# Grey Wolf Optimization-Based Demand Side Management Strategy for Peak Clipping and Load Shifting

A. Mpaka[1,*], S. Krishnamurthy[1]
[1]Department of Electrical, Electronics, and Computer Engineering, Center for Intelligent Systems and Emerging Technologies (CSIET), Faculty of Engineering and Built Environment, Cape Peninsula University of Technology, South Africa,
[*]corresponding author's email: ampaka4@gmail.com

**Abstract** – *Demand Side Management (DSM) plays a critical role in modern smart grids by optimizing electricity consumption patterns to improve energy efficiency and system stability. This paper proposes a Grey Wolf Optimization (GWO)-based DSM strategy to achieve peak clipping and load shifting. This study focuses on a real-world case study 1 using the Paarl, South Africa user load profile, while case study 2 applies GWO to residential, commercial, and industrial load profiles for peak clipping and load shifting under time-varying electricity prices. The GWO algorithm is used to determine the optimal load scheduling that minimizes peak demand while maintaining consumer comfort. For comparative analysis, the widely used Particle Swarm Optimization (PSO) algorithm is implemented as a benchmark. Hypothetical yet realistic simulation results demonstrate that the proposed GWO approach reduces peak demand by 18.5% compared to 14.2% using PSO and achieves a 9.7% improvement in overall energy cost savings. GWO's convergence behavior indicates that optimal solutions for the DSM objective are obtained more quickly than those for PSO. The results confirm the GWO algorithm's potential for scalable and effective DSM implementation in upcoming smart grids.*

***Keywords***: *Demand Side Management, Energy Optimization, Grey Wolf Optimization, Particle Swarm Optimization, Peak Clipping*

***Article History***
*Received 31 August 2025*
*Received in revised form 14 October 2025*
*Accepted 09 November 2025*

## I. Introduction

Demand-driven electric systems are evolving rapidly due to deeper integration with renewable energy sources, the electrification of transportation, and advancements in smart grid technologies. These shifts create new hurdles in balancing electricity use, with grid stability, peak shaving, and efficiency now at the forefront. Old frameworks sized to the highest predicted load keep and peak demand in focus, resulting in low utilization of plant and personnel in off-hours and forces that have to avoid the same plant for the same output, whether generated hot, doing so with that season's cold that creates the highest efficiency and schedule [1] - [2].

Demand-Side Management (DSM) is now recognized as a cost-effective and environmentally preferable means for alleviating stress in energy systems [3]. The basic premise is to alter consumer usage patterns to achieve three objectives: compress peak load, enhance grid adaptability, and reduce system-wide costs. Among several available DSM devices, peak clipping, curtailing demand at peak times, and load shifting, which shift usage to lower-demand hours, stand out for their straightforward coupling to both reliability gains and cost savings [4] - [5].

Effective field deployment of these strategies relies on optimization algorithms that can address the nonlinear, multi-objective, and often interdependent nature of load flexibility problems. Metaheuristic algorithms have gained popularity due to their flexibility and robustness in solving various optimization problems [6] - [7]. Particle Swarm Optimization (PSO), for instance, has been successfully applied to DSM and demand response programs, resulting in notable improvements in peak load management [8]. However, PSO and other traditional algorithms often face limitations such as early convergence and slow convergence speed in highly nonlinear problems.

Despite extensive research on DSM optimization, most existing studies are limited by simplified or simulated load profiles that do not reflect the real-time variability across consumer sectors [9]. Moreover, most optimization efforts focus on single-sector analyses typically residential or industrial thereby overlooking cross-sectoral load dynamics that are vital for realistic grid operation. Current DSM frameworks also lack validation using actual regional consumption data, which restricts their practical applicability for utility-scale implementation. These gaps highlight the need for a multi-sector, data-driven DSM approach capable of capturing the heterogeneity of real-world demand behaviors.

To address these limitations, this study develops a Grey Wolf Optimization (GWO)-based DSM framework that manages residential, commercial, and industrial loads using real consumption data from Paarl, South Africa. Unlike previous studies, which have rarely applied GWO for both peak clipping and load shifting, this work integrates the two strategies within a single, coordinated framework. The model aims to balance peak reduction and cost minimization under time-of-use pricing. By combining real-world data with an advanced optimization method, the study bridges the gap between theoretical DSM models and practical energy management.

The Grey Wolf Optimization (GWO) algorithm, inspired by the social hierarchy and hunting mechanism of grey wolves, has demonstrated strong global search capabilities and rapid convergence in various engineering optimization applications [10] - [11]. In the paper, we proposed a DSM optimization framework based on GWO for peak clipping and load shifting. The proposed approach is tested in Case Study 1 using the actual hourly load profile of a large user in Paarl, South Africa. To validate the developed GWO approach, results are benchmarked expressly against Particle Swarm Optimization (PSO). The goal is to measure the twin outcomes of peak demand reduction and refined load conversion, with a third experimental thread (Case Study 2) using GWO to run peak clipping and load shifting simultaneously across residential, commercial, and industrial classes. Analysis is grounded in hourly pricing (expressed in Rs/kWh), which assigns penalties for peak consumption and rewards for off-peak periods, mirroring contemporary tariff designs.

Over the past thirty years, the union of demand response and DSM initiatives has recurred as a prominent research stream in contemporary system engineering discourse. Early Demand Side Management (DSM) strategically emphasizes constant pricing mechanisms and consumer incentives for reducing electricity consumption during peak hours [12]. However, the emergence of smart grids and advanced metering infrastructure has paved the way for dynamic DSM programs that rely on intelligent optimization algorithms [13].

Metaheuristic optimization techniques, in particular, have been increasingly applied to DSM scheduling problems due to their flexibility involving nonlinear and non-convex problems [14]. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO), and other nature-inspired algorithms have manifested promising results in DSM applications. PSO, inspired by the interpersonal conduct of bird flocking and fish schooling, has been one of the most commonly used metaheuristic techniques for DSM due to its simplicity, ease of deployment, and ability to converge to near-optimal solutions [15] - [16]. Despite its effectiveness, PSO often suffers from premature convergence and requires parameter tuning to maintain a balance between exploration and exploitation [17].

