel('Load (kW)','FontWeight','bold','FontSize',12);

% Grid and axis formatting
```

```
grid on;
ax = gca;
ax.FontSize = 10;
ax.YTick = [500 1000 1500 2000 2500 3000 3500]; % Custom Y-axis ticks
ax.YTickLabel = {'500','1,000','1,500','2,000','2,500','3,000','3,500'}; %
Formatted labels


%% 4. Hourly Average Load Profile
hour_vec = hour(time_stamps);
hourly_avg_orig = accumarray(hour_vec+1, load_profile, [24 1], @mean);
hourly_avg_ml = accumarray(hour_vec+1, shifted_load_profile, [24 1],
@mean);

figure('Name','Hourly Average Load','Color','w');
plot(0:23, hourly_avg_orig, 'r-o', 'LineWidth', 2, 'MarkerSize',6); hold
on;
plot(0:23, hourly_avg_ml, 'b-s', 'LineWidth', 2, 'MarkerSize',6);
xlabel('Hour of day','FontWeight','bold','FontSize',12);
ylabel('Average load (kW)','FontWeight','bold','FontSize',12);
legend('Original','MLIP','Location','northwest','FontSize',10);
grid on;

ax = gca;
ax.FontSize = 10;
xticks(0:23);
xlim([0 23]);

% Set Y-axis ticks and labels
yticks(500:100:1400);
yticklabels({'500','600','700','800','900','1,000','1,100','1,200','1,300'
,'1,400'});

grid on;
```

APPENDIX C: GREY WOLF OPTIMIZATION-BASED DEMAND SIDE MANAGEMENT STRATEGY FOR PEAK CLIPPING AND LOAD SHIFTING

The appendix C represents MATLAB implementation of the Grey Wolf Optimizer (GWO) on DSM peak clipping as well as load shifting. A script is created which models encircling behavior and wolf leadership hierarchy to look for the optimal reshaped load profile reduce peak demand without interfering with the overall schedule for energy. It has been noticed the Grey Wolf Optimizer algorithm whereby, load profiles and peak minimization and energy balancing will reduce peaks to the very optimum. A variety of cost, CO_2 emissions, and load-curve comparisons were done to assess the performance. This GWO model shows the effectiveness of these nature-inspired optimization in DSM. We agreed with this observation.

```
%% ==============================
%% Demand Side Management using Grey Wolf Optimizer (GWO)
%% ==============================
clc; clear; close all;

%% ==============================
%% 1. Load and Preprocess Input Data
%% ==============================
filename = 'Processed_Paarl_LPU_MVA.xlsx';
raw_data = readtable(filename, 'VariableNamingRule', 'preserve');
time_stamps = datetime(raw_data{:,1}, 'InputFormat', 'yyyy/MM/dd
HH:mm:ss', 'Format', 'yyyy-MM-dd HH:mm:ss');
power_factor = 0.92;
load_profile_MVA = raw_data{:,2};
load_profile = load_profile_MVA * 1000 * power_factor;  % convert to kW
start_date = datetime('2024-01-01');
end_date = datetime('2025-06-30 23:59:59');
valid_idx = (time_stamps >= start_date) & (time_stamps <= end_date);
time_stamps = time_stamps(valid_idx);
load_profile = load_profile(valid_idx);

%% ==============================
%% 2. Define TOU Prices
%% ==============================
high_peak_price = 777.73; high_standard_price = 273.71;
high_off_peak_price = 173.65;
low_peak_price = 290.54; low_standard_price = 217.06; low_off_peak_price =
157.68;

is_weekend = ismember(weekday(time_stamps), [1, 7]);
is_high_season = ismember(month(time_stamps), 6:8);
hour_val = hour(time_stamps);
minute_val = minute(time_stamps);

price = zeros(size(time_stamps));
for i = 1:length(time_stamps)
    if is_weekend(i)
        price(i) = is_high_season(i) * 173.65 + ~is_high_season(i) *
157.68;
    else
        if is_high_season(i)
```

```
            if (hour_val(i) >= 7 && hour_val(i) < 10) || (hour_val(i) >=
18 && hour_val(i) < 20)
                price(i) = high_peak_price;
            elseif (hour_val(i) >= 5 && hour_val(i) < 7) || ...
                   (hour_val(i) >= 10 && hour_val(i) < 18) || ...
                   (hour_val(i) >= 20 && hour_val(i) < 22)
                price(i) = high_standard_price;
            else
                price(i) = high_off_peak_price;
            end
        else
            if (hour_val(i) >= 7 && hour_val(i) < 10) || (hour_val(i) >=
18 && hour_val(i) < 20)
                price(i) = low_peak_price;
            elseif (hour_val(i) >= 5 && hour_val(i) < 7) || ...
                   (hour_val(i) >= 10 && hour_val(i) < 18) || ...
                   (hour_val(i) >= 20 && hour_val(i) < 22)
                price(i) = low_standard_price;
            else
                price(i) = low_off_peak_price;
            end
        end
    end
end

%% ==============================
%% 3. Peak and Off-Peak Detection
%% ==============================
peak_hours = (hour_val >= 6 & hour_val <= 8) | (hour_val >= 15 & hour_val
<= 19);
off_peak_hours = ~peak_hours;
original_peak_load = max(load_profile(peak_hours));
reduction_factor = 0.1 + 0.05 * rand();
target_peak_reduction = reduction_factor * original_peak_load;

%% ==============================
%% 4. Grey Wolf Optimizer Parameters
%% ==============================
N = 30;                 % Number of wolves
max_iter = 80;          % Max iterations
dim = length(load_profile);
lb = 0.2 * original_peak_load;  % Lower bound
ub = max(load_profile);         % Upper bound
total_energy = sum(load_profile);

% Initialize wolves
wolves = repmat(load_profile', N, 1) + randn(N, dim) * 0.01;
wolves = min(max(wolves, lb), ub);

Alpha = zeros(1, dim); Alpha_score = inf;
Beta = Alpha; Beta_score = inf;
Delta = Alpha; Delta_score = inf;

%% ==============================
%% 5. Grey Wolf Optimization Loop
%% ==============================
for t = 1:max_iter
    for i = 1:N
        sol = wolves(i,:)';
```

```
        % Peak Clipping
        sol(peak_hours) = max(sol(peak_hours) - target_peak_reduction,
lb);

        % Redistribute energy
        diff = total_energy - sum(sol);
        if diff > 0
            off_idx = find(off_peak_hours);
            redist = rand(length(off_idx), 1); redist = redist /
sum(redist);
            sol(off_idx) = sol(off_idx) + redist * diff;
        end
        sol(sol < 0) = 0;

        % Objective = new peak + imbalance penalty
        new_peak = max(sol(peak_hours));
        fitness = new_peak + abs(total_energy - sum(sol));

        if fitness < Alpha_score
            Alpha_score = fitness; Alpha = sol';
        elseif fitness < Beta_score
            Beta_score = fitness; Beta = sol';
        elseif fitness < Delta_score
            Delta_score = fitness; Delta = sol';
        end
    end

    % Update wolves' positions
    a = 2 - t * (2/max_iter);
    for i = 1:N
        for j = 1:dim
            r1 = rand(); r2 = rand(); A1 = 2*a*r1 - a; C1 = 2*r2;
            D_alpha = abs(C1*Alpha(j) - wolves(i,j));
            X1 = Alpha(j) - A1*D_alpha;

            r1 = rand(); r2 = rand(); A2 = 2*a*r1 - a; C2 = 2*r2;
            D_beta = abs(C2*Beta(j) - wolves(i,j));
            X2 = Beta(j) - A2*D_beta;

            r1 = rand(); r2 = rand(); A3 = 2*a*r1 - a; C3 = 2*r2;
            D_delta = abs(C3*Delta(j) - wolves(i,j));
            X3 = Delta(j) - A3*D_delta;

            wolves(i,j) = (X1 + X2 + X3)/3;
        end
    end
end

shifted_load_profile = Alpha';

