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RESEARCH ARTICLE

Optimized demand-side management for large power consumers using PSO and MLIP algorithms: A case study of the Western Cape municipality

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ABSTRACT

The increasing power demand, transmission line congestion, and increasing electricity traffic necessitate the effective implementation of demand-side management (DSM) strategies to improve energy efficiency and sustainability. This research presents an optimized DSM framework for large power consumers in the Western Cape municipality, utilizing particle swarm optimization (PSO) integrated with machine learning improved prediction algorithms to achieve peak clipping and reduce peak load power demand under real-time pricing conditions. The developed algorithms were validated using actual energy consumption data from large industrial customers in the Western Cape province. Simulation results indicate that the PSO-driven DSM framework significantly reduces peak demand, improves the load factor, and offers substantial cost savings compared to conventional load management techniques. This study highlights the potential of intelligent optimization methods to support municipalities and major energy users in adopting more flexible, affordable, and sustainable energy consumption practices.

1. Introduction

Demand-side management (DSM) plays a vital role in modern power systems by strategically managing consumer electricity usage to improve overall grid stability and operational efficiency. [1] Through DSM programs, utilities aim to reduce peak load, balance demand and supply, and optimize overall network performance. [2] As DSM practices evolved over time, integrated resource planning was introduced, broadening the scope of traditional planning by incorporating DSM resources into the power system alongside supply-side options to ensure a more balanced and efficient approach. [3] Some of the commonly applied DSM methods include peak clipping, which reduces demand during high-load periods, and load shifting, in which demand is shifted to off-peak periods. [4] The concept of DSM gained substantial momentum during the 1970s and 1980s, as utilities and regulators viewed it as a means to mitigate supply growth in response to rising energy demand, the oil crisis, and growing environmental awareness. [5]

More recently, advancements in smart grid technologies have enabled the integration of both model-based and model-free approaches to DSM, enhancing the efficiency and reliability of grid operations by leveraging distributed energy resources and adaptive learning strategies. [6,7]

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Among these approaches, particle swarm optimization (PSO) has emerged as one of the most widely used optimization techniques in DSM applications, primarily due to its ability to handle complex and nonlinear scheduling problems. It has been successfully employed to optimize load patterns, increase grid performance, and reduce overall operation costs. [8] Moreover, PSO has demonstrated strong compatibility with real-time analytics and demand-response systems, effectively mitigating peak demand challenges. [9]

A well-designed algorithm can perform computations far more efficiently than an inefficient one, even without changes to the underlying hardware. This implies that improvements in algorithmic design can, in effect, make computers "faster." Techniques such as precomputing components of a problem or streamlining solution methods exemplify how intelligent algorithm design can significantly enhance overall computational efficiency. [10? ,11]

Nevertheless, when the availability of renewable energy generation is low, offset measures such as regulated demand curtailment or the use of energy storage alternatives are usually essential. These conventional emergency methods, such as load shedding, in which certain consumers are temporarily disconnected, remain controversial because of their adverse social and economic impacts. Large-scale energy storage systems or grid reinforcement can serve as alternatives in many developing regions, but their implementation is often limited by high capital cost and long deployment timelines.

Recent advances in DSM have emerged through collaborative efforts among utility companies, environmental experts, and policymakers to maximize energy use and promote sustainability goals. [13] Inspired by natural phenomena such as bird flocking and fish schooling, a population-based stochastic algorithm known as PSO was first introduced by Kennedy and Eberhart. [5] Its simplicity and proven ability to identify optimal solutions for complex, nonlinear, and multi-dimensional problems have contributed to its widespread adoption across multiple engineering domains. [14] PSO facilitates the exploration of solution space through information sharing among particles, thereby enabling convergence toward optimal solutions. [15] In the field of DSM, PSO has been utilized to enhance load management, improve demand balance, and optimize energy use planning systems.

Peak clipping focuses on reducing power requirements during peak periods through direct load regulation, tariff-based incentives, and customer engagement measures. [16–18] This relieves pressure on the electricity network and reduces dependence on peaking power stations, which are typically expensive. Instead, the load shifting process utilizes time-of-use (TOU) pricing incentives and other mechanisms to encourage consumers to shift their consumption from peak hours to off-peak periods. [19] In addition, flexible load shaping dynamically adjusts the load profile (LP) of consumers to optimize grid utilization during times of low demand. [20]

Other energy efficiency measures, such as the use of high-efficiency appliances, smart control systems, and duty cycling, also reduce aggregate energy consumption levels. [21] 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, which are typified by clear highs and lows of LPs. These trends imply the necessity of refined load control: drastic decreases in demand can be caused by scheduled maintenance or interruptions, and high usage during peak business hours puts much stress on infrastructure and increases operational costs. [22,23]

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), [24] and TOU tariffs are recent innovations that have been shown to be effective in curbing peak demand and enhancing customer engagement in DSM. Nevertheless, these tariff structures are being refined to better 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, although these methods are usually limited in terms of their scalability, adaptability, and responsiveness to changes in grid dynamics. [25,26]

PSO is a well-established heuristic optimization technique, widely recognized by the technical community for its stability and effectiveness in solving complex, nonlinear optimization problems. Although PSO has demonstrated significant potential in several DSM applications, the current models are mostly limited to simulations or restricted to general datasets with limited verification using real-world utility datasets. Moreover, there is little research focused on integrating heuristic optimization with artificial intelligence (AI) and machine learning (ML). The machine-learning improved prediction (MLIP) formulation for one-dimensional cutting stock problems integrates the most common objectives into a single framework, with particular focus on reducing trim loss, that is, leftover material too small to be reused, while enabling adaptive control and predictive load management. [27–29]

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 exhibit challenges such as premature convergence and inadequate handling of system constraints under dynamic and 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. [30,31]

In response to changing demand patterns, ML approaches that enable adaptive and anticipatory load management are rarely incorporated into current DSM frameworks. Furthermore, most theoretical DSM models have not been sufficiently translated into practical applications; for instance, reliable tools and simulations—such as those created 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 effectively reduce grid congestion. 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 and provides insightful guidance to help utility companies, end users, and policymakers in supporting the development of a more intelligent and sustainable energy infrastructure.

2. Demand-side management formulation problem

Throughout the day, energy consumption fluctuates significantly, with periods of peak demand placing a substantial burden on the power infrastructure and leading to higher electricity prices. Load-shifting techniques aim to lower energy use during peak hours, thereby reducing peak demand. Conventional DSM techniques rely on fixed load reduction methods, which may not be the most effective means of ensuring grid stability and achieving cost savings.

To evaluate the effectiveness of the proposed PSO framework in a real-world context, this study applies the model to empirical energy consumption data obtained from a commercial customer located in Paarl, South Africa. The dataset covers a 1-year cycle, from July 2024 to June 2025, and reflects daily and seasonal fluctuations in LPs.

The identity of the commercial customer will not be disclosed due to privacy and data protection considerations.

The optimization scenario aims to control demand through load shifting, thereby minimizing total electricity costs and alleviating the burden on the power grid during periods of highest demand. The model is designed to transfer up to 1 MW of electrical load between peak and off-peak periods based on TOU electricity tariffs. This comparative analysis enables the evaluation of the PSO-based strategy's operational and economic benefits under real consumption conditions.

2.1. Mathematical formulation problem

Peak clipping and load shifting are key DSM strategies aimed at reducing total energy costs by optimizing LPs over time. Mathematically, the problem is formulated as an optimization model where the objective is to minimize the total cost of electricity consumption while satisfying system and operational constraints.

The objective function is to minimize total energy cost:

$$C_{total} = C_{peak} + C_{\text{off}-peak} \tag{1}$$

$$C_{peak} = \sum_{h \in peak} L_h \,.P_{peak} \tag{2}$$

$$C_{\text{off}-peak} = \sum_{h \in \text{off}-peak} L_h \,.P_{\text{off}-peak} \tag{3}$$

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:

$$Minimize : C = \sum_{t} (P(t) \ \times C_{rate}(t)) \tag{4}$$

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

2.2. Method 1: Peak clipping

Peak clipping is a significant DSM approach that establishes a "ceiling," which limits the supply of power during periods of peak load to prevent full power utilization and minimize peak demand ratings in electric power systems. Peak clipping can be calculated using Equation (5):

$$P_{clipped}(t) = min(P(t), \ P_{MAX}) \tag{5}$$

where P_{MAX} represents the upper allowable load limit, and $P(t)$ 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 costs associated with peak demand, and promote smoother and more efficient grid operation.

