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Article

Multi-Objective Intelligent Demand-Side Management Using Explainable PSO-Optimized LSTM in Renewable Energy-Based Smart Grids

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Abstract: The fast penetration of renewable energy resources, electric vehicles (EVs), and distributed energy systems has made demand-side management (DSM) in modern smart grids very complex. Traditional DSM methods usually consider load forecasting and scheduling as separate tasks, which results in suboptimal energy consumption, higher operational cost, greater carbon emissions, and lower grid stability under dynamic operating conditions. To address the above limitations, an Explainable Hybrid Particle Swarm Optimization-Long Short-Term Memory (PSO-LSTM) framework for intelligent multi-objective demand-side management in renewable energy-integrated smart grids is proposed. The proposed framework integrates the temporal learning capability of LSTM to accurately forecast the short-term electricity demand and the global optimization capability of PSO to optimally schedule appliances, coordinate EV charging, allocate renewable energy, and implement dynamic demand response. Hence, the optimization problem is formulated as a constrained multi-objective mathematical model to minimize the electricity cost, peak-to-average ratio (PAR), carbon emissions, and scheduling delay and to maximize the renewable energy utilization, consumer comfort, and grid reliability. The framework is validated on multivariate smart grid datasets, including historical electricity consumption, weather, photovoltaic generation, electricity prices, battery state-of-charge, EV charging profiles, and grid load data. Experimental results show that the proposed framework PSO–LSTM obtains an accuracy of 98.24% for forecasting and decreases RMSE and MAE to 0.081 and 0.061, respectively. Moreover, the proposed model achieves 24.76% peak-load reduction, 21.35% electricity cost savings, 91.42% renewable energy utilization, and significant reductions in carbon emissions compared with ANN, SVM, standalone LSTM, and Deep Reinforcement Learning (DRL) models. The statistical analysis also validates the robustness and superiority of the proposed framework in multiple performance metrics. The proposed explainable hybrid framework provides a scalable, computationally efficient, and real-time intelligent energy management solution for next-generation sustainable smart grids and smart city applications.
Keywords: Explainable Artificial Intelligence (XAI), Multi-objective Optimization, Smart Energy Management, Particle Swarm Optimization (PSO), Long Short-Term Memory (LSTM), Demand-Side Management (DSM), Energy Storage Systems, Deep Learning

1. Introduction

The energy sector worldwide is experiencing a fundamental transition, which is driven by rapid urbanization, increasing demand for electricity, widespread electrification of transportation, and accelerated deployment of renewable energy resources [1-4]. Worldwide, the electricity demand is growing as reported by international energy reports [1, 2]. This is due to the industrial growth, digitalization, and the increasing use of electric vehicles (EVs), heat pumps and distributed energy resources. Meanwhile, the integration of renewable energy has become one of the most urgent issues in modern power systems, since countries around the world have committed to carbon neutrality and net-zero greenhouse gas emissions by 2050 [2–4]. The International Energy Agency (IEA) forecasts that renewables will dominate the electricity generation worldwide in the next decades, with solar photovoltaic (PV) and wind energy representing the largest share of new installed generation capacity [1, 5]. Similarly, the International Renewable Energy Agency (IRENA) recognizes the need to significantly scale-up the generation of renewable electricity to meet the global climate targets and to secure a reliable electricity supply [3, 6]. The World Energy Outlook indicates that smart grids, advanced energy management systems, artificial intelligence, and digital technologies will be crucial in balancing electricity demand and renewable energy generation in future energy scenarios [1, 2, 7]. Smart grid refers to intelligent infrastructure for electricity that can support bidirectional power flow, distributed generation, real-time communication, advanced metering infrastructure, and autonomous decision making [8–10]. In contrast to traditional power systems, smart grids routinely collect operational data from smart meters, renewable energy systems, battery storage, electric vehicles, weather forecasting services, and electricity markets. Such capabilities allow utilities to improve operational efficiency, increase renewable energy penetration, and offer flexible demand response services [9–12].