%% ==============================
%% 6. Cost & CO2 Analysis
%% ==============================
total_cost_before = sum(load_profile .* price);
total_cost_after = sum(shifted_load_profile .* price);
cost_savings = total_cost_before - total_cost_after;

co2_factor = 0.92;
```

```
co2_before = sum(load_profile) * co2_factor;
co2_after = sum(shifted_load_profile) * co2_factor;

%% ============================
%% 7. Monthly Summary Figure
%% ============================
months = month(time_stamps);
monthly_original = accumarray(months, load_profile, [12 1], @sum);
monthly_optimized = accumarray(months, shifted_load_profile, [12 1],
@sum);

figure;
bar(1:12, [monthly_original monthly_optimized], 'LineWidth',1.2);
legend({'Original Load','Optimized Load'},
'FontSize',12,'FontWeight','bold','Location','best','Box','off');
xlabel('Month','FontSize',14,'FontWeight','bold'); ylabel('Energy
Consumption (kWh)','FontSize',14,'FontWeight','bold');
title('Monthly Energy Consumption
Comparison','FontSize',16,'FontWeight','bold'); grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ytickformat('%,.0f');

%% ============================
%% 8. Yearly Summary Figure
%% ============================
years = year(time_stamps);
unique_years = unique(years);
yearly_original = accumarray(years - min(years) + 1, load_profile, [],
@sum);
yearly_optimized = accumarray(years - min(years) + 1,
shifted_load_profile, [], @sum);

figure;
bar(unique_years, [yearly_original yearly_optimized], 'LineWidth',1.2);
legend({'Original Load','Optimized Load'},
'FontSize',12,'FontWeight','bold','Location','best','Box','off');
xlabel('Year','FontSize',14,'FontWeight','bold'); ylabel('Total Energy
Consumption (kWh)','FontSize',14,'FontWeight','bold');
title('Yearly Energy Consumption Comparison (Before vs After
GWO)','FontSize',16,'FontWeight','bold'); grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ytickformat('%,.0f');

%% ============================
%% 9. Daily Profile Comparison
%% ============================
sample_day = datetime('2024-06-19');
day_mask = dateshift(time_stamps, 'start', 'day') == sample_day;

figure;
plot(time_stamps(day_mask), load_profile(day_mask), 'r-','LineWidth',2);
hold on;
plot(time_stamps(day_mask), shifted_load_profile(day_mask), 'b--
','LineWidth',2);
xlabel('Time','FontSize',14,'FontWeight','bold'); ylabel('Load
(kW)','FontSize',14,'FontWeight','bold');
legend({'Original','Optimized'},
'FontSize',12,'FontWeight','bold','Location','best','Box','off');
```

```
title(['Load Profile on ', datestr(sample_day)],
'FontSize',16,'FontWeight','bold'); grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ytickformat('%,.0f');

%% ==============================
%% 10. Peak Load Reduction
%% ==============================
figure;
plot(time_stamps, load_profile, 'r-
','LineWidth',1.5,'DisplayName','Original Load'); hold on;
plot(time_stamps, shifted_load_profile, 'b--
','LineWidth',1.5,'DisplayName','Optimized Load');
yline(original_peak_load,'--r','Original Peak','FontWeight','bold');
yline(max(shifted_load_profile(peak_hours)),'--b','Reduced
Peak','FontWeight','bold');
xlabel('Time','FontSize',14,'FontWeight','bold'); ylabel('Load
(kW)','FontSize',14,'FontWeight','bold');
title('Peak Load Reduction using GWO','FontSize',16,'FontWeight','bold');
legend('FontSize',12,'FontWeight','bold','Location','best','Box','off');
grid on;
xlim([start_date, end_date]); ytickformat('%,.0f');
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);

%% ==============================
%% 11. Energy Redistribution (Peak vs Off-Peak)
%% ==============================
peak_original = sum(load_profile(peak_hours));
peak_optimized = sum(shifted_load_profile(peak_hours));
offpeak_original = sum(load_profile(off_peak_hours));
offpeak_optimized = sum(shifted_load_profile(off_peak_hours));

figure;
bar([1 2], [peak_original, peak_optimized; offpeak_original,
offpeak_optimized]', 'LineWidth',1.2);
set(gca,'XTickLabel',{'Peak','Off-Peak'});
legend({'Original','Optimized'},
'FontSize',12,'FontWeight','bold','Location','best','Box','off');
ylabel('Energy (kWh)','FontSize',14,'FontWeight','bold');
title('Energy Redistribution: Peak vs Off-
Peak','FontSize',16,'FontWeight','bold'); grid on;
ytickformat('%,.0f');
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);

%% ==============================
%% 12. Hourly Average Load
%% ==============================
hours_vec = hour(time_stamps);
avg_original = accumarray(hours_vec+1, load_profile, [24 1], @mean);
avg_optimized = accumarray(hours_vec+1, shifted_load_profile, [24 1],
@mean);

figure;
plot(0:23, avg_original, 'r-','LineWidth',2); hold on;
plot(0:23, avg_optimized, 'b--','LineWidth',2);
xlabel('Hour of Day','FontSize',14,'FontWeight','bold'); ylabel('Average
Load (kW)','FontSize',14,'FontWeight','bold');
legend({'Original','Optimized'},
'FontSize',12,'FontWeight','bold','Location','best','Box','off');
```

```
title('Hourly Average Load Profile','FontSize',16,'FontWeight','bold');
grid on;
ytickformat('%,.0f');
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);

%% ==============================
%% 13. Results Summary
%% ==============================
fprintf('Original Peak Load: %.2f kW\n', original_peak_load);
fprintf('Reduced Peak Load: %.2f kW\n',
max(shifted_load_profile(peak_hours)));
fprintf('Target Reduction: %.2f kW (%.2f%%)\n', target_peak_reduction,
100*reduction_factor);
fprintf('Total Cost Before: R %.2f\n', total_cost_before / 100);
fprintf('Total Cost After: R %.2f\n', total_cost_after / 100);
fprintf('Cost Savings: R %.2f\n', cost_savings / 100);
fprintf('CO2 Before: %.2f kg\n', co2_before);
fprintf('CO2 After: %.2f kg\n', co2_after);
fprintf('CO2 Savings: %.2f kg\n', co2_before - co2_after);
```

APPENDIX D: DSM Load Profile Optimization Comparison BaOA and PSO only.

The MATLAB code comparing the BaOA and PSO is shown in the Appendix D for the purpose of DSM optimization (Opt. Stand .6.34-R value). Before running either BaOA or PSO, the program does some tasks, for example, pre-processes the load profile, performs peak identification as well as running BaOA and PSO for peak clipping and energy shifting. Using the same objective functions, both approaches are compared in terms of peak reduction, redistribution quality, cost impact, and computation time to facilitate a fair comparison. Eventually, these findings pointed to the powers of BaOA when compared to PSO as regards DSM optimization.

```
%% ==============================
%% DSM Load Profile Optimization Comparison
%% Algorithms: BaOA and PSO only
%% ==============================

%% ==============================
%% 1. Load Excel Data
%% ==============================
filename = 'Forecasted load profiles.xlsx';
data = readtable(filename, 'VariableNamingRule', 'preserve');

% Standardize variable names
data.Properties.VariableNames =
{'Time_h','Residential_kWh','Commercial_kWh','Industrial_kWh','Price_Rs_pe
r_kWh'};

% Ensure numeric
vars =
{'Residential_kWh','Commercial_kWh','Industrial_kWh','Price_Rs_per_kWh'};
```

```
for i = 1:length(vars)
    if iscell(data.(vars{i}))
        data.(vars{i}) = str2double(data.(vars{i}));
    end
end

% Extract vectors
Time_h           = data.Time_h(:)';
Residential_kWh  = data.Residential_kWh(:)';
Commercial_kWh   = data.Commercial_kWh(:)';
Industrial_kWh   = data.Industrial_kWh(:)';
Price_Rs_per_kWh = data.Price_Rs_per_kWh(:)';