2.3. Method 2: Load shifting

Load shifting is a widely used DSM technique aimed at redistributing the electrical load from peak periods to off-peak hours without affecting the total amount of energy consumed. 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:

$$P_{shifted}(t) = P(t) - \Delta P(t) \tag{6}$$

$$\Delta P(t) = P_{excess}(t) \times S(t) \tag{7}$$

In Equation (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 (7) illustrates how the excess load $P_{excess}(t)$ is multiplied by a shift factor $S(t)$, which determines the proportion of excess load that must be shifted based on control logic or system conditions. This formulation is dynamic and adaptive, allowing the redistribution of loads during peak periods and the optimization of energy use within system limits.

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

Optimization techniques are essential for the effective implementation of DSM strategies. One of the most widely used techniques is PSO, which can be easily implemented and has been shown to be highly effective in solving complex optimization problems. This section discusses the potential challenges of applying optimization methods to DSM and provides a qualitative assessment of using PSO to enhance key DSM objectives, specifically peak clipping and load shifting. Additionally, it highlights the main advantages and limitations of employing PSO within this context.

DSM comprises a set of measures aimed at controlling energy system operations by managing consumer usage in real time. These programs seek to modify existing consumption patterns to better align with energy supply and demand, as shown in Figure 1. Successful DSM programs can lead to significant changes in consumer energy consumption patterns, thereby influencing the total load experienced by power utilities. DSM initiatives have the potential to reduce electricity costs and promote a more stable and reliable energy system by restructuring major components of the electrical distribution network, which involves LP shaping and maximum demand management. Such behavioral adjustments not only improve system reliability but also provide economic benefits for both utilities and end users.

2.4.1. 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 [24] is enabled through widespread adoption of the OpenADR 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. Such devices have been shown to achieve substantial load reduction in previous studies.

2.4.2. Peak clipping

In modern energy management, peak clipping has become a vital strategy for enhancing power grid efficiency and sustainability. It involves reducing the maximum load during periods of peak demand, thereby minimizing the need for additional, often less efficient, power generation resources.

Methods for peak clipping include:

(a) TOU pricing

A common approach to peak clipping is the implementation of TOU pricing. TOU pricing entails a time-based electricity tariff structure designed to encourage consumers to adjust the timing of their energy use. Studies have shown that TOU pricing can significantly reduce peak loads when consumers adjust their consumption patterns in response to the prevailing pricing schemes, as they seek to benefit from lower electricity rates during off-peak hours. [32,33]

(b) Critical peak pricing

Another approach that involves applying higher prices during critical peak periods is critical peak pricing (CPP). The strategy provides a strong financial incentive for consumers to reduce their electricity consumption during such periods. Previous studies have indicated that CPP holds strong potential for peak load reduction, particularly when combined with consumer awareness programs and the implementation of real-time feedback mechanisms. [34]

(c) ADR

ADR is a technology-driven system designed to automatically reduce load during peak periods. ADR systems can be integrated with smart meters and home automation technologies. Through the use of smart meters, appliances, as well as heating, ventilation, and air conditioning systems, in a residence can be controlled based on signals provided by the utility. This approach has demonstrated enhanced reliability and efficiency in peak clipping, as it minimizes the need for manual intervention. [35]

2.5. Particle swarm optimization

The proposed approach aims to successfully coordinate electricity consumption through peak clipping and load shifting strategies. The primary objective of these strategies is to reduce the system's peak load and flatten the overall LP, thereby enhancing grid stability and operational efficiency. Furthermore, this methodology seeks to lower operational costs in residential load management through the integration of renewable energy sources, including photovoltaic systems and energy storage batteries. [36] A key objective of this load management initiative is to reduce electricity demand during peak periods, particularly within the constrained evening hours.

Consumers participating in DSM programs operate under tariff agreements, in which they receive compensation for any surplus energy fed back into the grid. This general strategy can be adapted to accommodate a wider range of consumers with different operating conditions and resource capacities, thereby enhancing participation and overall program effectiveness.

PSO is an evolutionary optimization technique inspired by the collective behavior observed in natural swarms, such as flocks of birds. PSO

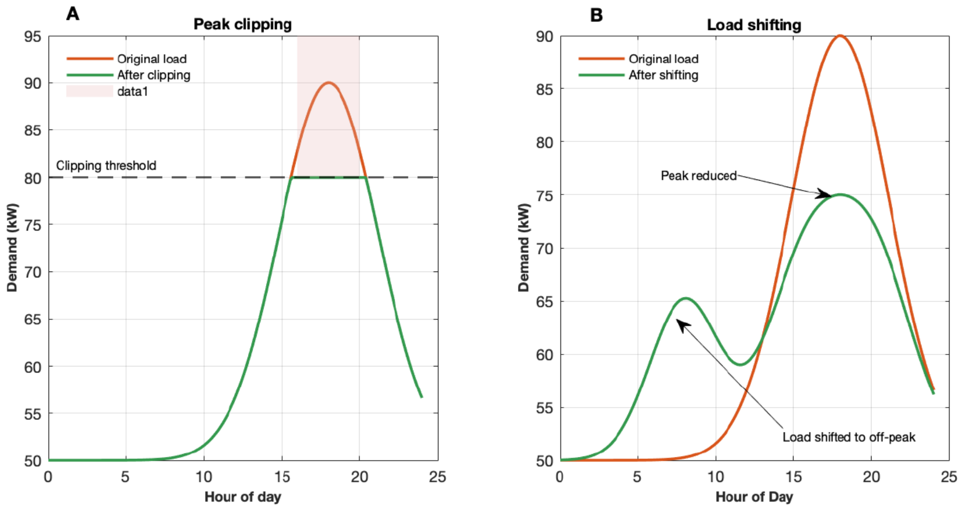

Figure 1. Demand-side management techniques: (A) peak clipping and (B) load shifting

employs an iterative model to optimize an objective function by continuously improving the positions of individual agents (also referred to as particles) in the solution space, until the swarm converges to an optimal or near-optimal solution. With respect to DSM, PSO has been applied to minimize peak demand through the smart redistribution of electrical loads within predetermined operational constraints, thereby achieving effective peak clipping and load shifting. [37]

2.5.1. 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 $X = (x_1,x_2, ..., x_D)$ represents a candidate solution in a D-dimensional search space.

A swarm consists of N particles, and each particle i has:

(i) Position vector: $x_i(k) = [x_{i,1}(k), \dots,$

$$x_{i,D}(k)] \text{ at iteration } k. \tag{8}$$

(ii) Velocity vector: $v_i(k) = [v_{i,1}(k), \dots,$

$$v_{i,D}(k)] \text{ at iteration } k. \tag{9}$$

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

$$p_i^{best} = arg \min_{x_i(j), j \le k} f(x_i(j)) \tag{10}$$

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

$$g^{best} = arg_{i=1,\dots,N}^{\min} f(p_i^{best}) \tag{11}$$

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

$$\begin{aligned} v_{i,d}(k+1) = w \cdot v_{i,d}(k) + c_1 \cdot r_1 \left(p_{i,d}^{best} - x_{i,d}(k)\right) \\ + c_2 \cdot r_2 \left(g_d^{best} - x_{i,d}(k)\right) \end{aligned} \tag{12}$$

$$x_{i,d}(k+1) = x_{i,d}(k) = v_{i,d}(k+1) \tag{13}$$

$$X(t+1) = X(t) + V(t) \tag{14}$$

$$\begin{aligned} V(t+1) = \omega \cdot V(t) + c_1 \cdot r_1 \cdot (P_{best} - X(t)) \\ + c_2 \cdot r_2 \cdot (G_{best} - X(t)) \end{aligned} \tag{15}$$

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 $r2 \sim U(0,1)$ are random scalars.
(iv) $p_{i,d}^{best}$ is the personal best position.
(v) g_d^{best} is the global best position.