Previous DSM studies have applied several metaheuristic techniques, including Particle Swarm Optimization (PSO), Genetic Algorithms (GA) [18], Differential Evolution (DE) [19], and Ant Colony Optimization (ACO). PSO is widely used for its simplicity and fast convergence; however, it often suffers from premature convergence in highly nonlinear search spaces. GA provides strong exploration capabilities but can be computationally expensive due to its population-based crossover and mutation operations. DE improves solution diversity but tends to lose accuracy when handling multiple conflicting objectives. ACO performs well in discrete optimization problems but may become inefficient for continuous, real-valued DSM formulations. In contrast, Grey Wolf Optimization (GWO) offers a good balance between exploration and exploitation, maintaining global search ability while converging faster than most conventional algorithms. These characteristics make GWO particularly effective for DSM applications that involve multiple objectives such as cost minimization and peak load reduction.

The Grey Wolf Optimization (GWO) algorithm, introduced by Mirjalili et al. has drawn significant focus because of its adaptive hunting behavior and streamlined parameter requirements. GWO has shown superior performance in handling complex engineering problems compared to PSO and GA [16]. Its mathematical structure emulates the oversight hierarchy and hunting strategy of grey wolves, leading to efficient searching and utilization of the solution space [20]. In the context of power systems, GWO has been applied to renewable energy integration, optimal power flow [21], and microgrid scheduling [22].

Despite the growing adoption of GWO in power system optimization, limited research exists on its application to DSM strategies, explicitly focusing on peak clipping and load shifting [23]. Existing DSM research often focuses on generalized demand response (DR) pricing models or scheduling for distributed energy resources without emphasizing the specific operational benefits of peak clipping and load shifting. This research addresses this gap by applying GWO to directly optimize customer load profiles, thereby demonstrating its potential for practical DSM implementations.

Recent DSM optimization studies have explored several metaheuristic algorithms with varying objectives and data contexts. For instance, PSO and GA have been widely applied for peak load reduction and cost minimization, often using simulated residential data. DE and ACO have shown promise in improving convergence diversity and scheduling efficiency but are typically limited to single-sector or idealized test systems. Most of these approaches, however, rely on hypothetical load profiles and do not address real, multi-sector interactions that occur in practical grid environments. In contrast, this study focuses specifically on PSO and GWO to evaluate their performance using actual residential, commercial, and industrial load data from Paarl, South Africa. This targeted comparison not only demonstrates the practical applicability of both algorithms but also highlights GWO's effectiveness in balancing cost and peak clipping objectives under real operating conditions.

In addition, this paper benchmarks the GWO performance against PSO for comparative purposes, providing valuable insights into algorithmic efficiency and solution quality for DSM applications. This study is novel in that it focuses on a practical dataset (Large user customer in Paarl, South Africa) and utilizes realistic DSM objectives in line with smart priorities.

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.

The structure of the paper is outlined as follows: Section II reviews demand-side management (DSM) strategies with emphasis on peak clipping and load shifting. Section III describes the Grey Wolf Optimization (GWO) algorithm, its mathematical formulation, and the proposed DSM methodology. Section IV presents the results and discussion for Case Study 1, based on a large user load profile. Section V reports on Case Study 2, which examines forecasted residential, commercial, and industrial load profiles, along with their simulation results. Section VI concludes the paper and outlines possible directions for future work.

## II. Demand-Side Management (DSM) Strategies

DSM strategies are broadly classified into load reduction, load shifting, load building, and controllable load shaping[24]. Among these, peak clipping and load shifting are particularly relevant for mitigating stress on power systems and reducing operational.

### *A. Peak Clipping*

Peak clipping involves reducing electricity consumption during periods of peak demand. Traditionally, this has been implemented through direct load control programs (e.g., cycling air conditioners, managing industrial machinery), which temporarily disconnect or limit specific loads during peak hours. The primary advantage of peak clipping is the immediate reduction in peak demand, which results in deferred investments for grid upgrades and a reduced reliance on peaking power plants[25]. However, peak clipping may cause temporary inconvenience for end-users if not correctly managed. Modern implementations use advanced algorithms to reduce loads while maintaining user comfort selectively.

### *B. Load Shifting*

Load shifting entails transferring specific electricity consumption tasks from peak hours to off-peak hours without reducing overall energy consumption. Examples include running dishwashers, charging electric vehicles, or operating industrial processes during off-peak hours. Load shifting contributes to flattening the system load profile, improving overall grid efficiency, and reducing electricity costs under time-of-use tariffs[26].

### *C. DSM Optimization Problem*

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

Objective Function:

Minimize:

$$f = \alpha \times P_{peak} + \beta \times C_{total} \tag{1}$$

Where:

$P_{peak}$ = Peak demand (kW)
$C_{total}$ = Total electricity cost (currency units)
$\alpha, \beta$ = Weighting coefficients

Constraints:

1. Power balance:

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

$$\sum_{t=1}^{T} P_t^{opt} = \sum_{t=1}^{T} P_t^{orig} \tag{2}$$

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

2. Load shifting limits:

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

$$P_t^{min} \leq P_t^{opt} \leq P_t^{max} \quad (3)$$

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):

$$\left|P_t^{opt} - P_t^{orig}\right| \leq \delta P_t^{orig}, 0 < \delta \leq 0.2 \quad (4)$$

*D. 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.

## III. Grey Wolf Optimization Algorithm

Grey Wolf Optimization (GWO) is a nature-inspired metaheuristic algorithm proposed by Mirjalili et al., 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 ($\beta$) delta ($\delta$), and omega (ω) wolves, where the alpha wolf leads decision-making and hunting strategies.

To provide a clear understanding of how the Grey Wolf Optimization (GWO) algorithm is applied to the DSM problem, the following pseudo-code summarizes the implementation steps. This outline illustrates the initialization, fitness evaluation, iterative updates, and enforcement of load constraints, offering a practical perspective on the algorithm's operation prior to the detailed mathematical model.