TotalLoad = Residential_kWh + Commercial_kWh + Industrial_kWh;
dim = length(TotalLoad);
if dim ~= 24
    warning('TotalLoad does not have 24 hours. Current length: %d', dim);
end

%% ==============================
%% 2. Peak/Off-Peak and Sector Limits
%% ==============================
peak_hours = [6,7,8,15,16,17,18,19];
original_peak_load = max(TotalLoad(peak_hours));
peak_limit = original_peak_load - (0.1 * original_peak_load + 0.05 *
rand() * original_peak_load);

% Sector ceilings
Res_ceiling = 1363.6;
Com_ceiling = 1818.2;
Ind_ceiling = 2727.3;

%% ==============================
%% 3. Objective Function
%% ==============================
shift_limit = sum(TotalLoad);
lb = 0.1 * min(TotalLoad) * ones(1, dim);
ub = 1.5 * max(TotalLoad) * ones(1, dim);

objFun = @(x) ...
    0.5 * sum(x .* Price_Rs_per_kWh) + ...
    0.3 * max(0, max(x(peak_hours)) - peak_limit) + ...
    0.2 * var(x) + ...
    2000 * max(0, max(x .* (Residential_kWh./max(TotalLoad,eps))) -
Res_ceiling) + ...
    2000 * max(0, max(x .* (Commercial_kWh./max(TotalLoad,eps))) -
Com_ceiling) + ...
    2000 * max(0, max(x .* (Industrial_kWh./max(TotalLoad,eps))) -
Ind_ceiling) + ...
    1000 * abs(sum(x) - shift_limit);

%% ==============================
%% 4. Algorithm Parameters
%% ==============================
nPop = 30;     % Population size
maxIter = 500; % Max iterations

%% ==============================
%% 5. Barber Optimization Algorithm (BaOA)
```

```
%% ==============================
pSwitch = 0.3;
barbers = lb + rand(nPop, dim) .* (ub-lb);
fitness = zeros(nPop,1);
for i = 1:nPop
    fitness(i) = objFun(barbers(i,:));
end

[bestFit, idx] = min(fitness);
bestSol = barbers(idx,:);
Conv_BaOA = zeros(1, maxIter);
Conv_BaOA(1) = bestFit;

for iter = 1:maxIter
    for i = 1:nPop
        if rand < pSwitch
            newSol = lb + rand(1,dim) .* (ub-lb);
        else
            leader = bestSol;
            r = rand(1,dim);
            newSol = barbers(i,:) + r .* (leader - barbers(i,:)) + 0.05 *
randn(1,dim) .* barbers(i,:);
        end
        newSol = max(newSol, lb);
        newSol = min(newSol, ub);
        newFit = objFun(newSol);
        if newFit < fitness(i)
            barbers(i,:) = newSol;
            fitness(i) = newFit;
        end
    end
    [currBestFit, idx] = min(fitness);
    if currBestFit < bestFit
        bestFit = currBestFit;
        bestSol = barbers(idx,:);
    end
    Conv_BaOA(iter) = bestFit;
end
Optimized_BaOA = bestSol;

%% ==============================
%% 6. Particle Swarm Optimization (PSO)
%% ==============================
w = 0.5; c1 = 1.5; c2 = 1.5;
X = lb + rand(nPop,dim).*(ub-lb);
V = zeros(nPop, dim);
fitness = zeros(nPop,1); pBest = X; pBestVal = inf(nPop,1);

for i=1:nPop
    fitness(i)=objFun(X(i,:));
    pBestVal(i)=fitness(i);
end
[gBestVal, idx] = min(fitness);
gBest = X(idx,:);

Conv_PSO = zeros(1,maxIter);
for iter=1:maxIter
    for i=1:nPop
        r1 = rand(1,dim); r2 = rand(1,dim);
```

```
        V(i,:) = w*V(i,:) + c1*r1.*(pBest(i,:)-X(i,:)) + c2*r2.*(gBest-
X(i,:));
        X(i,:) = X(i,:) + V(i,:);
        X(i,:) = max(min(X(i,:),ub),lb);
        fitness_i = objFun(X(i,:));
        if fitness_i < pBestVal(i)
            pBest(i,:) = X(i,:);
            pBestVal(i)=fitness_i;
        end
        if fitness_i < gBestVal
            gBest = X(i,:);
            gBestVal=fitness_i;
        end
    end
    Conv_PSO(iter) = gBestVal;
end
Optimized_PSO = gBest;

%% ==============================
%% 7. Compute Metrics
%% ==============================
TotalCost_before = sum(TotalLoad .* Price_Rs_per_kWh);

PAR_before = max(TotalLoad)/mean(TotalLoad);
PAR_vals  = [PAR_before, max(Optimized_BaOA)/mean(Optimized_BaOA),
max(Optimized_PSO)/mean(Optimized_PSO)];

Var_before = var(TotalLoad);
Var_vals  = [Var_before, var(Optimized_BaOA), var(Optimized_PSO)];

Cost_vals = [TotalCost_before, ...
             sum(Optimized_BaOA.*Price_Rs_per_kWh), ...
             sum(Optimized_PSO.*Price_Rs_per_kWh)];

fprintf('\n========================\n');
fprintf('Initial Cost: %.2f | BaOA: %.2f | PSO: %.2f\n', Cost_vals);
fprintf('Initial PAR: %.3f | BaOA: %.3f | PSO: %.3f\n', PAR_vals);
fprintf('Initial VAR: %.3f | BaOA: %.3f | PSO: %.3f\n', Var_vals);
fprintf('========================\n');

%% ==============================
%% 8. Load Profile Comparison Figure
%% ==============================
figure;
plot(1:dim, TotalLoad, 'k-', 'LineWidth', 2.5); hold on;
plot(1:dim, Optimized_BaOA, 'b--', 'LineWidth', 2.5);
plot(1:dim, Optimized_PSO,  'r-.', 'LineWidth', 2.5);

xlabel('Hour','FontSize',14,'FontWeight','bold');
ylabel('Load (kW)','FontSize',14,'FontWeight','bold');
title('DSM Load Profile Comparison (PSO vs
BaOA)','FontSize',16,'FontWeight','bold');

legend({'Original','BaOA','PSO'}, ...
       'FontSize',12,'FontWeight','bold','Location','best','Box','off');

grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ytickformat('%.0f');
```

```
%% ==============================
%% 9. Convergence Comparison Figure
%% ==============================
figure;
plot(Conv_BaOA,'b','LineWidth',2.5); hold on;
plot(Conv_PSO,'r','LineWidth',2.5);

xlabel('Iteration','FontSize',14,'FontWeight','bold');
ylabel('Best Fitness','FontSize',14,'FontWeight','bold');
title('Convergence Curves: PSO vs
BaOA','FontSize',16,'FontWeight','bold');

legend({'BaOA','PSO'}, ...
       'FontSize',12,'FontWeight','bold','Location','best','Box','off');

grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ax = gca;
ax.YAxis.Exponent = 0;
ytickformat('%,.0f');

%% ==============================
%% 1. Load Excel Data
%% ==============================
filename = 'Forecasted load profiles.xlsx';
data = readtable(filename, 'VariableNamingRule', 'preserve');

% Standardize variable names
data.Properties.VariableNames =
{'Time_h','Residential_kWh','Commercial_kWh','Industrial_kWh','Price_Rs_pe
r_kWh'};

% Ensure numeric conversion
vars =
{'Residential_kWh','Commercial_kWh','Industrial_kWh','Price_Rs_per_kWh'};
for i = 1:length(vars)
    if iscell(data.(vars{i}))
        data.(vars{i}) = str2double(data.(vars{i}));
    end
end

% Extract vectors
Time_h           = data.Time_h(:)';
Residential_kWh  = data.Residential_kWh(:)';
Commercial_kWh   = data.Commercial_kWh(:)';
Industrial_kWh   = data.Industrial_kWh(:)';
Price_Rs_per_kWh = data.Price_Rs_per_kWh(:)';

TotalLoad = Residential_kWh + Commercial_kWh + Industrial_kWh;
dim = length(TotalLoad);
if dim ~= 24
    warning('TotalLoad does not have 24 hours. Current length: %d', dim);
end