(a) Electricity tariff The electricity tariff at each

time step t is determined by considering the season, type of day, and hour:

$$\text{Price}(t) = \begin{cases} \text{High Peak Price}, & t \in \text{High-season peak hours} \\ \text{High Standard Price}, & t \in \text{High-season standard hours} \\ \text{High Off Peak Price}, & t \in \text{High-season off-peak hours} \\ \text{Low Peak Price}, & t \in \text{Low-season peak hours} \\ \text{Low Standard Price}, & t \in \text{Low-season standard hours} \\ \text{Low Off Peak Price}, & t \in \text{Low-season off-peak hours} \\ \text{Weekend Price}, & t \in \text{Weekend} \end{cases} \tag{16}$$

(b) Peak and off-peak hours

Peak-hour indicator:

$$Peak(t) = \begin{cases} 1, \; if \;\; t \in [6{:}00-8{:}00] \cup [15{:}00-19{:}00] \\ 0, \; otherwise \end{cases} \tag{17}$$

Off-peak-hour indicator:

$$\text{Offpeak}(t) = 1 - \text{peak}(t) \tag{18}$$

Original peak load

$$P_{peak,original} = \max_{t \,\in\, peak \;\, hours} P_{load}(t) \tag{19}$$

(c) Target peak reduction

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

$$\alpha \sim \text{Uniform}(0.10, 0.15)$$

$$P_{peak,target} = \alpha \times P_{peak,original} \tag{20}$$

(d) Peak clipping constraint

The shifted load during peak hours is calculated as:

$$P_{shifted}(t) = max(P_{shifted}(t) - P_{peak,target}, \\ 0.2 \times P_{peak,original}, t \in \text{peak hours} \tag{21}$$

(e) Energy conservation and redistribution

Total energy before shifting:

$$E_{before} = \sum_t P_{load}(t) \tag{22}$$

Total energy after shifting:

$$E_{after} = \sum_t P_{shifted}(t) \tag{23}$$

Energy lost due to clipping:

$$E_{lost} = E_{before} - E_{after} (\text{should be non-negative}) \tag{24}$$

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

$$P_{shifted}(t) = P_{shifted}(t) + \beta_t \times E_{lost}, \\ t \in \text{off peak hours} \tag{25}$$

where weights β_t satisfy:

$$\sum_{t \in \text{offpeak}} \beta_t = 1, \;\; \beta_t \geq 0 \tag{26}$$

(f) Fitness (objective) function

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

$$Fitness = \max_{t \in peak} P_{shifted}(t) + |E_{before} - E_{after}| \tag{27}$$

Cost calculation before and after shifting:

$$C_{before}(t) = \sum_t P_{load}(t) \times \text{price}(t) \tag{28}$$

$$C_{after}(t) = \sum_t P_{shifted}(t) \times \text{price}(t) \tag{29}$$

Cost savings:

$$\Delta C = C_{before} - C_{after} \tag{30}$$

Under the PSO model used in DSM, a given solution is represented by each particle in the swarm. In this context, a load management strategy constitutes a potential solution, defined by specific values of shifted and clipped loads. The parameters guiding the optimization process include the particle velocities, the positions of particles, the inertia weight, and the acceleration coefficients. The effectiveness of each particle is calculated using the objective function, which takes into account factors such as load flattening, peak demand minimization, and overall system efficiency. The ultimate goal is to determine the optimal balance between enhancing grid stability and minimizing the cost of energy consumption.

During the iterative process, the algorithm checks the convergence criteria, typically by reaching the maximum number of iterations or observing minimal differences in fitness values across consecutive iterations. If these criteria are not met, the PSO updates are applied to adjust each particle's position and velocity, enabling particles to explore the solution space by learning from their individual best-known positions and the collective best-known positions of the swarm.

Once the convergence condition is fulfilled, the method proceeds with two crucial DSM operations:

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

An optimized LP exhibiting a more stable, efficient, and manageable demand curve is obtained after the application of these strategies. These processes yield a system that can guide future planning and policy development or be incorporated into grid operations.

A structured approach for PSO-based electricity demand optimization is shown in Figure 2. By continuously modifying customer demand patterns through load shifting and peak clipping, this nature-inspired optimization technique effectively regulates LPs. Particle positions and PSO parameters are initialized at the beginning of the process.

Figure 2 illustrates the effective implementation of PSO in an applied DSM environment, addressing operational challenges with both adaptability and computational efficiency. The specified load targets—including a 1 MW load shift and a 0.2 MW load clipping—represent constraints defined within the model, emphasizing practical and applicable approaches to energy management. This study contributes significantly to the field by demonstrating how nature-inspired optimization can enhance the intelligence and sustainability of power systems.

2.6. Machine learning improved prediction algorithm

The initial step in the MLIP process is data acquisition, during which past and real-time energy consumption data are extracted from distributed energy resources, smart meters, and transmission lines within substations. To ensure quality and consistency, preprocessing is performed. Techniques commonly employed to prepare the dataset for the prediction model include noise filtering, missing value imputation, and data normalization. This preprocessed data are then fed into the MLIP model, which—through ML techniques such as gradient boosting algorithms or neural networks—generates both short- and long-term load forecasts.

Having obtained the forecasted load, DSM decision engine optimization techniques are employed to identify predicted peaks and valleys using two DSM strategies:

(i) Through a load-shifting approach, non-essential energy consumption is relocated to off-peak hours, thereby flattening the load curve and reducing grid stress.
(ii) Using a peak-clipping strategy, the algorithm identifies periods of highest consumption and employs automated control systems (e.g., battery storage or appliance cycling) to reduce demand during these times. The strategy is then optimized through an optimization loop that continuously adjusts performance parameters to enhance overall efficiency. This phase may involve redesigning DSM techniques, modifying parameters within the ML model, or revising forecasts based on new data or operational constraints.

The optimized control signals are then transmitted to utility control centers or end-user systems to perform load shifting and peak clipping in real time. The primary objectives are to stabilize the grid, reduce energy costs, and improve overall system efficiency.

To ensure accurate forecasting, the data incorporate LPs, tariffs, and weather trends. Figure 3 illustrates the MLIP flowchart, which focuses on load shifting and peak clipping and provides a structured framework for integrating predictive analytics with DSM optimization.

The primary objective of the MLIP model is to optimize load curves by reducing peak demand and achieving energy savings without compromising system efficiency or customer comfort, through:

(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.

2.6.1. Key principles of the machine learning improved prediction method

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

(a) Data-driven load prediction

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

(i) Time of day.
(ii) Seasonality (e.g., summer, winter).
(iii) Tariff structure (TOU pricing).
(iv) Type of day (e.g., weekend, weekday).
(v) Weather conditions (if available).

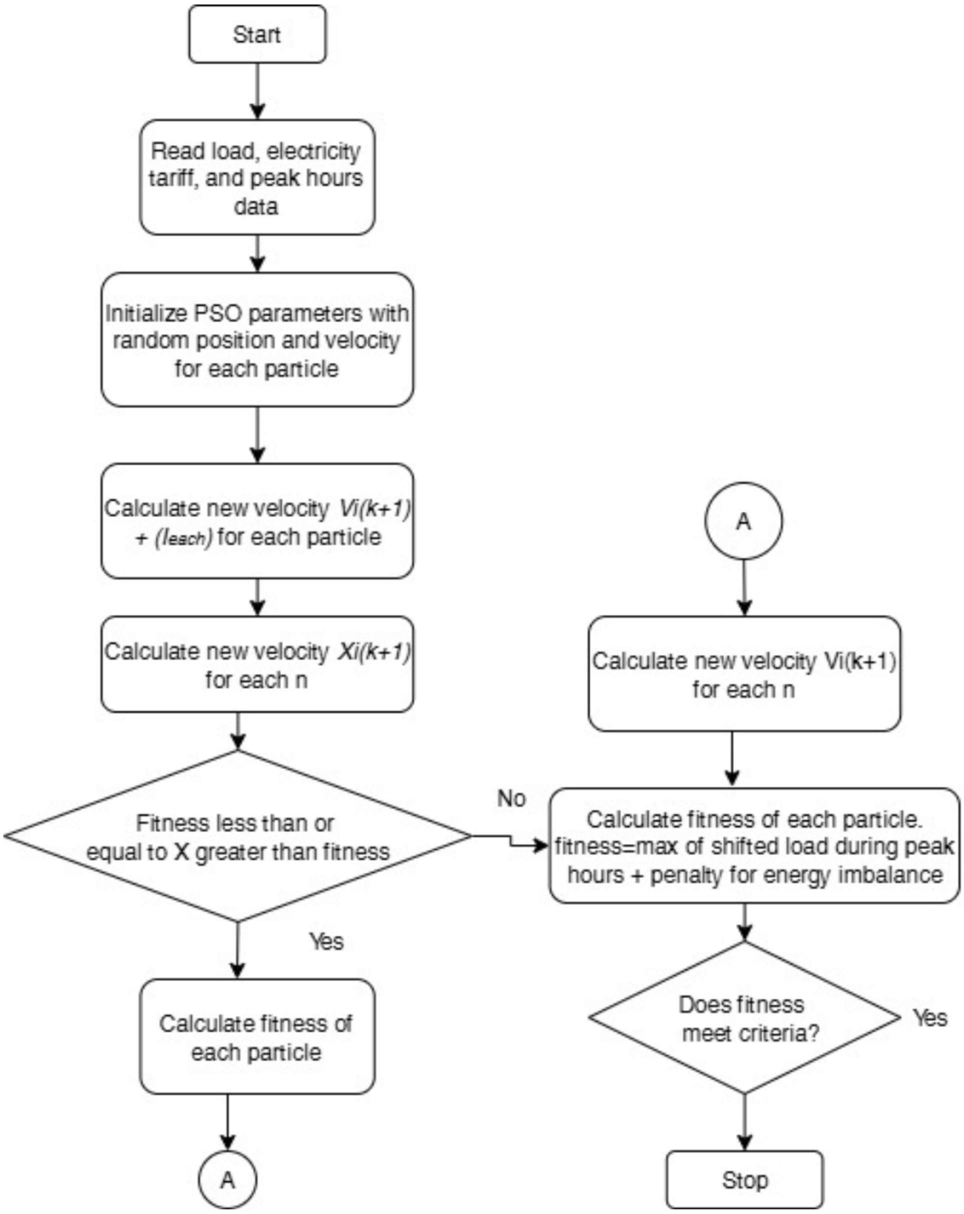

Figure 2. Flowchart of the PSO-based demand-side management process incorporating load shifting and peak clipping
Abbreviation: PSO: Particle swarm optimization.