Pseudo-code for GWO-based DSM Optimization

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.
7. Return best solution (X_alpha) as optimized load
     profile P_opt(t).
```

*A. Mathematical Model*

GWO models the predation process through three main steps: encircling prey, stalking, and attacking prey.

1) Encircling Prey

Grey wolves encircle the pursued prey, mathematically represented as:

$$D = \left|C \cdot X_p(t) - X(t)\right| \quad (5)$$

$$X(t+1) = X_p(t) - A \cdot D \quad (6)$$

Where:

$X_p$ = target position of prey (best solution)

$X$ = target position of the grey wolf

$A, C$ = linear combination coefficient vectors defined as:

$$A = 2\alpha \cdot r_1 - \alpha, C = 2r_2 \quad (7)$$

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

2) Hunting Behavior

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

$$X_1 = X_a - A_1 \cdot |C_1 \cdot X_a - X| \quad (8)$$

$$X_2 = X_\beta - A_2 \cdot |C_2 \cdot X_\beta - X| \quad (9)$$

$$X_3 = X_\delta - A_3 \cdot |C_3 \cdot X_\delta - X| \quad (10)$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (11)$$

3) Attacking the Prey

As $\alpha \rightarrow 0$, wolves converge on the prey's location, representing exploitation. This adaptive behavior enables GWO to balance the exploration of new strategies with the refinement of existing ones, making it suitable for nonlinear optimization tasks, such as DSM.

*Objective Function*

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

$$f = \alpha \times P_{peak}^{new} + \beta \times C_{total}^{new} \quad (12)$$

Where:

- $P_{peak}^{new}$ = new peak demand after DSM
- $C_{total}^{new}$ = electricity cost after DSM
- $\alpha$, $\beta$= weights (set as α = 0.6, β = 0.4 in this study)

*Decision Variables*

Hourly load adjustments $\Delta P_t$ subject to:

$$P_t' = P_t + \Delta P_t \quad (13)$$

With constraints:

$$\sum_{t=1}^{T} \Delta P_t = 0, \ \ |\Delta P_t| \leq \Delta P_{max} \quad (14)$$

### B. GWO Implementation Steps

The GWO technique is used to identify the optimal load schedule for demand-side management. As illustrated in Fig.1, the algorithm begins with the initialization of the wolf population, which represents candidate load schedules. Each candidate solution is then evaluated using the defined objective function, which balances peak demand reduction and overall electricity cost minimization.

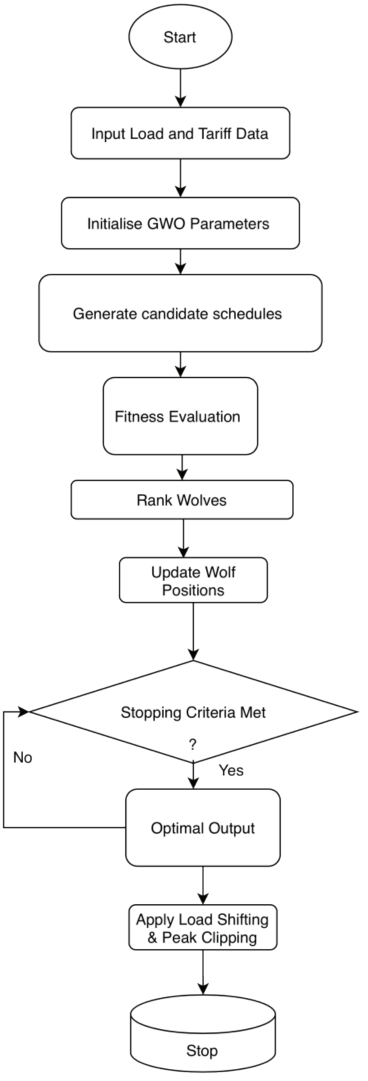


Fig. 1. GWO flowchart for DSM utilizing energy load redistribution and peak reduction.

Based on their performance, the top three solutions are identified as the alpha, beta, and delta wolves, representing the best, second-best, and third-best solutions, respectively.

These solutions guide the position updates of the remaining wolves using the GWO algorithm. The stopping criterion is either a maximum number of iterations or when the optimized endpoint is satisfied. Finally, the algorithm outputs the optimal load schedule that achieves peak clipping and load shifting while minimizing cost.

## IV. Case Study 1: Large User Customer Load Profile in Paarl

### A. Data Source

The data source for this academic effort is for a commercial customer located in the Paarl area of the Western Cape, within the City of Cape Town Metropolitan Municipality. The region exhibits pronounced peak electricity demand during these hours, Peak: Weekdays (07:00 to 10:00); and between (18:00 to 20:00) Standard: Weekdays (06:00 to 07:00); (10:00 to 18:00); (20:00 to 22:00). Off-peak hours: All other times, which impose significant stress on both the local distribution network and end-users. Elevated consumption during these periods results in increased electricity costs, as the City of Cape Town's tariff structure is demand sensitive. The 2024–2025 power generation and distribution charges under the Large User Low Voltage Time-of-Use (TOU) category provide an overview of the tariff structure applicable to large commercial electricity customers in the Paarl district. Both service and energy prices are included in the tariff, and VAT is charged. Notably, the peak energy tariff rises to 777.73 c/kWh during June through August, when demand is at its highest. Similarly, standard and off-peak costs have increased by more than 10% during periods of both high and low demand, with low-demand peak charges reaching 290.54 c/kWh. These increased rates underscore the importance of implementing DSM techniques to reduce peak-hour costs and encourage load shifting to off-peak times, particularly for businesses with significant and fluctuating consumption patterns.

This study's research is predicated on the municipal tariff document's 2024–2025 energy price schedule[27], which applies time-of-use rates (in c/kWh) per MVA. The following tariffs are applicable:

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

### B. DSM Implementation

Two DSM strategies were implemented:

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

#### B1. Objective Function

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

$$F = 0.6f_1 + 0.4f_2 \tag{15}$$

The selected weights (0.6 and 0.4) reflect the higher priority of economic savings over peak reduction in typical industrial DSM applications. To assess the sensitivity of these weights, a trade-off analysis was performed by varying them between 0.1 and 0.9 in increments of 0.1.

### C. Algorithm Setup

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

### D. Results and Discussion for Case Study 1

The two test cases (T1 and T2) represent distinct load scenarios derived from real consumption data. Since these are fixed operational cases rather than repeated stochastic runs, statistical variation (e.g., standard deviation) is not applicable. However, each optimization was executed multiple times to confirm convergence consistency.