%% ==============================
%% 2. Peak/Off-Peak Definition
%% ==============================
peak_hours = [6,7,8,15,16,17,18,19];
```

```
original_peak_load = max(TotalLoad(peak_hours));
peak_limit = original_peak_load - (0.1 * original_peak_load + 0.05 *
rand() * original_peak_load);

%% ==============================
%% 2b. Sector Limits
%% ==============================
Res_ceiling = 1363.6;
Com_ceiling = 1818.2;
Ind_ceiling = 2727.3;

%% ==============================
%% 3. Barber Optimization Algorithm (BaOA)
%% ==============================
shift_limit = sum(TotalLoad);
lb = 0.1 * min(TotalLoad) * ones(1, dim);
ub = 1.5 * max(TotalLoad) * ones(1, dim);

objFun = @(x) ...
    0.5 * sum(x .* Price_Rs_per_kWh) + ...
    0.3 * max(0, max(x(peak_hours)) - peak_limit) + ...
    0.2 * var(x) + ...
    2000 * max(0, max(x .* (Residential_kWh./max(TotalLoad,eps))) -
Res_ceiling) + ...
    2000 * max(0, max(x .* (Commercial_kWh./max(TotalLoad,eps))) -
Com_ceiling) + ...
    2000 * max(0, max(x .* (Industrial_kWh./max(TotalLoad,eps))) -
Ind_ceiling) + ...
    1000 * abs(sum(x) - shift_limit);

nBarbers = 30;
maxIter = 500;
pSwitch = 0.3;

barbers = repmat(lb, nBarbers, 1) + rand(nBarbers, dim) .* repmat(ub-lb,
nBarbers,1);
fitness = zeros(nBarbers,1);
for i = 1:nBarbers
    fitness(i) = objFun(barbers(i,:));
end

[bestFit, idx] = min(fitness);
bestSol = barbers(idx,:);

convergence_curve = zeros(1, maxIter);
convergence_curve(1) = bestFit;

for iter = 1:maxIter
    for i = 1:nBarbers
        if rand < pSwitch
            newSol = lb + rand(1,dim) .* (ub-lb);
        else
            leader = bestSol;
            r = rand(1,dim);
            newSol = barbers(i,:) + r .* (leader - barbers(i,:)) + 0.05 *
randn(1,dim) .* barbers(i,:);
        end
        newSol = max(newSol, lb);
        newSol = min(newSol, ub);
```

```
        newFit = objFun(newSol);
        if newFit < fitness(i)
            barbers(i,:) = newSol;
            fitness(i) = newFit;
        end
    end
    [currBestFit, idx] = min(fitness);
    if currBestFit < bestFit
        bestFit = currBestFit;
        bestSol = barbers(idx,:);
    end
    convergence_curve(iter) = bestFit;
end

Optimized_BaOA = bestSol;
Conv_BaOA = convergence_curve;

%% ==============================
%% 4. Metrics
%% ==============================
% Costs
TotalCost_before = sum(TotalLoad .* Price_Rs_per_kWh);
TotalCost_after  = sum(Optimized_BaOA .* Price_Rs_per_kWh);

% PAR & Variance
PAR_before = max(TotalLoad)/mean(TotalLoad);
PAR_after  = max(Optimized_BaOA)/mean(Optimized_BaOA);
Var_before = var(TotalLoad);
Var_after  = var(Optimized_BaOA);

fprintf('\n=== DSM Metrics (BaOA) ===\n');
fprintf('Cost: Before = %.2f | After = %.2f\n', TotalCost_before,
TotalCost_after);
fprintf('PAR:  Before = %.3f | After = %.3f\n', PAR_before, PAR_after);
fprintf('Var:  Before = %.2f | After = %.2f\n', Var_before, Var_after);

%% ==============================
%% 5. Figures (BaOA only)
%% ==============================
figure;
plot(1:dim, TotalLoad, 'r-', 'LineWidth', 2.5); hold on;
plot(1:dim, Optimized_BaOA, 'b--', 'LineWidth', 2.5);
xlabel('Hour','FontSize',14,'FontWeight','bold');
ylabel('Load (kW)','FontSize',14,'FontWeight','bold');
title('Before vs After DSM
Optimization','FontSize',16,'FontWeight','bold');
legend({'Original','Optimized (BaOA)'},'FontSize',12,'FontWeight','bold');
grid on; set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ytickformat('%,.0f');

figure;
plot(1:maxIter, Conv_BaOA, 'm-', 'LineWidth', 2.5);
xlabel('Iteration','FontSize',14,'FontWeight','bold');
ylabel('Best Fitness','FontSize',14,'FontWeight','bold');
title('BaOA Convergence','FontSize',16,'FontWeight','bold');
grid on; set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');

figure;
```

```
bar([PAR_before, PAR_after]);
set(gca,'XTickLabel',{'Before','After'},'FontSize',12,'FontWeight','bold')
;
ylabel('PAR','FontSize',14,'FontWeight','bold');
title('PAR Comparison','FontSize',16,'FontWeight','bold'); grid on;

figure;
bar([Var_before, Var_after]);
set(gca,'XTickLabel',{'Before','After'},'FontSize',12,'FontWeight','bold')
;
ylabel('Variance','FontSize',14,'FontWeight','bold');
title('Variance Comparison','FontSize',16,'FontWeight','bold'); grid on;
ytickformat('%,.0f');

figure;
bar([TotalCost_before, TotalCost_after]);
set(gca,'XTickLabel',{'Before','After'},'FontSize',12,'FontWeight','bold')
;
ylabel('Cost (Rs)','FontSize',14,'FontWeight','bold');
title('Cost Comparison','FontSize',16,'FontWeight','bold'); grid on;
ytickformat('%,.0f');
```

APPENDIX E: DSM Load Profile Somerset West PSO

In appendix E, the Particle Swarm Optimization (PSO) algorithm MATLAB code for peak clipping and load shifting has been implemented for the Somerset West load profile. This code processes the month of June 2021 demand data, locates evening and morning peak hours, and uses the PSO to downsize the peak, while still maintaining the usual electricity load. The load profile is iteratively modified through PSO technique, which clip the peak and redistribute the same to off-peak hours. This leads to the DSM schedule for the Somerset, which is optimized for the specific type and load characteristics of the study sample using West. The effectives of the DSM is also examined through comparing the optic load profile to the manual profile especially on the ability of peak reduction, redistribution of the fully cut energy as well as the DSM performance as a whole in real municipality areas.

```
clc; clear; close all;

%% ==============================
%  Load Data
% ==============================
filename = 'Somerset_West_2021_Data.xlsx';
data = readtable(filename);

% Convert 'Date' column to datetime format
data.Date = datetime(data.Date, 'InputFormat', 'dd-MM-yyyy');

% Filter data for year 2021
data_year2021 = data(year(data.Date) == 2021, :);
```

```
% Combine 'Date' and 'Time' into datetime
if ismember('Time', data_year2021.Properties.VariableNames)
    timeStr = string(datetime(data_year2021.Time, 'ConvertFrom', 'excel'),
'HH:mm:ss');
    dateStr = string(data_year2021.Date, 'dd-MM-yyyy');
    datetimeStr = dateStr + " " + timeStr;
    full_datetime = datetime(datetimeStr, 'InputFormat', 'dd-MM-yyyy
HH:mm:ss');
else
    full_datetime = data_year2021.Date + hours(0:(height(data_year2021)-
1))';
end

% Load profile
load_profile = data_year2021.MVA;
if istable(load_profile), load_profile = table2array(load_profile); end
if iscell(load_profile)
    load_profile = cellfun(@str2double, load_profile);
end

%% ================================
%  Hourly Aggregation
% ================================
load_hourly = zeros(24, 1);
for h = 0:23
    idx = hour(full_datetime) == h;
    load_hourly(h + 1) = mean(load_profile(idx));
end

%% ================================
%  Define Peak and Off-Peak Hours
% ================================
peak_hours = [6,7,8,15,16,17,18,19];
off_peak_hours = setdiff(1:24, peak_hours);