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

(b) Dynamic peak load identification

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

$$\text{Peak}(t) = \left\{ \begin{array}{l} 1,\ t\in[06{:}00{-}08{:}00] \cup [15{:}00{-}19{:}00] \\ 0,\ otherwise \end{array} \right\} \quad (31)$$

Original peak load:

$$P_{peak,original} = \max_{t\,\in\,peak} \widehat{P}_{load}(t) \quad (32)$$

(c) Target peak reduction strategy

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

$$P_{peak,target} = \alpha \times P_{peak,original} \quad (33)$$

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

$$P_{shifted}(t) = max(\widehat{P}_{load}(t) - P_{peak,target}, 0.2 \times P_{peak,original}) \quad (34)$$

(d) Energy balance through redistribution

The load reduction results in lost energy:

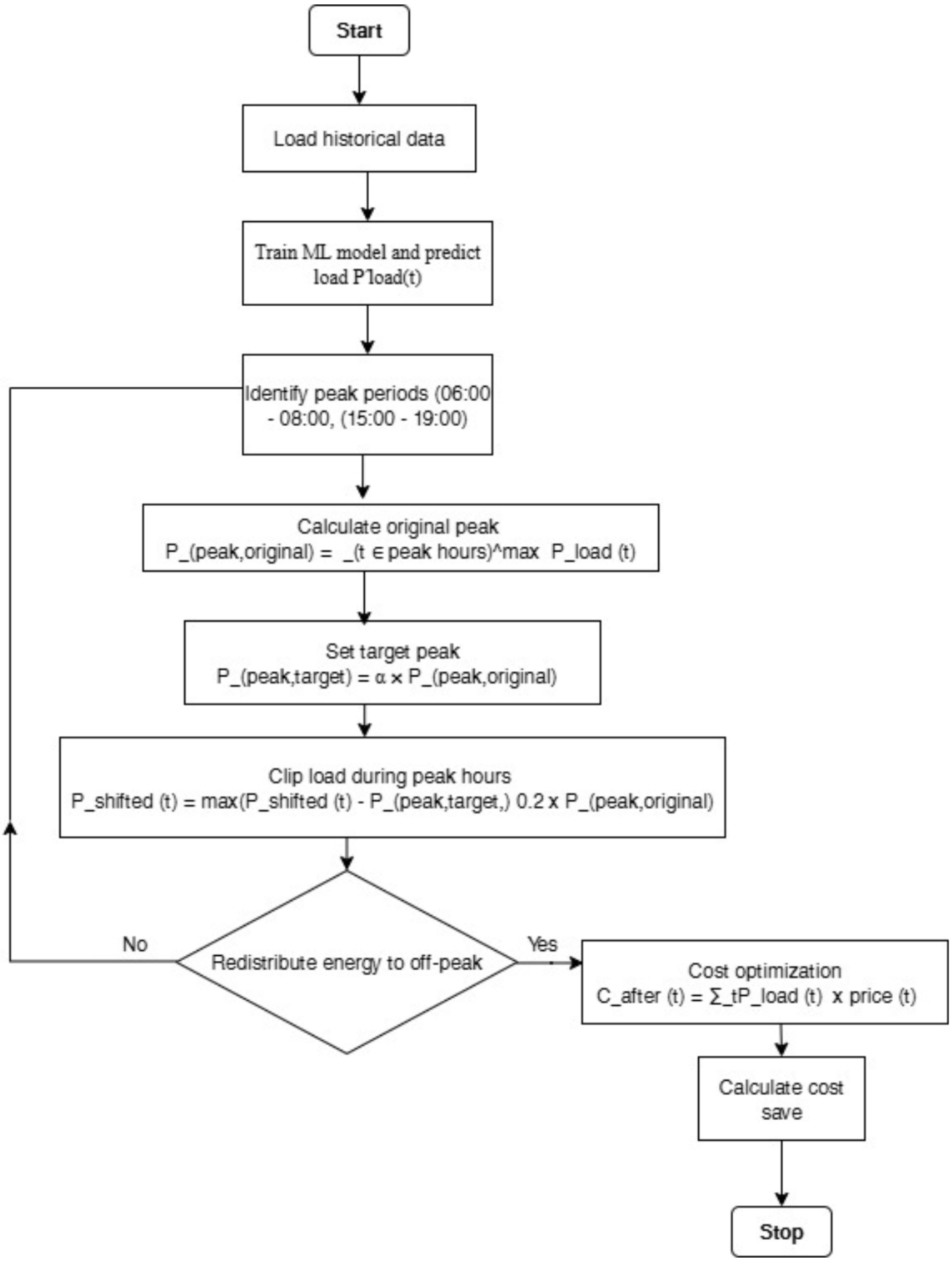

Figure 3. The flowchart of the ML improved prediction–based demand-side management process incorporating load shifting and peak clipping
Abbreviation: ML: Machine learning.

$$E_{lost}=\sum_{t} \widehat{P}_{load}(t) - \sum_{t} P_{shifted}(t) \tag{35}$$

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

$$P_{shifted}(t) = P_{shifted}(t) + \beta_t \times E_{lost}, t \in \text{off-peak} \tag{36}$$

subject to:

$$\sum_{t \in \text{off - peak}} \beta_t = 1,\ \beta_t \geq 0 \tag{37}$$

The weights β_t can be:

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

(e) Objective function

The objective function balances peak minimization and energy conservation:

$$F = \max_{t \in peak} P_{shifted}(t) + |E_{before}\text{-}E_{after}| \tag{38}$$

This ensures that the solution minimizes peak load while maintaining energy integrity.

Cost optimization is incorporated by including tariff data, and MLIP evaluates the cost impact:

$$C_{before}(t) = \sum_{t} \widehat{P}_{load}(t) x\ price(t) \tag{39}$$

The MLIP flowchart outlines an ML-based approach for DSM, focusing on peak clipping and load shifting. The algorithm begins by reading historical load, tariff, and external parameter data. Feature descriptors are calculated to capture demand characteristics, which are then used to train a predictive model. A loss function evaluates prediction accuracy, and gradients are computed to update model parameters iteratively. The process repeats until convergence is achieved or the maximum number of iterations is reached. The resulting trained MLIP model accurately forecasts LPs and informs optimal energy shifting strategies, ensuring peak demand reduction while maintaining energy balance and supporting smart grid efficiency goals.

3. Load management optimization for a commercial customer in the Paarl area

This study focuses on optimizing load management for a commercial customer in the Paarl area of the Western Cape, within the City of Cape Town Metropolitan Municipality. The region exhibits pronounced peak electricity demand during the following periods:

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

Elevated consumption during these periods resulted in increased electricity costs, as the City of Cape Town's tariff structure was demand-sensitive. Table 1 presents the 2024–2025 power generation and distribution charges under the Large User Low Voltage TOU category and provides an overview of the tariff structure applicable to large commercial electricity customers in the Paarl district. Both service and energy prices were included in the tariff, and value-added tax was charged.

Notably, the peak energy tariff increased by 11.58% (reaching 777.73 c/kWh) during June through August, when demand was at its highest. Similarly, standard and off-peak tariffs increased by more than 10% during both high- and low-demand periods, with low-demand peak charges reaching 290.54 c/kWh. These increased rates highlight the importance of implementing DSM techniques to reduce peak-period costs and encourage load shifting to off-peak times, especially for businesses with significant and fluctuating consumption patterns, where peak demand reached 0.2 MW.