Even with these technological advances, efficient demand-side management (DSM) is still one of the hardest problems in smart grid operation [13–15]. Renewable energy sources, such as solar and wind, are intrinsically intermittent and highly dependent on environmental conditions, which leads to significant uncertainty in the generation of electricity [13, 16]. Simultaneously, the quick penetration of EVs leads to new stochastic charging demand, which may raise peak loads and overload local distribution networks [17, 18]. Moreover, electricity prices are dynamic and change according to the market conditions, and consumers' demand is also dynamic and changes according to the weather conditions, occupancy behavior, and industrial activities [19, 20]. These uncertainties tend to cause peak demand, voltage instability, increased operating costs, higher carbon emissions, and decreased grid reliability [14, 20]. Recently, artificial intelligence (AI) and machine learning (ML) have demonstrated remarkable potential in solving said challenges [21–23]. Deep learning models such as Long Short-Term Memory (LSTM) networks have shown great success in capturing the nonlinear temporal correlations in electricity consumption data and achieved high-accuracy short-term load forecasting [22–24]. Accurate forecasts allow utilities to effectively plan generation resources, reduce reserve requirements, and increase overall system reliability [23–25]. However, load forecasting alone is inadequate to address the DSM problem, as there are numerous conflicting objectives in electricity scheduling, including reducing the electricity cost and Peak-to-Average Ratio (PAR), increasing the utilization of renewable energy, decreasing the carbon emissions, EV charging coordination, and customer comfort [13,20,26]. Thus, metaheuristic optimization algorithms have attracted much attention to solve complex multi-objective optimization problems [26–28].

Particle Swarm Optimization (PSO), among these methods, has been widely used because of its easy implementation, fast convergence, and strong global search ability [27–29]. However, the conventional PSO often suffers from premature convergence, reduced exploration ability in high-dimensional search spaces, and performance degradation under the highly dynamic operating environments [28, 29]. Likewise, Genetic Algorithms (GAs) are effective in global optimization but usually need longer convergence times, greater computational resources, and delicate parameter tuning [30, 31]. Recently, Deep Reinforcement Learning (DRL) has demonstrated adaptive sequential decision-making capability. However, DRL-based approaches require large training data, long training periods, and high computational complexity, which hinder real-time deployment [32–34]. However, the forecasting accuracy is high [22–24], but the LSTM networks cannot finish the optimal scheduling and multi-objective decision-making by themselves. Therefore, the combination of deep learning-based forecasting and intelligent optimization has become an important research direction for next-generation smart grids [28, 32, 35]. The hybrid optimization framework can take advantage of the forecasting capability of LSTM and the global optimization capability of PSO simultaneously to improve operational efficiency with multiple system constraints satisfied [29, 35, 36]. Some hybrid intelligent energy management models have been proposed, but most of the existing studies have one or more important limitations [35–39]. Many do forecasting and optimization separately rather than in an integrated manner. Some ignore intermittency of renewable energy, price fluctuations in electricity, EV charging behaviors, weather uncertainty, state-of-charge of batteries, and consumer comfort at the same time [36–39]. Besides, most of the existing models have limited explainability, lack statistical validation, and do not consider minimizing carbon emissions and rarely consider computational complexity and real-time scalability for practical deployment [37–40]. To address these limitations, this paper proposes an explainable hybrid PSO-LSTM framework for intelligent multi-objective demand-side management in renewable energy-integrated smart grids. The framework proposed integrates LSTM-based short-term electricity demand forecasting with PSO-based multi-objective scheduling to optimize appliance operation, renewable energy allocation, EV charging coordination, and demand response simultaneously. The optimization problem is formulated as a constrained multi-objective mathematical model that minimizes electricity cost, peak-to-average ratio (PAR), and carbon emissions while maximizing renewable energy utilization, consumer comfort, and grid stability. Extensive experiments show that the proposed framework can achieve better forecasting accuracy, higher renewable energy utilization, lower operational costs, improved grid reliability, and lower computational complexity compared to the existing machine learning and optimization-based approaches.