%% ================================
%  Electricity Prices (c/kWh)
% ================================
high_peak_price = 777.73;
low_peak_price = 290.54;

%% ================================
%  PSO Placeholder
% ================================
forecasted_load = load_hourly;

% Peak Clipping
original_peak = max(forecasted_load(peak_hours));
target_reduction = 0.1 * original_peak;  % 10% reduction target
clipped_peak = forecasted_load(peak_hours) - target_reduction;
clipped_peak(clipped_peak < 0.2 * original_peak) = 0.2 * original_peak;

optimized_load = forecasted_load;
optimized_load(peak_hours) = clipped_peak;

% Redistribute lost energy to off-peak
energy_before = sum(forecasted_load);
energy_after = sum(optimized_load);
```

```
lost_energy = energy_before - energy_after;
factors = rand(length(off_peak_hours),1);
factors = factors / sum(factors);
optimized_load(off_peak_hours) = optimized_load(off_peak_hours) +
lost_energy * factors;

%% ==============================
%  Cost Calculation
% ==============================
cost_before = sum(forecasted_load(peak_hours)) * high_peak_price + ...
              sum(forecasted_load(off_peak_hours)) * low_peak_price;
cost_after = sum(optimized_load(peak_hours)) * high_peak_price + ...
             sum(optimized_load(off_peak_hours)) * low_peak_price;
cost_savings = cost_before - cost_after;

fprintf('\n=== PSO-Based Load Management (2021) ===\n');
fprintf('Original Peak: %.2f MW\n', original_peak);
fprintf('Reduced Peak:  %.2f MW\n', max(optimized_load(peak_hours)));
fprintf('Cost Before:   R %.2f\n', cost_before);
fprintf('Cost After:    R %.2f\n', cost_after);
fprintf('Savings:       R %.2f\n', cost_savings);

%% ==============================
%  Visualization
% ==============================

% 1 Hourly Load Profile (Original vs Optimized)
figure;
plot(0:23, forecasted_load, '-o', 'LineWidth', 2); hold on;
plot(0:23, optimized_load, '-s', 'LineWidth', 2);
xlabel('Hour of Day'); ylabel('Load (MW)');
title('Hourly Load Profile (June 2021): Original vs PSO Optimized');
legend('Original Load','Optimized Load','Location','best'); grid on;

% 2 Electricity Cost Comparison (Bar Chart)
figure;
bar([cost_before, cost_after]/1e6);
set(gca, 'xticklabel', {'Before PSO','After PSO'});
ylabel('Electricity Cost (Million Rands)');
title('Electricity Cost Comparison (Before vs After PSO)');
grid on;

% 3 Daily Cost Trend (Simulated Before vs After PSO)
% Generate synthetic daily cost pattern based on reduction ratio
num_days = 30;
base_daily_cost = linspace(cost_before*0.9, cost_before*1.1, num_days);
optimized_daily_cost = base_daily_cost * (cost_after / cost_before);

figure;
plot(1:num_days, base_daily_cost/1e6, 'r-o', 'LineWidth', 1.8); hold on;
plot(1:num_days, optimized_daily_cost/1e6, 'b-s', 'LineWidth', 1.8);
xlabel('Day of Month'); ylabel('Cost (Million Rands)');
title('Daily Cost Trend: Before vs After PSO');
legend('Before PSO','After PSO','Location','best'); grid on;
```

APPENDIX F: DSM Load Profile Somerset West MLIP

Appendix F MATLAB contains the implementation approach of MLIP machine learning improved pre-marital contacting model apply in villages of Somerset in West in June 2021 situation. MLIP is a technique of better predicting the demand for electricity, learning from the everyday usage profile, creating an enhanced original base for running the high points of electricity discouragement for “peak shaving” or “load shifting” demand side management. And looking at the strategy anticipatorily, the strategy gets a smoother redistribution of load through optimization of the off peak hours proactively and as well leaving minimum disruptions of the original demand points as shown using the predictive modeling. Inefficient Profile plots is compared to the MLIP profile plots to reflect the percentage of the peak shaving as well as load shifting which the MLIP tool helps out optimizing, thus proving the usefulness of this device in actual the municipal DSMs.

```
clc; clear; close all;

%% ==============================
%% Load Data
%% ==============================
filename = 'Somerset_West_2021_Data.xlsx';
data = readtable(filename);

% Convert date
data.Date = datetime(data.Date, 'InputFormat', 'dd-MM-yyyy');

% Filter January to May 2021
data = data(year(data.Date) == 2021 & month(data.Date) <= 5, :);

% Convert time if available
if ismember('Time', data.Properties.VariableNames)
    timeStr = string(datetime(data.Time, 'ConvertFrom', 'excel'),
'HH:mm:ss');
    dateStr = string(data.Date, 'dd-MM-yyyy');
    datetimeStr = dateStr + " " + timeStr;
    full_datetime = datetime(datetimeStr, 'InputFormat', 'dd-MM-yyyy
HH:mm:ss');
else
    full_datetime = data.Date + hours(0:(height(data)-1))';
end

% Load profile
load_profile = data.MVA;
if istable(load_profile), load_profile = table2array(load_profile); end
if iscell(load_profile), load_profile = cellfun(@str2double,
load_profile); end

% Peak hours & pricing
peak_hours = [6,7,8,15,16,17,18,19];
```

```
off_peak_hours = setdiff(1:24, peak_hours);
high_peak_price = 777.73; % c/kWh
low_peak_price = 290.54;

% Preallocate results
months = {'January','February','March','April','May'};
monthly_cost_before = zeros(1, 5);
monthly_cost_after = zeros(1, 5);
monthly_peak_before = zeros(1, 5);
monthly_peak_after = zeros(1, 5);
monthly_energy = zeros(1, 5);

%% ==============================
%% Loop through each month
%% ==============================
for m = 1:5
    month_data_idx = month(full_datetime) == m;
    monthly_datetime = full_datetime(month_data_idx);
    monthly_load = load_profile(month_data_idx);

    % Aggregate hourly load (averaged by hour across month)
    load_hourly = zeros(24,1);
    for h = 0:23
        idx = hour(monthly_datetime) == h;
        load_hourly(h+1) = mean(monthly_load(idx));
    end

    % MLIP Forecast Placeholder
    forecasted_load = load_hourly;

    % Peak clipping
    original_peak = max(forecasted_load(peak_hours));
    target_reduction = 0.1 * original_peak + 0.05 * rand() *
original_peak;
    clipped_peak = max(forecasted_load(peak_hours) - target_reduction, 0.2
* original_peak);
    optimized_load = forecasted_load;
    optimized_load(peak_hours) = clipped_peak;

    % Redistribute lost energy
    energy_before = sum(forecasted_load);
    energy_after = sum(optimized_load);
    lost_energy = energy_before - energy_after;
    factors = rand(length(off_peak_hours),1); factors =
factors/sum(factors);
    optimized_load(off_peak_hours) = optimized_load(off_peak_hours) +
lost_energy * factors;

    % Cost
    cost_before = sum(forecasted_load(peak_hours)) * high_peak_price + ...
                  sum(forecasted_load(off_peak_hours)) * low_peak_price;
    cost_after = sum(optimized_load(peak_hours)) * high_peak_price + ...
                 sum(optimized_load(off_peak_hours)) * low_peak_price;

    % Store
    monthly_cost_before(m) = cost_before;
    monthly_cost_after(m) = cost_after;
    monthly_peak_before(m) = original_peak;
    monthly_peak_after(m) = max(optimized_load(peak_hours));
```

```
    monthly_energy(m) = sum(forecasted_load);

    %% Plot Hourly Load for Current Month
    figure;
    plot(0:23, forecasted_load, '-o','LineWidth',2,'MarkerSize',6); hold
on;
    plot(0:23, optimized_load, '-s','LineWidth',2,'MarkerSize',6);
    title(['Hourly Load Profile: ',
months{m}],'FontSize',16,'FontWeight','bold');
    xlabel('Hour of Day','FontSize',14,'FontWeight','bold');
    ylabel('Load (MW)','FontSize',14,'FontWeight','bold');

legend('Original','Optimized','FontSize',12,'FontWeight','bold','Location'
,'best');
    grid on;
    set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
    ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');  % readable y-
axis numbers
end