The electricity tariffs and original peak loads for different demand seasons are summarized in Table 2. During the high-demand season, the peak tariff was significantly higher at 777.73 c/kWh (7.7773 R/kWh) compared to the low-demand season (290.54 c/kWh; 2.9054 R/kWh). The standard and off-peak tariffs, as well as the original peak load, are also provided in Table 2 to illustrate seasonal variations.

This study was based on the municipal tariff document's 2024–2025 energy price schedule, [38] which applied TOU rates in c/kWh. The following tariffs were applicable:

(i) Original peak load = 2,718.69 kW
(ii) High-peak tariff = 777.73 c/kWh

$$\text{Conversion to Rands (ZAR)} : \frac{777.73}{100} = 7.7773\ R/kWh \tag{40}$$

Cost calculations:

$$Cost = Load(kWh) \ \times \ Tariff(R/kWh) \tag{41}$$

$$Cost = 2,718.69\ kWh \ \times \ 7.7773\ R/kWh$$

$$Cost = ZAR\ 21,137.88$$

Two methods were employed to assess the effectiveness of DSM strategies. The PSO algorithm was applied for peak clipping (Section 2.2), while a hybrid MLIP approach was used for load shifting (Section 2.3). Results indicated that PSO-driven load management techniques offered significant potential for cost reductions when comparing pre- and post-optimization situations, particularly for peak clipping. These findings highlight the effectiveness of intelligent optimization strategies in reducing peak demand and associated electricity costs in business operations.

Table 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	2024/20025	% increase
Service charge	R/day	y	175.74	0.00	175.74	202.10	11.78%
Energy charge: High demand (June–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–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" indicates the 15% current value added tax in South Africa.

Table 2. Electricity tariffs during high- and low-demand season

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

3.1. Particle swarm optimization for load management

Prior to optimization, electricity costs were elevated due to high peak demand. Following the implementation of PSO optimization, the peak load was successfully reduced while maintaining overall energy balance. Demand was shifted to less expensive off-peak hours, and both consumers and the municipality benefited from lower peak-demand charges and improved grid stability.

Simulation results indicate that the PSO algorithm effectively reduced peak load demand and shifted energy consumption to off-peak hours. Compared with conventional DSM strategies, PSO achieved optimal load-shifting performance when applied with 20 particles and 50 iterations.

4. Simulation results and analysis of the demand-side management problem

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

The "peak load reduction over time" plot (Figure 4) illustrates the effectiveness of PSO in flattening the LP of a commercial client in Paarl between January 2024 and June 2025. The original and optimized load curves are presented in a time-series format. Figure 4 depicts both the original and optimized LPs, with horizontal lines representing the original and reduced peak demand levels.

The LP exhibited notable peaks prior to optimization during high-demand periods, particularly from 6:00 to 8:00 and from 15:00 to 19:00, which corresponded to the TOU pricing structure of the area. These peaks placed a significant strain on the grid and resulted in higher energy costs. After optimization, a significant reduction in peak load was observed, and excess demand was effectively redistributed to off-peak hours.

Figure 5 represents the LP comparison before and after the PSO-based DSM in June 2024 over a single day. Following the implementation of the PSO algorithm, the optimized LP showed a reduction in overall monthly energy usage, with a significant decrease during peak months. These findings indicate that, particularly during high-tariff periods, the algorithm effectively redistributes or reduces shiftable and discretionary loads while maintaining the commercial customer's overall operational needs.

Figure 6 presents a comparison of the hourly average LP between the original and optimized loads. The red line represents the original load, while the blue dashed line represents the optimized load after applying peak clipping and load-shifting techniques. The findings revealed that the peak-hour loads in the morning and evening were effectively reduced, with energy shifted to off-peak periods, leading to a smoother and more balanced daily LP.

By improving load consistency, the optimization technique reduces intra-day and seasonal peaks. In addition to helping consumers lower electricity costs, it also contributes to grid stability, particularly during periods of high regional demand. These findings confirm that the PSO framework serves as an effective tool for seasonal DSM planning.

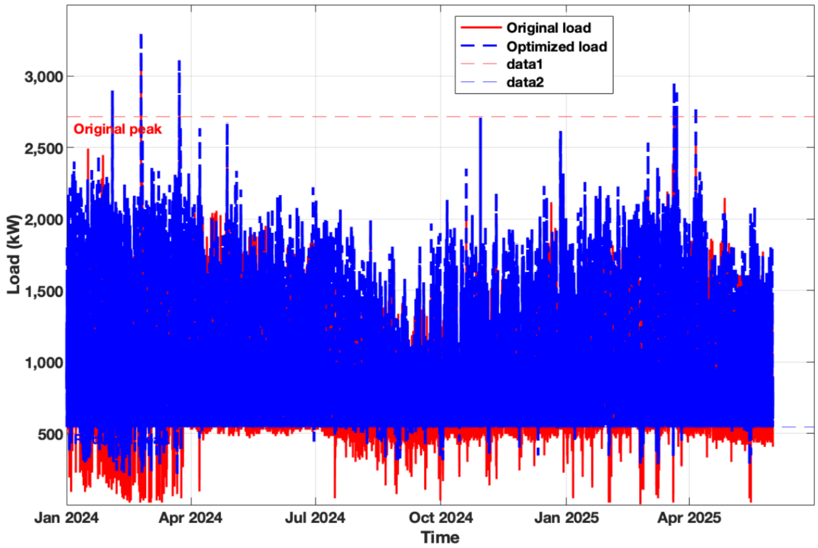

Figure 4. Peak load reduction over time using particle swarm optimization-based demand-side management

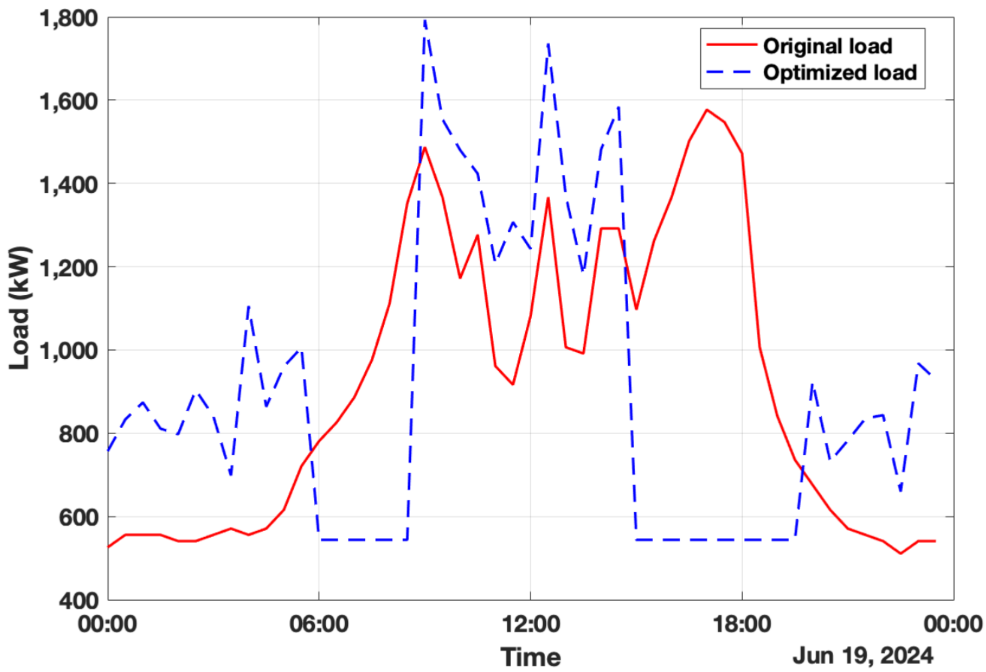

Figure 5. Load profile comparison before and after particle swarm optimization-based demand-side management

Table 3 summarizes the key performance indicators before and after optimization using PSO- and MLIP-based optimization techniques for load management in a commercial facility located in Paarl. The findings revealed that DSM performance was significantly enhanced when the PSO algorithm was applied to the LP of the commercial client in Paarl. With a peak clipping impact exceeding the intended reduction of 307.98 kW (11.33%), the optimization successfully reduced the peak demand from 2718.69 kW to 543.74 kW. In addition to smoothing the daily load curve, this pronounced clipping and subsequent load redistribution also reduced grid strain during critical peak hours.