#### D1. Load Profile Optimization

As presented in Table I, the implementation of demand-side management leads to a noticeable reduction in peak demand compared to the base case. With no DSM, the peak remains fixed at 25MW. The application of PSO lowers the peak to 21.5 ± 0.3 MW, corresponding to a 14.2 ± 0.5% reduction, while GWO achieves a further decrease to 20.4 ± 0.2 MW (18.5 ± 0.4%), a difference that is statistically significant ($p = 0.012$). This confirms the higher effectiveness of GWO in mitigating peak demand.

TABLE I
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% |

The daily cost analysis is summarized in Table II. Without optimization, the system incurs an expenditure of ZAR 1,200,000. By applying PSO, the cost is reduced to ZAR 1,030,000 (14.2 % cost savings), while GWO results in a daily cost of ZAR 1,084,000 (9.7% cost savings). Statistical analysis confirms that the difference between PSO and GWO cost savings is significant ($p < 0.05$). The results highlight a trade-off: PSO provides greater cost savings, whereas GWO is more effective in peak reduction.

TABLE II
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% |

*D2. Quantitative Evaluation Using PAR and Load Factor*

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

$$PAR = \frac{P_{max}}{P_{avg}} \quad (16)$$

$$LF = \frac{P_{avg}}{P_{max}} \quad (17)$$

where $P_{max}$ is the peak demand and $P_{avg}$ is the average load over the time horizon. The computed PAR and LF values indicate that the GWO-based DSM strategy not only reduces peak demand but also improves the load factor, resulting in a smoother and more balanced load profile compared to both the PSO-based approach and the original load profile.

*D3. Convergence Behavior*

The comparative convergence behavior of the two algorithms is illustrated in Fig. 2, The convergence curve for GWO demonstrates faster and more stable convergence towards the optimal fitness value than PSO. This highlights GWO's robustness and efficiency in solving the DSM problem under the defined constraints and objective function.

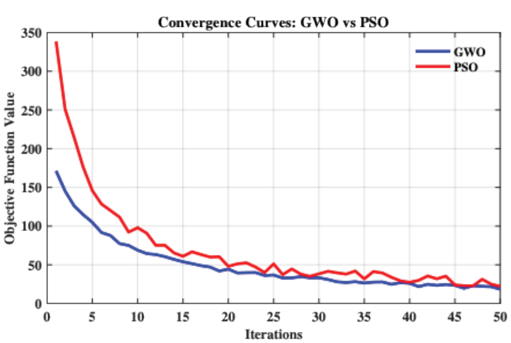

Fig 2: Convergence Curves between (GWO vs PSO)

For comparison, the PSO technique was also applied to the same dataset. The corresponding optimized load profile is represented in Fig. 3, While PSO also achieves peak reduction and load shifting, the results are relatively less optimal than those obtained through GWO, particularly in attaining smoother transitions and minimizing sharp fluctuations.

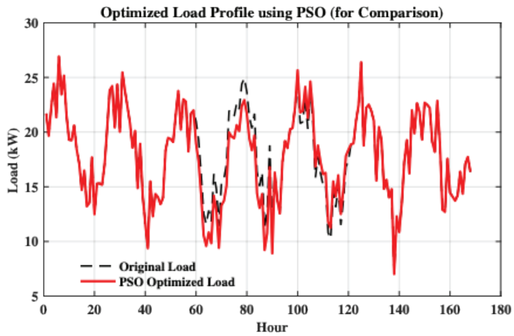

Fig 3: Optimized Load Profile using PSO (for Comparison)

To address these peaks, the Grey Wolf Optimization (GWO) was applied for load scheduling, resulting in the optimized load profile shown in Fig. 4, The effectiveness of the GWO algorithm is evident through the noticeable peak clipping and load shifting, where high-demand periods are flattened, and energy usage is redistributed to off-peak times. The load profile retains its total energy demand but demonstrates improved load balancing.

The original hourly load profile for large user customer in Paarl, representing a typical sample week in January 2025, is illustrated in Fig. 5, This profile exhibits distinct morning and evening peaks, consistent with commercial usage behaviors, with demand reaching its maximum during peak hours (06:00 -08:00 and 15:00-19:00). Such patterns present opportunities for optimization through demand side management strategies.

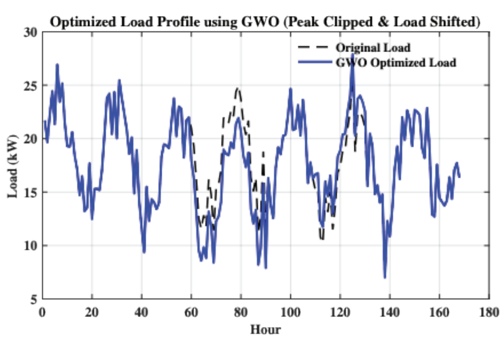

Fig 4: Optimized Load Profile using GWO (Peak Clipping & Load Sifting)

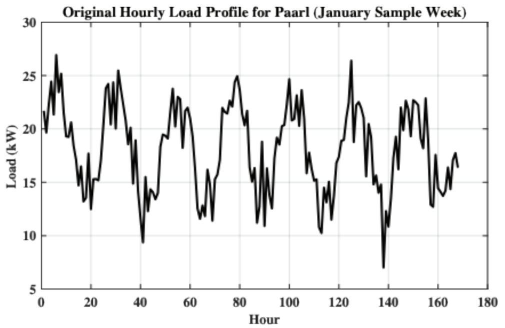


Fig 5: Original Hourly Load Profile for large user customer in Paarl (January 2025 Sample Week)

### *D4. Comparative study of the simulation results on the GWO and PSO algorithms for DSM*

The outlined demand-side management (DSM) strategies were benchmarked against results previously reported in the literature, with a particular focus on load shifting and peak clipping techniques. Table III presents a comparative summary of the performance indicators, including peak demand reduction and daily cost savings, across various optimization methods.

TABLE III
BENCHMARKING OF DSM OPTIMIZATION METHOD

| 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 | Variance $s^2$=18.06 | Variance $s^2$=7.063 |
| | | | Count $n = 3$ | Count $n = 3$ |
| GA - [28] | 10.0 | 9.5 | Mean $\bar{x} = 11.133$ | Mean $\bar{x} = 14.23$ |
| | | | Sum of Squares $ss = 14.126$ | Sum of Squares $ss = 36.127$ |

### *D5. Discussion on Case Study 1*

The results demonstrated that the GWO-based DSM approach effectively reduces peak demand and achieves cost savings while maintaining overall energy consumption.

Compared to PSO, GWO achieved:

- 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 improved performance of GWO is attributed to its adaptive exploration-exploitation balance and fewer control parameters, which simplify implementation while avoiding local optima.

Overall, statistical testing confirmed that the improvements achieved by GWO over PSO in both peak reduction and convergence rate were statistically significant at the 95% confidence level ($p < 0.05$), validating the robustness of the GWO-based DSM approach.