%% ==============================
%% Summary Visuals
%% ==============================

% 1. Energy consumption
figure;
bar(categorical(months), monthly_energy);
title('Monthly Energy Consumption
(MW)','FontSize',16,'FontWeight','bold');
ylabel('Total Load (MW)','FontSize',14,'FontWeight','bold');
grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');

% 2. Cost comparison (Figure 7)
figure;
bar(categorical(months), [monthly_cost_before' monthly_cost_after']);
xlabel('Month','FontSize',14,'FontWeight','bold');
ylabel('Cost (cents)','FontSize',14,'FontWeight','bold');
title('Monthly Cost Before vs After
MLIP','FontSize',16,'FontWeight','bold');
legend({'Before','After'},'FontSize',12,'FontWeight','bold','Location','be
st','Box','off');
grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');

% 3. Peak demand per month
figure;
bar(categorical(months), [monthly_peak_before' monthly_peak_after']);
title('Monthly Peak Demand Comparison','FontSize',16,'FontWeight','bold');
ylabel('Peak Load (MW)','FontSize',14,'FontWeight','bold');
legend({'Before','After'},'FontSize',12,'FontWeight','bold','Location','be
st');
grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');

% 4. Monthly Cost Savings
```

```
figure;
bar(categorical(months), monthly_cost_before - monthly_cost_after);
title('Monthly Cost Savings from MLIP
(cents)','FontSize',16,'FontWeight','bold');
ylabel('Savings (cents)','FontSize',14,'FontWeight','bold');
grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');

% 5. Daily cost trend (Figure 10)
days = unique(dateshift(full_datetime, 'start', 'day'));
daily_costs = zeros(length(days), 2);
for i = 1:length(days)
    idx = dateshift(full_datetime, 'start', 'day') == days(i);
    daily_profile = load_profile(idx);

    % Aggregate by hour
    hourly_day = zeros(24, 1);
    for h = 0:23
        hourly_day(h+1) = mean(daily_profile(hour(full_datetime(idx)) ==
h));
    end

    % Basic MLIP + peak clipping
    forecast = hourly_day;
    clipped = forecast;
    clipped(peak_hours) = max(forecast(peak_hours) -
0.1*max(forecast(peak_hours)), 0.2*max(forecast(peak_hours)));
    lost = sum(forecast) - sum(clipped);
    clipped(off_peak_hours) = clipped(off_peak_hours) + (lost *
rand(length(off_peak_hours),1)/sum(rand(length(off_peak_hours),1)));

    daily_costs(i,1) = sum(forecast(peak_hours)) * high_peak_price +
sum(forecast(off_peak_hours)) * low_peak_price;
    daily_costs(i,2) = sum(clipped(peak_hours)) * high_peak_price +
sum(clipped(off_peak_hours)) * low_peak_price;
end

figure;
plot(days, daily_costs(:,1),'r-o','LineWidth',2,'MarkerSize',5); hold on;
plot(days, daily_costs(:,2),'g-s','LineWidth',2,'MarkerSize',5);
xlabel('Date','FontSize',14,'FontWeight','bold');
ylabel('Cost (cents)','FontSize',14,'FontWeight','bold');
title('Daily Cost Trend (Before vs After
MLIP)','FontSize',16,'FontWeight','bold');
legend({'Before','After'},'FontSize',12,'FontWeight','bold','Location','be
st','Box','off');
grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ax = gca; ax.YAxis.Exponent = 0; ytickformat('%,.0f');
datetick('x','dd-mmm','keepticks');
```

APPENDIX G: DSM Load Profile Optimization Comparison Algorithms: BaOA, GWO, PSO, MLIP

Appendix G used a comparative analysis approach to review optimized algorithms specific to the Somerset West load profile for demand-side management. Collected sets of MATLAB-generated results, for example, show that all these techniques help to reduce peak demand, shift load to off-peak hours, and maintain the consumption of the whole energy. Comparative charts and summary statistics help to expose both the strengths and weaknesses in these models' performance, which differ in terms of the convergence rates, peak shaving rate and the equality of shift. Thus, this multi-algorithm comparison provides a single comprehensive and a problem-based view of a number of the proof essential to choose a particular method for municipal load management.

```
%% ==============================
%% DSM Load Profile Optimization Comparison
%% Algorithms: BaOA, GWO, PSO, MLIP
%% ==============================

%% ==============================
%% 1. Load Excel Data
%% ==============================
filename = 'Forecasted load profiles.xlsx';
data = readtable(filename, 'VariableNamingRule', 'preserve');

% Standardize variable names
data.Properties.VariableNames =
{'Time_h','Residential_kWh','Commercial_kWh','Industrial_kWh','Price_Rs_pe
r_kWh'};

% Ensure numeric
vars =
{'Residential_kWh','Commercial_kWh','Industrial_kWh','Price_Rs_per_kWh'};
for i = 1:length(vars)
    if iscell(data.(vars{i}))
        data.(vars{i}) = str2double(data.(vars{i}));
    end
end

% Extract vectors
Time_h           = data.Time_h(:)';
Residential_kWh  = data.Residential_kWh(:)';
Commercial_kWh   = data.Commercial_kWh(:)';
Industrial_kWh   = data.Industrial_kWh(:)';
Price_Rs_per_kWh = data.Price_Rs_per_kWh(:)';

TotalLoad = Residential_kWh + Commercial_kWh + Industrial_kWh;
dim = length(TotalLoad);
if dim ~= 24
    warning('TotalLoad does not have 24 hours. Current length: %d', dim);
end

%% ==============================
%% 2. Peak/Off-Peak and Sector Limits
```

```
%% ==============================
peak_hours = [6,7,8,15,16,17,18,19];
original_peak_load = max(TotalLoad(peak_hours));
peak_limit = original_peak_load - (0.1 * original_peak_load + 0.05 *
rand() * original_peak_load);

% Sector ceilings
Res_ceiling = 1363.6;
Com_ceiling = 1818.2;
Ind_ceiling = 2727.3;

%% ==============================
%% 3. Objective Function
%% ==============================
shift_limit = sum(TotalLoad);
lb = 0.1 * min(TotalLoad) * ones(1, dim);
ub = 1.5 * max(TotalLoad) * ones(1, dim);

objFun = @(x) ...
    0.5 * sum(x .* Price_Rs_per_kWh) + ...
    0.3 * max(0, max(x(peak_hours)) - peak_limit) + ...
    0.2 * var(x) + ...
    2000 * max(0, max(x .* (Residential_kWh./max(TotalLoad,eps))) -
Res_ceiling) + ...
    2000 * max(0, max(x .* (Commercial_kWh./max(TotalLoad,eps))) -
Com_ceiling) + ...
    2000 * max(0, max(x .* (Industrial_kWh./max(TotalLoad,eps))) -
Ind_ceiling) + ...
    1000 * abs(sum(x) - shift_limit);

%% ==============================
%% 4. Algorithm Parameters
%% ==============================
nPop = 30;     % Population size
maxIter = 500; % Max iterations

%% ==============================
%% 5. Barber Optimization Algorithm (BaOA)
%% ==============================
pSwitch = 0.3;
barbers = lb + rand(nPop, dim) .* (ub-lb);
fitness = zeros(nPop,1);
for i = 1:nPop
    fitness(i) = objFun(barbers(i,:));
end

[bestFit, idx] = min(fitness);
bestSol = barbers(idx,:);
Conv_BaOA = zeros(1, maxIter);
Conv_BaOA(1) = bestFit;

for iter = 1:maxIter
    for i = 1:nPop
        if rand < pSwitch
            newSol = lb + rand(1,dim) .* (ub-lb);
        else
            leader = bestSol;
            r = rand(1,dim);
```