In financial terms, the DSM approach resulted in significant savings. The total cost of electricity before optimization was ZAR 51,281,393.11, which decreased to ZAR 48,831,664.25 after optimization. Strategic load shifting from costly peak

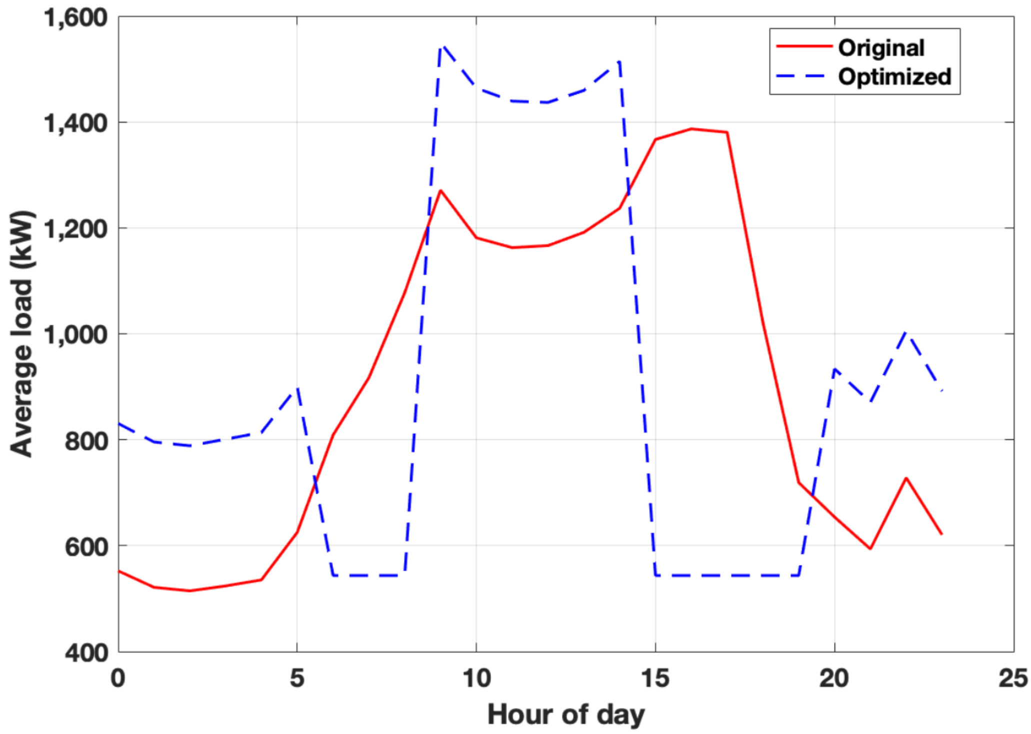

Figure 6. Hourly average load profiles of original and optimized loads following demand-side management

Table 3. Summary of demand-side management performance using particle swarm optimization and machine learning improved prediction.

Metric	PSO	MLIP
Original peak load (kW)	2718.69	2718.69
Reduced peak load (kW)	543.74	1450.31
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

Abbreviations: MLIP: Machine learning improved prediction; PSO: Particle swarm optimization.

periods to lower-tariff off-peak hours yielded a total cost saving of ZAR 2,449,728.86. These findings indicate that PSO is both technically feasible and financially viable for DSM in commercial settings with high loads under TOU tariff structures.

The findings further demonstrate that ML-enhanced forecasting and load control can effectively reduce peak loads and minimize operating costs. The application of the MLIP algorithm exhibited strong DSM capabilities for a commercial client's LP in Paarl. A significant peak reduction was achieved, with the initial peak load of 2718.69 kW reduced to 1450.31 kW. By surpassing the target reduction of 328.98 kW, or 12.10% of the initial peak, the MLIP-based DSM framework demonstrated high predictive accuracy and effective dynamic control performance.

The MLIP approach also resulted in significant operating cost savings. Energy costs were ZAR 51,281,393.11 before optimization, decreasing to ZAR 48,740,484.33 after optimization. This corresponds to a slightly higher total cost saving of ZAR 2,540,908.78 compared to the PSO-based strategy. Intelligent forecasting and precise load redistribution offset the relatively higher retained peak load in MLIP compared with PSO, highlighting the efficacy of hybrid AI-augmented DSM systems under fluctuating tariff conditions.

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

Figure 7 illustrates the impact of the MLIP optimization algorithm on peak load during the January 2024–June 2025 simulation period. The red and blue lines represent the initial and optimized

LPs generated by MLIP, respectively. The original peak load (2718.69 kW) and the reduced MLIP peak load (1450.31 kW) are shown as horizontal dashed lines, indicating the upper load boundaries before and after optimization.

The time-series analysis demonstrated that MLIP effectively performs peak clipping by significantly reducing acute demand spikes that lead to high energy costs and grid instability. By redistributing the clipped load to off-peak periods, the optimization preserves the overall energy balance while achieving a target reduction of 328.98 kW, equivalent to 12.10% of the original peak.

In contrast to conventional load management techniques, the MLIP algorithm adapts demand seamlessly and intelligently while maintaining load continuity. A steadier and grid-friendly LP was produced by flattening high-demand periods from March to October 2024.

Overall, the MLIP algorithm exhibits strong performance in demand leveling and operational cost control, validating its applicability for real-world DSM under TOU tariff structures.

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 8.

Figure 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.

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

Table 4 provides a comparative summary of the statistical and performance indicators. The evaluated DSM strategies were benchmarked against previously reported results, emphasizing load-shifting and peak-clipping techniques.

5. Discussion

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.

5.1. Peak load mitigation

The MLIP approach achieved a lower peak of 1450.31 kW, equivalent to a 12.10% reduction compared to PSO. Although the PSO technique had a target reduction of 11.33%, it ultimately reached the same lowered peak, indicating that it operated under a more conservative redistribution.

These findings underscore the flexibility of metaheuristic techniques in tailoring the optimization process to different DSM priorities, whether minimizing stress on infrastructure or ensuring customer-side operational continuity.

5.2. Cost optimization and tariff sensitivity

The economic outcomes of the optimization methods indicate cost savings exceeding ZAR 2.4 million across both techniques, reinforcing the financial feasibility of load shifting.

With the most significant cost reduction of ZAR 2,540,908.78, MLIP proved to be the most effective in aligning LPs with low-tariff periods. This is likely attributable to its emphasis on forecasting and rule-based shifting, which prioritizes cost-efficient operating windows.

PSO achieved a peak reduction equivalent to cost savings of ZAR 2,459,652.84. However, when the clipped loads are redirected to mid-tariff hours instead of low-tariff hours, it suggests that aggressive peak clipping might not necessarily yield the greatest cost savings.

This highlights a crucial trade-off: cost-oriented optimization may not always align with objectives aimed at minimizing peak load, and vice versa. Consequently, the utility's DSM goals, whether focused on reducing tariff costs or improving grid reliability, should guide the selection of the most appropriate optimization technique.

5.3. Algorithmic behavior and load redistribution

Each algorithm's inherent behavior influences how it redistributes energy:

(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.

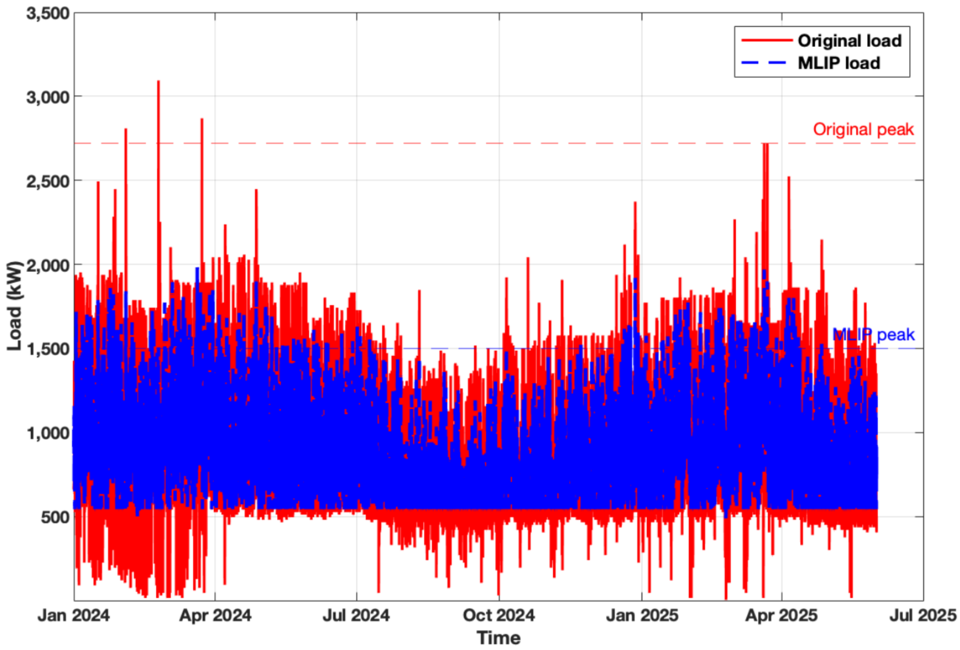

Figure 7. Peak load reduction using MLIP
Abbreviation: MLIP: Machine learning improved prediction.