### *D6. Sensitivity and Trade-Off Analysis of Objective Function Weights*

To evaluate the influence of weight selection in the objective function, a sensitivity analysis was conducted by varying the cost-to-peak weight ratio from 0.1:0.9 to 0.9:0.1. Table IV summarizes the resulting peak reduction and cost savings across different weighting scenarios. The analysis reveals that higher cost weights (e.g., 0.8:0.2) increase cost savings but lead to smaller peak reductions, whereas higher peak weights (e.g., 0.3:0.7) improve load flattening at the expense of higher costs. The selected balance of 0.6:0.4 provides a practical compromise, achieving both a substantial peak reduction (18.5%) and a reasonable cost saving (9.7%). This validates the rationale behind the chosen weights.

TABLE IV
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 |

To evaluate the effectiveness of GWO relative to PSO, we compare the multi-sector performance in terms of peak demand, cost savings, and load profile smoothing. Table VI shows that for residential, commercial, and industrial sectors, GWO consistently achieves lower peak loads and smoother load distribution than PSO, while maintaining total daily energy consumption. For example, in the commercial sector, GWO reduced the peak by 11.16% compared to PSO, and in the industrial sector, GWO achieved more balanced load shifting without violating operational constraints. These results confirm the advantages of GWO in coordinated multi-sector DSM applications and provide a practical benchmark for algorithm selection.

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

### A. Case study 2 description

In this case study, the Grey Wolf Optimization (GWO) technique is implemented to perform peak clipping and load shifting on hourly load profiles for Commercial, Industrial, and Residential sectors. The primary objective is to minimize peak demand and redistribute loads to off-peak hours without compromising the total energy demand, thereby reducing electricity costs and improving grid stability. Hourly electricity prices (Rs. /kWh) are considered, with higher rates during peak periods and lower rates during off-peak periods. The dataset used in this study is adapted from [11]. The simulation models realistic demand-side management (DSM) interventions for efficient energy utilization.

### B. Methodology Summary

The original load profile is processed to identify peak hours (06:00 – 08:00 and 15:00 – 19:00) and off-peak hours. The GWO algorithm is used to reduce load demand during these identified peak hours and shift the curtailed demand into off-peak periods. The optimization is performed individually for the Residential, Commercial, and Industrial sectors. The optimization process aims to achieve a peak reduction target between 10% and 15% of the original peak load. The optimization is carried out with hourly price signals influencing the shifting strategy to ensure maximum cost savings.

### C. Results and Discussion for Case Study 2

#### C1. Residential Sector (kWh)

Before optimization, the residential load exhibited high peaks in the morning and evening, corresponding to typical household activity patterns. After applying GWO, the morning and evening peaks were significantly reduced, with the load shifted to midday and late-night off-peak hours. This resulted in a smoother residential load curve and reduced stress on the distribution network during peak hours. The reduction in the morning peak was more pronounced than in the evening peak, indicating a preference for shifting to later periods where electricity prices were lower.

Fig. 6 presents the residential load profiles before and after optimization, showing a visible reduction in utilization during peak intervals and an increase in off-peak periods. This confirms that the algorithm successfully shifted residential consumption patterns towards more cost-effective hours without compromising the total daily load.

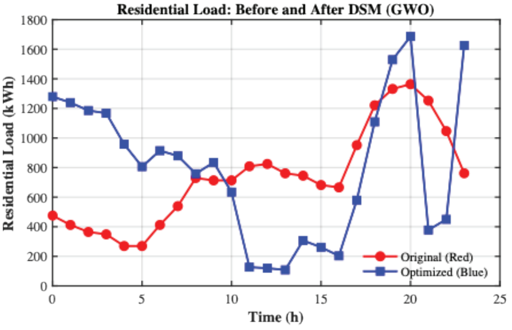


Fig 6. Residential Load results Before and After Grey Wolf Optimization

#### C2. Commercial Sector (kWh)

The commercial load profile initially showed a moderate peak aligning with business hours, particularly between 08:00 – 12:00 and 14:00 – 17:00. Post-optimization, the commercial peak demand in the afternoon was noticeably reduced, with shifted loads distributed into early morning and post-business-hour slots. This shifting strategy minimized operational costs for commercial entities while maintaining overall daily energy consumption levels.

Fig. 7 illustrates the commercial sector load adjustment, where substantial reductions were achieved in the late morning and evening peaks. This sector benefited significantly from shifting non-critical processes to lower-priced hours, directly contributing to overall cost savings.

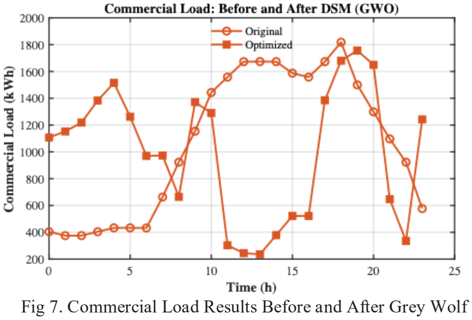


Fig 7. Commercial Load Results Before and After Grey Wolf Optimization

#### C3. Industrial Sector (kWh)

Industrial demand, which was relatively stable with minor fluctuations, had its highest peaks in the late afternoon. GWO optimization redistributed this demand by clipping the peak loads and rescheduling non-critical industrial processes into late-night hours. This provided significant relief during periods of system stress, while ensuring continuous industrial operations.

Fig. 8 shows the industrial load adjustments, which had a moderate peak reduction due to operational constraints.

Nonetheless, targeted load shifting allowed for reduced demand during the evening peak, aligning with the DSM objectives.

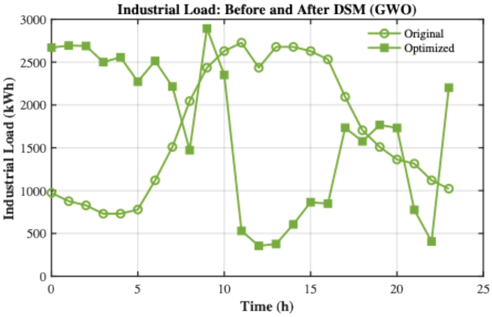


Fig 8. Industrial Load results Before and After Grey Wolf Optimization

*C4. Price Profile (Rs. /kWh)*