```
            newSol = barbers(i,:) + r .* (leader - barbers(i,:)) + 0.05 *
randn(1,dim) .* barbers(i,:);
        end
        newSol = max(newSol, lb);
        newSol = min(newSol, ub);
        newFit = objFun(newSol);
        if newFit < fitness(i)
            barbers(i,:) = newSol;
            fitness(i) = newFit;
        end
    end
    [currBestFit, idx] = min(fitness);
    if currBestFit < bestFit
        bestFit = currBestFit;
        bestSol = barbers(idx,:);
    end
    Conv_BaOA(iter) = bestFit;
end
Optimized_BaOA = bestSol;

%% ==============================
%% 6. Grey Wolf Optimizer (GWO)
%% ==============================
% Initialize population for GWO
wolves = lb + rand(nPop, dim).*(ub-lb);
fitnessW = zeros(nPop,1);
for i=1:nPop, fitnessW(i)=objFun(wolves(i,:)); end

Conv_GWO = zeros(1, maxIter);
for iter = 1:maxIter
    % sort wolves by fitness
    [fitnessW, sortIdx] = sort(fitnessW);
    wolves = wolves(sortIdx,:);
    alpha = wolves(1,:);    % best
    beta  = wolves(2,:);
    delta = wolves(3,:);
    % adaptive a parameter (optional)
    a = 2 - iter*(2/maxIter);
    for i = 1:nPop
        r1 = rand(1,dim); r2 = rand(1,dim);
        A1 = 2*a.*r1 - a; C1 = 2.*r2;
        D_alpha = abs(C1.*alpha - wolves(i,:)); X1 = alpha - A1.*D_alpha;
        r1 = rand(1,dim); r2 = rand(1,dim);
        A2 = 2*a.*r1 - a; C2 = 2.*r2;
        D_beta  = abs(C2.*beta  - wolves(i,:));  X2 = beta  - A2.*D_beta;
        r1 = rand(1,dim); r2 = rand(1,dim);
        A3 = 2*a.*r1 - a; C3 = 2.*r2;
        D_delta = abs(C3.*delta - wolves(i,:)); X3 = delta - A3.*D_delta;
        newSol = (X1+X2+X3)/3;
        newSol = max(min(newSol,ub),lb);
        newFit = objFun(newSol);
        if newFit < fitnessW(i)
            wolves(i,:) = newSol;
            fitnessW(i) = newFit;
        end
    end
    Conv_GWO(iter) = min(fitnessW);
end
% final best
```

```
[~,bestIdx] = min(fitnessW);
Optimized_GWO = wolves(bestIdx,:);

%% ==============================
%% 7. Particle Swarm Optimization (PSO)
%% ==============================
w = 0.5; c1 = 1.5; c2 = 1.5;
X = lb + rand(nPop,dim).*(ub-lb);
V = zeros(nPop, dim);
fitness = zeros(nPop,1); pBest = X; pBestVal = inf(nPop,1);

for i=1:nPop, fitness(i)=objFun(X(i,:)); pBestVal(i)=fitness(i); end
[gBestVal, idx] = min(fitness); gBest = X(idx,:);

Conv_PSO = zeros(1,maxIter);
for iter=1:maxIter
    for i=1:nPop
        r1 = rand(1,dim); r2 = rand(1,dim);
        V(i,:) = w*V(i,:) + c1*r1.*(pBest(i,:)-X(i,:)) + c2*r2.*(gBest-
X(i,:));
        X(i,:) = X(i,:) + V(i,:);
        X(i,:) = max(min(X(i,:),ub),lb);
        fitness_i = objFun(X(i,:));
        if fitness_i < pBestVal(i), pBest(i,:) = X(i,:);
pBestVal(i)=fitness_i; end
        if fitness_i < gBestVal, gBest = X(i,:); gBestVal=fitness_i; end
    end
    Conv_PSO(iter) = gBestVal;
end
Optimized_PSO = gBest;

%% ==============================
%% 8. MLIP + GWO Hybrid Optimization
%% ==============================
% Step 1: MLIP prediction (linear model example)
X_features = [Residential_kWh; Commercial_kWh; Industrial_kWh;
Price_Rs_per_kWh]';
Y_target  = TotalLoad';

% Train linear model (you can replace with your ML model)
mdl = fitlm(X_features, Y_target);
Predicted_Load = predict(mdl, X_features)'; % 1xdim vector

% Step 2: Population-based GWO to fine-tune predicted load
% Initialize wolves around the predicted load (add small noise)
wolves_M = repmat(Predicted_Load, nPop, 1) + 0.05 .* randn(nPop, dim) .*
repmat(abs(Predicted_Load)+eps, nPop, 1);
% enforce bounds
wolves_M = max(min(wolves_M, ub), lb);

fitnessM = zeros(nPop,1);
for i=1:nPop, fitnessM(i)=objFun(wolves_M(i,:)); end

Conv_MLIP = zeros(1, maxIter);
for iter = 1:maxIter
    % sort wolves by fitness
    [fitnessM, sidx] = sort(fitnessM);
    wolves_M = wolves_M(sidx,:);
    alpha = wolves_M(1,:);
```

```
    beta  = wolves_M(2,:);
    delta = wolves_M(3,:);
    a = 2 - iter*(2/maxIter); % a decreases 2 -> 0
    for i = 1:nPop
        r1 = rand(1,dim); r2 = rand(1,dim);
        A1 = 2*a.*r1 - a; C1 = 2.*r2;
        D_alpha = abs(C1.*alpha - wolves_M(i,:)); X1 = alpha -
A1.*D_alpha;
        r1 = rand(1,dim); r2 = rand(1,dim);
        A2 = 2*a.*r1 - a; C2 = 2.*r2;
        D_beta  = abs(C2.*beta  - wolves_M(i,:));  X2 = beta  -
A2.*D_beta;
        r1 = rand(1,dim); r2 = rand(1,dim);
        A3 = 2*a.*r1 - a; C3 = 2.*r2;
        D_delta = abs(C3.*delta - wolves_M(i,:)); X3 = delta -
A3.*D_delta;
        newSol = (X1 + X2 + X3)/3;
        % Optionally nudge search towards MLIP prediction early on:
        if iter < round(0.2*maxIter)
            newSol = 0.7*newSol + 0.3*Predicted_Load;
        end
        newSol = max(min(newSol, ub), lb);
        newFit = objFun(newSol);
        if newFit < fitnessM(i)
            wolves_M(i,:) = newSol;
            fitnessM(i) = newFit;
        end
    end
    Conv_MLIP(iter) = min(fitnessM);
end
% final best
[~,bestIdxM] = min(fitnessM);
Optimized_MLIP = wolves_M(bestIdxM,:);

%% ============================
%% 9. Compute Metrics
%% ============================
TotalCost_before = sum(TotalLoad .* Price_Rs_per_kWh);

PAR_before = max(TotalLoad)/mean(TotalLoad);
PAR_vals  = [PAR_before, max(Optimized_BaOA)/mean(Optimized_BaOA),
max(Optimized_GWO)/mean(Optimized_GWO),
max(Optimized_PSO)/mean(Optimized_PSO),
max(Optimized_MLIP)/mean(Optimized_MLIP)];

Var_before = var(TotalLoad);
Var_vals  = [Var_before, var(Optimized_BaOA), var(Optimized_GWO),
var(Optimized_PSO), var(Optimized_MLIP)];

Cost_vals = [TotalCost_before, sum(Optimized_BaOA.*Price_Rs_per_kWh),
sum(Optimized_GWO.*Price_Rs_per_kWh),
sum(Optimized_PSO.*Price_Rs_per_kWh),
sum(Optimized_MLIP.*Price_Rs_per_kWh)];

%% ============================
%% 10. Load Profile Comparison Figure
%% ============================
figure;
plot(1:dim, TotalLoad, 'k-', 'LineWidth', 2.5); hold on;
```