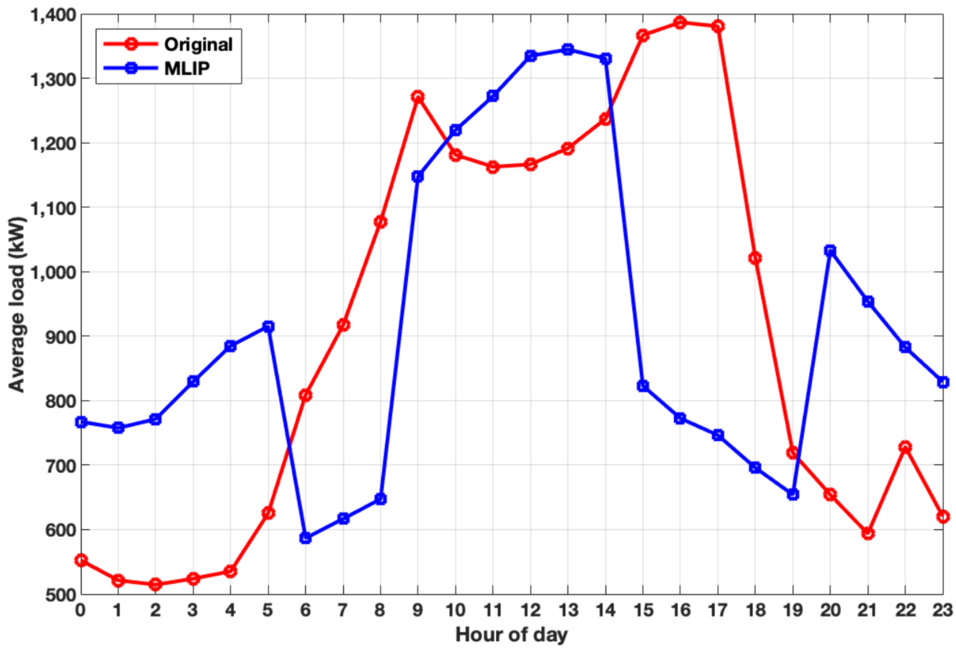

Figure 8. Comparison between the original and MLIP-based hourly average load profiles
Abbreviation: MLIP: Machine learning improved prediction.

5.4. Practical implications and utility strategies

From the utility's perspective, the findings align with a multi-objective DSM framework that optimizes both technical and economic parameters. 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.

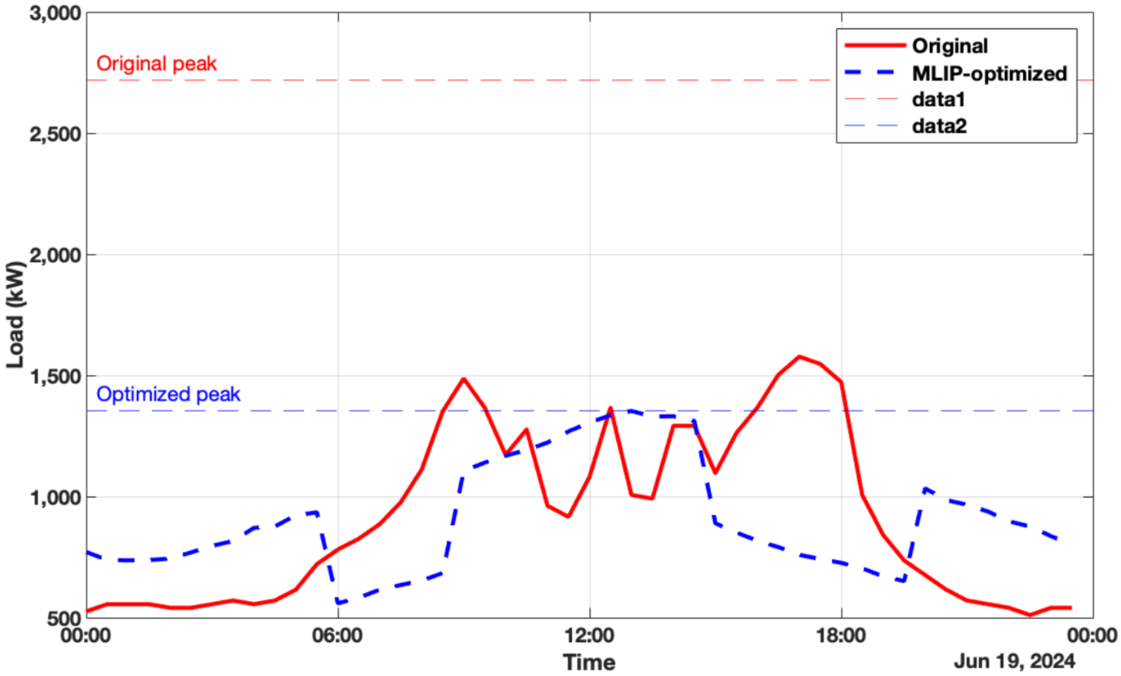

Figure 9. Daily load profile on June 19, 2024, showing peak load reduction achieved through MLIP optimization
Abbreviation: MLIP: Machine learning improved prediction.

Table 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]	Benchmark DSM (peak clipping)[b]	Proposed PSO optimization	Proposed MLIP optimization
Maximum power (kW)/reduced peak load	8.890	6.170	543.73	1450.31
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	1150.00
Median power (kW)	5.000	2.899	355.00	1140.00
RMS power (kW)	5.190	3.873	365.00	1160.00
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

Notes: [a]Data adapted from Philipo et al. [39] [b]Data adapted from Faia et al. [40]
Abbreviations: DSM, demand-side management; MLIP, machine learning improved prediction; PSO, particle swarm optimization; RMS, root mean square.

Furthermore, a hybrid approach that integrates the predictive forecasting capability of MLIP with the search-based optimization strength of PSO could yield enhanced peak reduction and cost-saving results.

6. Conclusion

This study demonstrated the successful integration of PSO and MLIP models as effective approaches for optimizing DSM among large power consumers in the Western Cape Municipality. The proposed hybrid framework enables more accurate load forecasting and cost-efficient load scheduling, leading to improved energy efficiency, lower peak demand, and reduced operational costs. The integration of ML techniques, particularly in forecasting consumption patterns, enhances the responsiveness and reliability of DSM strategies, allowing the PSO algorithm to make more informed scheduling decisions. The MLIP solution achieved a cost reduction of ZAR 2.54 million, compared with PSO, which achieved an 11.33% reduction in peak load and a corresponding cost saving of ZAR 2.45 million. Simulation results indicate that the proposed approach outperforms traditional DSM methods by adaptively responding to dynamic demand and tariff conditions. Overall, this research highlights the potential of integrating AI-driven forecasting with metaheuristic optimization to enhance energy management at both municipal and industrial scales. Future studies could focus on real-time applications, integration with renewable energy systems, and the application of advanced deep learning models for more accurate load forecasting.

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Conflict of interest

The authors declare they have no competing interests.

Author contributions

Conceptualization: Senthil Krishnamurthy
Formal analysis: All authors
Investigation: Abuyile Mpaka
Methodology: All authors
Software: All authors
Writing–original draft: Abuyile Mpaka
Writing–review & editing: Senthil Krishnamurthy

Availability of data

Data is available from the corresponding author upon reasonable request.

AI tools statement

All authors confirm that no AI tools were used in the preparation of this manuscript.