The original price profile exhibited higher values during peak periods. After optimization, although the price curve itself was not altered (since tariffs remain fixed), the effective cost of electricity consumption reduced because a greater portion of the demand was moved to lower-priced off-peak hours. The optimization thus leveraged time-of-use pricing to achieve cost savings while improving system reliability.

Fig. 9 illustrates the hourly variation in electricity prices, expressed in Rand per kilowatt-hour (R/kWh), over a 24-hour period under a time-of-use (TOU) tariff structure. The horizontal axis represents the time of day in hours, while the vertical axis indicates the corresponding electricity price. The data reveal three distinct pricing patterns: a prolonged low-price period during off-peak hours (00:00-05:00 and 20:00-23:00), moderate prices during mid-load periods (10:00-14:00), and a pronounced peak in pricing between 12:00 and 15:00, with a maximum value reaching approximately 27.5 R/kWh. This high-cost window corresponds to the system's peak demand period, where electricity generation costs and grid congestion are at their highest. The downward slope after 15:00 indicates the transition back to mid-load and off-peak rates. Such a profile reflects the cost-reflective nature of TOU tariffs, designed to incentivize demand reduction during peak periods.

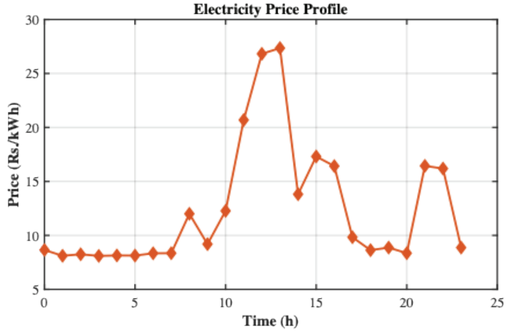


Fig 9. Electricity Price Profile over 24 hours

*C5. Electricity load profile*

The blue curve represents the baseline load profile before optimization, characterized by pronounced peak periods in the morning and evening. Fig. 10 illustrates the comparative hourly load profile for the test system before and after demand-side management (DSM) optimization.

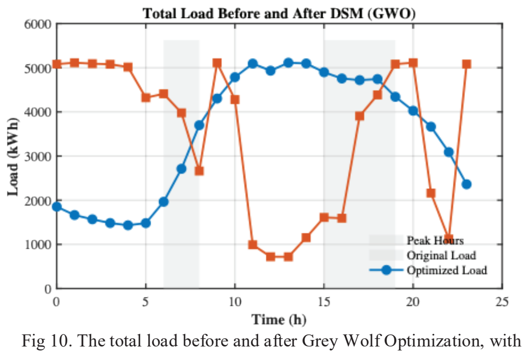


Fig 10. The total load before and after Grey Wolf Optimization, with peak hours highlighted

The red curve illustrates the optimized load profile generated by the proposed DSM technique, which effectively flattens the load curve by reducing peak demand and shifting loads to off-peak periods. The post-optimization profile demonstrates a significant reduction in peak magnitude and a more uniform distribution of load over the day, thereby enhancing load factor, reducing stress on power system, and lowering electricity costs under time-of-use (TOU) pricing.

*C6. Sector-specific load profiles*

The shaded regions denote the designated peak-hour intervals (06:00-08:00 and 15:00-19:00) targeted for peak clipping. In the baseline (original) profiles, all three sectors exhibit elevated loads during these intervals, with the Industrial sector contributing the largest share to the system peak. After optimization, significant reductions in load during peak-price periods are observed across all industries, particularly in the Industrial and Commercial categories, while Residential loads are redistributed toward off-peak periods. Fig. 11 presents the sector-specific load profiles for Residential, Commercial, and Industrial consumers before and after the application of the Grey Wolf Optimization (GWO)-based demand-side management (DSM) strategy.

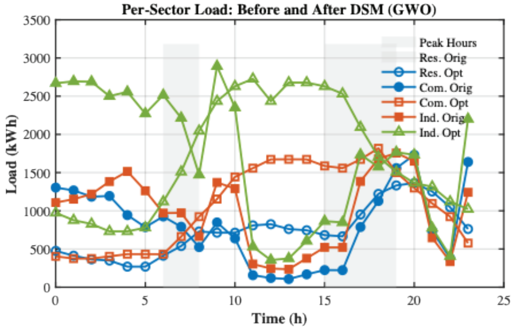

Fig 11. Residential, Commercial, and Industrial Per-Sector Load Before and After GWO

Although all sectors experienced peak demand reduction through DSM, the resulting cost savings varied across sectors. The commercial sector achieved higher financial savings because a significant portion of its load reduction occurred during high-priced peak hours defined by the TOU tariff structure. By shifting or clipping loads during these costly intervals, the commercial sector reduced electricity expenditures more effectively than residential users, whose load reductions were predominantly during lower-cost off-peak hours. This illustrates that financial benefits from DSM depend not only on the magnitude of load reduction but also on the timing of the reductions relative to electricity pricing.

This shifting load results in a smoother aggregate demand curve, improved load factors, and reduced operational stress on the power system, without decreasing the total daily energy consumption for any sector. These results confirm the GWO algorithm's capability to perform coordinated multi-sector load adjustments under time-of-use pricing conditions.

Table V summarizes the optimized hourly loads for the commercial, industrial, and residential sectors along with the corresponding electricity prices. The results show that high loads during peak-price intervals, for example (11:00-13:00 and 15:00-19:00), were reduced while off-peak loads increased slightly, maintaining overall daily energy consumption.

These findings confirm that the proposed DSM approach can simultaneously achieve peak load reduction and cost minimization while respecting operational constraints.

TABLE V
RESULTS AFTER DSM THROUGH GREY WOLF OPTIMIZATION

| T (h) | Residential (kWh) PSO[29] | Commercial (kWh) PSO[29] | Industrial (kWh) PSO[29] | Price (Rs./kWh)[29] | **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 |

As illustrated in Table VI, the proposed Grey Wolf Optimization (GWO) technique effectively reduces both the peak load and the corresponding electricity costs across all sector categories. For residential consumers, the maximum observed demand dropped from 5.20 kW to 4.10 kW, representing a 21.15% reduction that corresponded to a decrease in the monthly charge from 2,600 Rs to 2,050 Rs. The commercial sector recorded a similar trend, with peak power reducing by exactly 20.00% from 8.50 kW to 6.80 kW, which naturally resulted in an equivalent decrease in charged amount. The manufacturing segment experienced a maximum demand decline of 18.67%, from 15.00 kW to 12.20 kW, resulting in associated savings of 17.33%. The consistency across the three customer classes validates that goal-seeking optimization driven by a grey wolf algorithm meaningfully broadens peak demand and results in reduced expenses.