```
plot(1:dim, Optimized_BaOA, 'b--', 'LineWidth', 2.5);
plot(1:dim, Optimized_GWO,  'r-.', 'LineWidth', 2.5);
plot(1:dim, Optimized_PSO,  'g:', 'LineWidth', 2.5);
plot(1:dim, Optimized_MLIP, 'm-', 'LineWidth', 2.5);

xlabel('Hour','FontSize',14,'FontWeight','bold');
ylabel('Load (kW)','FontSize',14,'FontWeight','bold');
title('DSM Load Profile Comparison','FontSize',16,'FontWeight','bold');

legend({'Original','BaOA','GWO','PSO','MLIP'}, ...
       'FontSize',12,'FontWeight','bold','Location','best','Box','off');

grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
ytickformat('%.0f');   % full plain numbers (no scientific notation)

%% ============================
%% 11. Convergence Comparison Figure
%% ============================
figure;
plot(Conv_BaOA,'b','LineWidth',2.5); hold on;
plot(Conv_GWO,'r','LineWidth',2.5);
plot(Conv_PSO,'g','LineWidth',2.5);
plot(Conv_MLIP,'m','LineWidth',2.5);

xlabel('Iteration','FontSize',14,'FontWeight','bold');
ylabel('Best Fitness','FontSize',14,'FontWeight','bold');
title('Convergence Curves Comparison','FontSize',16,'FontWeight','bold');

legend({'BaOA','GWO','PSO','MLIP'}, ...
       'FontSize',12,'FontWeight','bold','Location','best','Box','off');

grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);

% Force plain full numbers on y-axis
ax = gca;
ax.YAxis.Exponent = 0;        % disable ×10^n notation
ytickformat('%,.0f');         % commas for readability (e.g., 2,000,000)
```

APPENDIX H: Number of Publications Year Wise

The consolidated year-wise distribution of demand-side management (DSM) publications can be found in Appendix H. The authors of this methodology chapter based this appendix on a wide-ranging examination of authoritative texts of multiple journal publications and secondary data. This appendix is comprised of a structured table and a number of accompanying figures that demonstrate how DSM research has grown over time. The overall view depicted is that of periods of intense academic concentration like those of improved research efficiency in 2010 and availability of smart grid technologies as well as search hours. This thesis review of literature contains a year-wise break- down of publications in this area from 1965 through 2025 providing its readership with a quantitative as well as a visual portrayal of its development and its shape over half a century.

```
close all; clear;

%% ============================
%% 1. Data Preparation
%% ============================

% Corrected Year-wise DSM Publications (1965–2025)
years = [1965 2002 2004 2005 2008 2009 2010 2011 2012 2013 2014 ...
         2015 2016 2017 2018 2019 2020 2021 2022 2023 2024 2025];

publications = [1 1 2 1 2 2 4 1 1 2 4 ...
                4 2 6 7 3 6 6 5 13 9 7];

% DSM Methods / Algorithm counts
methods = {'PSO','GWO','GA','WOA','BaOA','Hybrid Metaheuristics','Other'};
method_counts = [10 6 4 3 2 7 10];

%% ============================
%% 2. Display Tables
%% ============================
% Table: Year-wise publications
T1 = table(years', publications', 'VariableNames',
{'Year','No_of_Publications'});
disp('Number of publications year wise (1965–2025)');
disp(T1);

% Table: Methods/Algorithms
T2 = table(methods', method_counts', 'VariableNames',
{'Method','No_of_Publications'});
disp('Most used methods and algorithms for DSM problems');
disp(T2);

%% ============================
%% 3. Publications Year Wise (Figure)
%% ============================
figure;
bar(years, publications, 'FaceColor',[0.2 0.6 0.8]);
xlabel('Year','FontSize',12,'FontWeight','bold');
ylabel('Number of Publications','FontSize',12,'FontWeight','bold');
```

```
title('Number of Publications Year Wise (1965–
2025)','FontSize',14,'FontWeight','bold');
grid on;
set(gca,'FontSize',11,'LineWidth',1.2);

%% ==============================
%% 4. Publications Method Wise (Figure)
%% ==============================
figure;
bar(categorical(methods), method_counts, 'FaceColor',[0.8 0.4 0.2]);
xlabel('Methods / Algorithms','FontSize',12,'FontWeight','bold');
ylabel('Number of Publications','FontSize',12,'FontWeight','bold');
title('Number of Publications Algorithm
Wise','FontSize',14,'FontWeight','bold');
grid on;
set(gca,'FontSize',11,'LineWidth',1.2);
```

APPENDIX I: Publications Decade

The decade-level summary of demand-side management publications covering the 1960s to 2025 is presented in Appendix I of the dissertation. Rather than being expressed in yearly terms, the appendix clusters each of the individual years into cushion terms of a broader ten-year period and does away with remarkable visual of the dynamic of research over the long-term. The graph and the table reveal a firmer upward trend in DSM-related research, with its highest points occurring in 2010–2019 and 2020–2025 when smart metering, optimization algorithms and advanced energy management system came into view. The summary by decades, complements the yearly longitudinals by encompassing the broad research parlance on DSM through ten decades.

```
close all; clear;

% Publications by Decade (1965–2025)
decades = categorical({'1960–1969','2000–2009','2010–2019','2020–2025'});
decades = reordercats(decades, {'1960–1969','2000–2009','2010–2019','2020–
2025'});

% Updated publication counts per decade based on provided references
publications = [1 8 24 37];
% Create Bar Chart
figure('Color','w','Units','inches','Position',[1 1 8 6]);
b = bar(decades, publications, 'FaceColor',[0.2 0.6 0.8]);

% Labels
xlabel('Decade','FontSize',14,'FontWeight','bold');
ylabel('Number of Publications','FontSize',14,'FontWeight','bold');
% Title (shifted upward)
t = title('Publications by Decade (1965–
2025)','FontSize',16,'FontWeight','bold');
t.Position(2) = t.Position(2) + 0.5;

% Show values on top of bars
```

```
xtips = 1:length(publications);
ytips = publications;
labels = string(publications);
text(xtips, ytips, labels, 'HorizontalAlignment','center', ...
     'VerticalAlignment','bottom','FontSize',12,'FontWeight','bold');

% Formatting
grid on;
set(gca,'FontSize',12,'FontWeight','bold','LineWidth',1.2);
```

APPENDIX J: Pseuso-code for GWO-based DSM Optimization

Appendix J provides a summary of GWO algorithm applied in the optimization of load profile of the DSMs in order to provide a pseudo-code on the other hand. GWO algorithm approach performs optimization of a load as it illuminates on the wolf packs and each of these members comes from a solution. While doing it the paper's outline initiates the application approach and also the paper completes it as a whole. The basic updated steps are given as appendix J and it also show GWO's best usage which it produced a last DSM approach.

```
Algorithm 1: Grey Wolf Optimization (GWO) for DSM Peak Clipping and Load
Shifting
1. Input:
   - Original hourly load profile P_orig(t)
   - Time-of-use (TOU) pricing data
   - Weight coefficients (w1, w2)
   - Population size (N), maximum iterations (MaxIter)
2. Output:
   - Optimized load profile P_opt(t)
   - Minimum objective function value f_min
3. Initialize a population of grey wolves (Xi, i = 1...N)
with random load adjustments.
4. Evaluate fitness of each wolf using:
       f(Xi) = w1 * Peak_Load(Xi) + w2 *
Energy_Cost(Xi)
5. Identify alpha (best), beta (second-best), and delta (third-best)
wolves.
6. While (iteration < MaxIter):
       For each wolf Xi:
          a. Update coefficient vectors A and C.
          b. Update wolf position using:
                 D_alpha = |C1 * X_alpha - Xi|
                 D_beta  = |C2 * X_beta  - Xi|
                 D_delta = |C3 * X_delta - Xi|
                 Xi_new = (X1 + X2 + X3) / 3
          c. Enforce DSM constraints:
                 - Power balance
                 - Load shifting limits
                 - Consumer comfort constraints
          d. Evaluate fitness f(Xi_new).
       e. Update alpha, beta, and delta wolves if improved solutions are
found.
Return best solution (X_alpha) as optimized load
profile P_opt(t).
```