References

1. Palensky P, Dietrich D. Demand side management: demand response, intelligent energy systems, and smart loads. *IEEE Trans Industr Inform.* 2011;7(3):381–388. https://doi.org/10.1109/TII.2011.2158841
2. Strbac G. Demand side management: benefits and challenges. *Energy Policy.* 2008;36(12):4419–4426. https://doi.org/10.1016/j.enpol.2008.09.030
3. Zheng Y, Hu Z, Wang J, Wen Q. IRSP (integrated resource strategic planning) with interconnected smart grids in integrating renewable energy and implementing DSM (demand side management) in China. *Energy.* 2014;76:863–874. https://doi.org/10.1016/j.energy.2014.08.087
4. Albadi MH, El-Saadany EF. A summary of demand response in electricity markets. *Electr Power Syst Res.* 2008;78(11):1989-1996. https://doi.org/10.1016/j.epsr.2008.04.002.
5. Kennedy J, Eberhart R. Particle swarm optimization. *Proc IEEE Int Conf Neural Netw.* 1995;4:1942-1948. https://doi.org/10.1109/ICNN.1995.488968.
6. Qin J, Wan Y, Li F, Kang Y, Fu W. *Distributed Economic Operation in Smart Grid: Model-based and Model-free Perspectives.* Singapore: Springer Nature; 2023. https://doi.org/10.1007/978-981-19-8594-2
7. Giedraityte A, Rimkevicius S, Marciukaitis M, Radziukynas V, Bakas R. Hybrid renewable energy systems—a review of optimization approaches and future challenges. *Appl Sci.* 2025;15(4):1744. https://doi.org/10.3390/app15041744
8. Ahmad MS, Mansor NN, Mokhlis H, Naidu K, Mohamad H, Ramadhani F. Demand response program towards sustainable power supply: current status, challenges, and prospects in Malaysia. *IEEE Access.* 2025;13: 34706-34731. https://doi.org/10.1109/ACCESS.2025.3541841
9. Bertineti DP, Canha LN, Medeiros AP, De Azevedo RM, Da Silva BF. Heuristic scheduling algorithm for load shift DSM strategy in smart grids and IoT scenarios. In: *2019 IEEE PES Innovative Smart Grid Technologies Conference - Latin America (ISGT Latin America), Gramado, Brazil.* 2019:1-6. https://doi.org/10.1109/ISGT-LA.2019.8895488
10. Zaini FA, Sulaima MF, Razak IAWA, Zulkafli NI, Mokhlis H. A review on the applications of PSO-based algorithm in demand side management: challenges and opportunities. *IEEE Access.* 2023;11:53373-53400. https://doi.org/10.1109/ACCESS.2023.3278261
11. Ahmad AA, Saffer KM, Sari M, Uslu H. Prediction of anemia with a particle swarm optimization-based approach. *Int J Optim Control Theor Appl.* 2023;13(2):214–223. https://doi.org/10.11121/ijocta.2023.1269

12. Köppchen B, Stadler I, Nebel A. Effects of non-industrial decentralized demand-side-management on energy costs and battery storage requirement in Germany's power grid. *Energy.* 2025;323:135892. https://doi.org/10.1016/j.energy.2025.135892
13. Meng F, Lu Z, Li X, et al. Demand-side energy management reimagined: a comprehensive literature analysis leveraging large language models. *Energy.* 2024;291:130303. https://doi.org/10.1016/j.energy.2024.130303
14. Mataifa H, Krishnamurthy S, Kriger C. Comparative analysis of the particle swarm optimization and primal-dual interior-point algorithms for transmission system Volt/VAR optimization in rectangular voltage coordinates. *Mathematics.* 2023;11(19):4093. https://doi.org/10.3390/math11194093
15. Sun H, Cui X, Latifi H. Optimal management of microgrid energy by considering demand side management plan and maintenance cost with developed particle swarm algorithm. *Electr Power Syst Res.* 2024;231:110312. https://doi.org/10.1016/j.epsr.2024.110312
16. Andruszkiewicz J, Lorenc J, Weychan A. Price-based demand side response programs and their effectiveness on the example of tou electricity tariff for residential consumers. *Energies (Basel).* 2021;14(2):287. https://doi.org/10.3390/en14020287
17. Gorman W, Barbose G, Baik S, Miller C, Carvallo JP. Backup power or bill savings? How electricity tariffs impact residential solar-plus-storage usage in the United States. *Util Policy.* 2025;96:102035. https://doi.org/10.1016/j.jup.2025.102035
18. Tijjani Dahiru A, Wei Tan C, Salisu S, Yiew Lau K, Ling Toh C, Lawan Bukar A. A review of demand side management strategies and electricity tariffs in distributed grids. *ELEKTRIKA J Electr Eng.* 2022;21(3):13–22. https://doi.org/10.11113/elektrika.v21n3.358. Available: https://elektrika.utm.my
19. Tzanes GT, Zafirakis DP, Kaldellis JK. Practice of a load shifting algorithm for enhancing community-scale RES utilization. *Sustainability (Switzerland).* 2024;16(13):5679. https://doi.org/10.3390/su16135679
20. Jasim AM, Jasim BH, Neagu BC, Alhasnawi BN. Efficient optimization algorithm-based demand-side management program for smart grid residential load. *Axioms.* 2023;12(1):33. https://doi.org/10.3390/axioms12010033
21. Wang Y, Chen Q, Hong T, Kang C. Review of smart meter data analytics: applications, methodologies, and challenges. *IEEE Trans Smart Grid.* 2019;10(3):3125–3148. https://doi.org/10.1109/TSG.2018.2818167
22. Mohammad Rozali NE, Wan Alwi SR, Manan ZA, Klemeš JJ. Peak-off-peak load shifting for hybrid power systems based on Power Pinch Analysis. *Energy.* 2015;90:128–136. https://doi.org/10.1016/j.energy.2015.05.010
23. Aghajani GR, Shayanfar HA, Shayeghi H. Demand side management in a smart micro-grid in the presence of renewable generation and demand response. *Energy.* 2017;126:622–637. https://doi.org/10.1016/j.energy.2017.03.051
24. Maneebang K, Methapatara K, Kudtongngam J. 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.; 2020:30–35. https://doi.org/10.1109/SGES51519.2020.00013
25. Oskouei MZ, Şeker AA, Tunçel S, et al. 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.* 2022;14(4):2110. https://doi.org/10.3390/su14042110
26. Ahmad S, Ahmad A, Naeem M, Ejaz W, Kim HS. A compendium of performance metrics, pricing schemes, optimization objectives, and solution methodologies of demand side management for the smart grid. *Energies (Basel).* 2018;11(10):2801. https://doi.org/10.3390/en11102801
27. Bilal M, Algethami AA, Imdadullah, Hameed S. Review of computational intelligence approaches for microgrid energy management. *IEEE Access.* 2024;12:123294-123321. https://doi.org/10.1109/ACCESS.2024.3440885
28. Sharifhosseini SM, Niknam T, Taabodi MH, et al. Investigating intelligent forecasting and optimization in electrical power systems: a comprehensive review of techniques and applications. *Energies.* 2024;17(21):5385. https://doi.org/10.3390/en17215385
29. Khan MA, Saleh AM, Waseem M, Sajjad IA. Artificial intelligence enabled demand response: prospects and challenges in smart grid environment. *IEEE Access.* 2023;11:1477-1505. https://doi.org/10.1109/ACCESS.2022.3231444
30. Anand A, Suganthi L. Hybrid GA-PSO optimization of artificial neural network for forecasting electricity demand. *Energies (Basel).* 2018;11(4):728. https://doi.org/10.3390/en11040728
31. Rácz A. A MILP model for one dimensional cutting stock problem with adjustable leftover threshold and cutting cost. *Int J Optim Control Theor Appl.* 2025;15(2):215–224. https://doi.org/10.36922/ijocta.1660
32. Saleem MU, Usman MR, Usman MA, Politis C. Design, deployment and performance evaluation of an IoT based smart energy management system for demand side management in smart grid. *IEEE Access.* 2022;10:15261–15278. https://doi.org/10.1109/ACCESS.2022.3147484

33. Alquthami T, Milyani AH, Awais M, Rasheed MB. An incentive based dynamic pricing in smart grid: a customer's perspective. *Sustainability (Switzerland)*. 2021;13(11):6066. https://doi.org/10.3390/su13116066
34. Guzman C, Cardenas A, Agbossou K. Local estimation of critical and off-peak periods for grid-friendly flexible load management. *IEEE Syst J*. 2020;14(3):4262–4271. https://doi.org/10.1109/JSYST.2020.2970001
35. Siano P. Demand response and smart grids – a survey. *Renew Sustain Energy Rev*. 2014;30:461–478. https://doi.org/10.1016/j.rser.2013.10.022
36. Garip S, Ozdemir S. Optimization of PV and battery energy storage size in grid-connected microgrid. *Appl Sci (Switzerland)*. 2022;12(16):8247. https://doi.org/10.3390/app12168247
37. Paul K, Jyothi B, Kumar S, et al. Optimizing sustainable energy management in grid connected microgrids using quantum particle swarm optimization for cost and emission reduction. *Sci Rep*. 2025;15(1):5843. https://doi.org/10.1038/s41598-025-90040-0
38. 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
39. Philipo GH, Kakande JN, Krauter S. Neural network-based demand-side management in a stand-alone solar pv-battery microgrid using load-shifting and peak-clipping. *Energies (Basel)*. 2022;15(14):5215. https://doi.org/10.3390/en15145215
40. Faia R, Faria P, Vale Z, Spinola J. Demand response optimization using particle swarm algorithm considering optimum battery energy storage schedule in a residential house. *Energies (Basel)*. 2019;12(9):1645. https://doi.org/10.3390/en12091645

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