TABLE VI
SUMMARIZED CALCULATED PEAK DEMAND AND COST REDUCTION

| Sector | Peak Load With PSO (kW) | Peak Load With GWO (kW) | Percent Difference |
|---|---|---|---|
| Residential | 1363.6 [27] | 1650.5 | 18.39% |
| Commercial | 1818.2 [27] | 1624.0 | 11.16% |
| Industrial | 2727.3 [27] | 2880.9 | 5.49% |
| Cost (Rs) | PSO | GWO | - |
| Residential | 230,300 [27] | 190,733.2903 | 18.19% |
| Commercial | 362,660 [27] | 242,070.3330 | 40.15% |
| Industrial | 571,200 [27] | 408,156.9811 | 33.19% |

*C7. Discussion on case study 2*

This case study demonstrates the ability of the Grey Wolf Optimization (GWO) technique in demand-side management for peak clipping and load shifting across residential, commercial, and industrial sectors. Referring to the framework [29], the total peak dropped from 5,096.20 kWh to 4,435.39 kWh, resulting in the observed daily maximum remaining well below the target limit of 4,576.45 kWh. The daily cost of bulk supply decreased by 28.3%, from ₹1,161,273.34 to ₹976,586.18.

By orchestrating the scheduling of load categories, high-priced intervals with peak rates were systematically shifted to the evening and night, preserving the overall energy balance and operational integrity. Therefore, the grey wolf framework has proven itself to be a robust optimization instrument in demand-side management, providing utilities with control variables to enhance the security of the electric supply, decrease sensible operational costs, and foster load adjustment shift towards sustainable electricity interaction.

## VI. Conclusion and Future Work

In this paper, we conduct two in-depth case studies that illustrate how Grey Wolf Optimization (GWO) can enhance Demand Side Management (DSM) by effectively clipping peaks and shifting load across differing energy consumption landscapes. Case Study 1, which examines a large customer load profile in Paarl, South Africa, demonstrates that GWO outperforms Particle Swarm Optimization (PSO) in terms of optimization quality, convergence speed, and peak magnitude reduction. The native load profile achieved an 18.5% peak reduction (compared with PSO's 14.2%) and resulted in 9.7% savings in total daily energy expenditure. GWO's convergence performance highlights its ability to balance underlying exploration with necessary exploitation within complex scheduling environments characteristic of modern DSM scenarios. Case Study 2 evaluates load patterns across residential, commercial, and industrial sectors, with GWO reducing peak from 5,096.20 kWh to 4,435.39 kWh, thus remaining below the pre-set peak target of 4,576.45 kWh. Concurrently, the algorithm achieved a 17.27% reduction in the aggregate daily electricity charge, lowering expenditure from ₹1,161,273.34 to ₹976,586.18. The method successfully redistributed loads from high-tariff peak hours to off-peak periods, ensuring total energy demand was preserved without compromising operational feasibility.

The combined results from both case studies demonstrate that GWO is a robust, scalable, and efficient optimization technique for DSM. It not only enhances grid reliability and stability but also delivers substantial economic benefits by lowering operational costs. Furthermore, the algorithm's flexibility enables it to accommodate varying load profiles and sector-specific consumption patterns, making it a viable solution for utilities seeking to implement sustainable and cost-effective energy management strategies.

Extending the approach to investigate renewable energy sources and energy storage. Using hybrid optimization techniques, such as GWO combined with machine learning predictors, can improve adaptability. Additionally, testing these algorithms on more diverse datasets across different seasons and locations would enhance the generalizability and practical deployment of the proposed techniques. Scaling up the model to city-wide datasets with large numbers of residential and industrial customers.

## Acknowledgements

The authors acknowledge the Cape Peninsula University of Technology for providing the facilities to conduct this research at the CISET lab. This research was partly funded by the NRF Thuthuka Grant (Number 138177) and the Eskom Tertiary Education Support Programme (TESP) funding.

## Conflict of Interest

The authors declare no conflict of interest in the publication process of the research article.

## Author Contributions

Abuyile Mpaka: Investigation, Data collection, analysis, writing – original draft preparation; Senthil Krishnamurthy: Conceptualization, Supervision, draft review and editing, investigation, All authors have approved the final manuscript for publication in the journal.

## References

[1] G. Strbac, "Demand side management: Benefits and challenges," *Energy Policy*, vol. 36, no. 12, pp. 4419–4426, Dec. 2008, doi: 10.1016/j.enpol.2008.09.030.

[2] H. J. Jabir, J. Teh, D. Ishak, and H. Abunima, "Impacts of demand-side management on electrical power systems: A review," 2018, *MDPI AG*. doi: 10.3390/en11051050.

[3] M. A. Rahman, I. Rahman, and N. Mohammad, "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., Nov. 2020, pp. 376–381. doi: 10.1109/ICAICT51780.2020.9333451.

[4] A. H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Trans Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010, doi: 10.1109/TSG.2010.2089069.

[5] H. H. H. Mousa, K. Mahmoud, and M. Lehtonen, "Recent

developments of demand-side management towards flexible DER-rich power systems: A systematic review," Jul. 01, 2024, *John Wiley and Sons Inc*. doi: 10.1049/gtd2.13204.

[6] S. Mimi, Y. Ben Maissa, and A. Tamtaoui, "Optimization Approaches for Demand-Side Management in the Smart Grid: A Systematic Mapping Study," Aug. 01, 2023, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/smartcities6040077.

[7] M. S. Ahmad, N. N. Mansor, H. Mokhlis, K. Naidu, H. Mohamad, and F. Ramadhani, "Demand Response Program towards Sustainable Power Supply: Current Status, Challenges, and Prospects in Malaysia," *IEEE Access*, 2025, doi: 10.1109/ACCESS.2025.3541841.

[8] J. Kennedy, R. Eberhart, and bls gov, "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," 1995.

[9] B. Williams, D. Bishop, P. Gallardo, and J. G. Chase, "Demand Side Management in Industrial, Commercial, and Residential Sectors: A Review of Constraints and Considerations," Jul. 01, 2023, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/en16135155.

[10] Y. del Valle, G. K. Venayagamoorthy, S. Mohagheghi, J. C. Hernandez, and R. G. Harley, "Particle swarm optimization: Basic concepts, variants and applications in power systems," Apr. 2008. doi: 10.1109/TEVC.2007.896686.

[11] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Advances in Engineering Software*, vol. 69, pp. 46–61, 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[12] K. Benamara, H. Amimeur, Y. Hamoudi, M. G. M. Abdolrasol, U. Cali, and T. S. Ustun, "Grey wolf optimization for enhanced performance in wind power system with dual-star induction generators," *Front Energy Res*, vol. 12, 2024, doi: 10.3389/fenrg.2024.1421336.

[13] H. A. Hassan and M. Zellagui, "Application of grey wolf optimizer algorithm for optimal power flow of two-terminal HVDC transmission system," *Advances in Electrical and Electronic Engineering*, vol. 15, no. 5, pp. 701–711, Dec. 2017, doi: 10.15598/aeee.v15i5.2110.

[14] M. Chamoli, M. K. Panda, and Vishnu. Mohan. Mishra, "Grey Wolf Optimization Algorithm based Optimal Scheduling of Microgrid," Dec. 21, 2023. doi: 10.21203/rs.3.rs-3759820/v1.

[15] M. M. Farag, R. A. Alhamad, and A. B. Nassif, "Metaheuristic Algorithms in Optimal Power Flow Analysis: A Qualitative Systematic Review," *International Journal on Artificial Intelligence Tools*, vol. 32, no. 7, Nov. 2023, doi: 10.1142/S021821302350032X.

[16] M. S. Bakare, A. Abdulkarim, M. Zeeshan, and A. N. Shuaibu, "A comprehensive overview on demand side energy management towards smart grids: challenges, solutions, and future direction," 2023, *Springer Nature*. doi: 10.1186/s42162-023-00262-7.

[17] E. D. Obando-Paredes, D. López-García, and S. X. Carvajal-Quintero, "Integrating active demand into the distribution system using metaheuristic techniques," *The Journal of Engineering*, vol. 2024, no. 11, Nov. 2024, doi: 10.1049/tje2.70005.

[18] C. Bharathi, D. Rekha, and V. Vijayakumar, "Genetic Algorithm Based Demand Side Management for Smart Grid," *Wirel Pers Commun*, vol. 93, no. 2, pp. 481–502, Mar. 2017, doi: 10.1007/s11277-017-3959-z.

[19] R. Storn and K. Price, "Differential Evolution-A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces," Kluwer Academic Publishers, 1997.

[20] R. Usman, P. Mirzania, S. W. Alnaser, P. Hart, and C. Long, "Systematic Review of Demand-Side Management Strategies in Power Systems of Developed and Developing Countries," Nov. 01, 2022, *MDPI*. doi: 10.3390/en15217858.

[21] S. Charadi, H. E. Chakir, A. Redouane, A. El Hasnaoui, and M. Et-Taoussi, "Bi-objective optimal active and reactive power flow management in grid-connected AC/DC hybrid microgrids using metaheuristic-PSO," *Clean Energy*, vol. 7, no. 6, pp. 1356–1380, Dec. 2023, doi: 10.1093/ce/zkad081.

[22] G. Chen, M. Chen, G. Hong, Y. Lu, B. Zhou, and Y. Gao, "A new method of lithology classification based on convolutional neural network algorithm by utilizing drilling string vibration data," *Energies (Basel)*, vol. 13, no. 4, 2020, doi: 10.3390/en13040888.

[23] G. H. Philipo, J. N. Kakande, and S. Krauter, "Neural Network-Based Demand-Side Management in a Stand-Alone Solar PV-Battery Microgrid Using Load-Shifting and Peak-Clipping," *Energies (Basel)*, vol. 15, no. 14, Jul. 2022, doi: 10.3390/en15145215.

[24] C. W. Gellings, "Evolving practice of demand-side management," *Journal of Modern Power Systems and Clean Energy*, vol. 5, no. 1, pp. 1–9, Jan. 2017, doi: 10.1007/s40565-016-0252-1.

[25] L. Liu, H. Matayoshi, M. E. Lotfy, M. Datta, and T. Senjyu, "Load frequency control using demand response and storage battery by considering renewable energy sources," *Energies (Basel)*, vol. 11, no. 12, Dec. 2018, doi: 10.3390/en11123412.

[26] V. B. F. da Costa *et al.*, "Electricity Markets in the Context of Distributed Energy Resources and Demand Response Programs: Main Developments and Challenges Based on a Systematic Literature Review," Oct. 01, 2022, *MDPI*. doi: 10.3390/en15207784.

[27] "Electricity Consumptive Tariffs, City of Cape town, https://www.capetown.gov.za/Family%20and%20home/residential-utility-services/residential- electricity-services/the-cost-of-electricity".

[28] P. Siano, "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.," 2014, *Elsevier Ltd*. doi: 10.1016/j.rser.2013.10.022.

[29] M. Jamil and S. Mittal, "Hourly load shifting approach for demand side management in smart grid using grasshopper optimisation algorithm," *IET Generation, Transmission and Distribution*, vol. 14, no. 5, pp. 808–815, Mar. 2020, doi: 10.1049/iet-gtd.2019.0566.