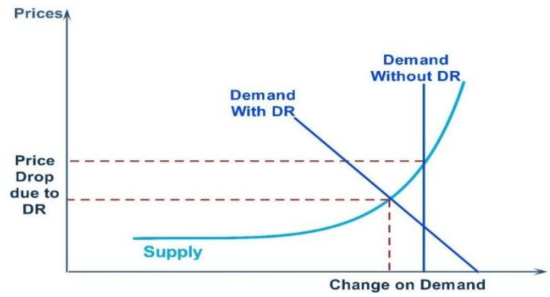


Fig. 1 Graph with and without DSM

Regarding the electricity system, real-time coordination between supply and demand is crucial for maintaining stability. However, this presents several potential challenges, including outages and load changes, which can lead to rapid oscillations in supply and demand. For optimal system operation and reduction of wholesale market price volatility, Demand Response (DR) is considered a cost-effective alternative.

The main contributions of this work are summarized as follows: A novel Explainable Hybrid PSO–LSTM framework is proposed for integrated forecasting and intelligent demand side management. A constrained multi-objective optimization model is applied to minimize electricity cost, PAR, and carbon emissions, and maximize utilization of renewable energy and consumer comfort simultaneously. The optimization framework takes into account multiple heterogeneous datasets simultaneously, including the electricity demand, weather data, photovoltaic generation, electricity prices, EV charging profiles and battery state-of-charge. Development of a real-time intelligent scheduling mechanism for appliance scheduling, renewable energy allocation and EV charging coordination. To perform comprehensive comparative analysis against ANN, SVM, GA, DRL and standalone LSTM models, multiple forecasting and energy management performance metrics are utilized. The robustness and scalability of the proposed framework for next-generation sustainable smart grids are demonstrated through statistical validation, computational analysis, and practical applicability.

Table 1. Research Gap Comparison

Author	Method	Dataset	Accuracy	Limitation
ANN-based DSM [21]	ANN	Smart Meter	90–94%	Poor temporal learning
SVM-based DSM [22]	SVM	Residential Load	91–95%	Sensitive to kernel parameters
GA-based DSM [30]	Genetic Algorithm	Smart Home	92–95%	Slow convergence
PSO-based DSM [27]	PSO	Microgrid	94–96%	Premature convergence
DRL-based DSM [32]	Deep Reinforcement Learning	Smart Grid	95–97%	High computational complexity
LSTM-based DSM [23]	LSTM	Electricity Load	96–98%	Forecasting only; no scheduling

Proposed Method	Explainable PSO–LSTM	Multivariate Smart Grid Dataset	98.24%	Integrated forecasting, optimization, renewable energy, EV coordination, and multi-objective DSM

1.1 Demand Response Program Categorisation

Such disaster recovery programs would be a major instrument in the performance demand management. Two main types are: accessible or incentive based schemes and non-dispatchable or price-based programs (PBP). The substation load is dispatched by several dispatchable programs such as market based strategies like Demand Bidding (DB) and Capacity Market Programs (CMP) and traditional techniques like Direct Load Control (DLC). PBP systems require changing rates such as Time of Use (TOU) or Real-Time Pricing (RTP). This forward bargaining is to set maximum clearance prices (MCPs) according to supply and demand bids. This method improves the marketplace and lets the merchants earn their maximum profit.

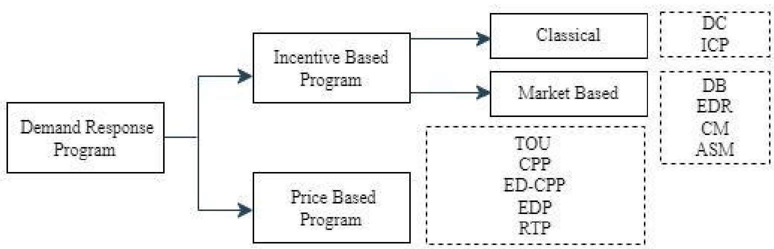


Fig. 2 Classification of DR programs

Demand Response (DR) programs provide incentives for consumers to alter their electricity usage to improve grid reliability, reduce peak electricity demand, and increase market efficiency . Incentive based or hybrid of incentive and price based remuneration programs are used to move consumption from peak periods to off peak periods. DR also provides the integration of renewable energy sources such as solar and wind by addressing their intermittency through flexible load scheduling. Finally, utilities can use consumer behavior to design demand response programs that are targeted to promote higher participation, lower operating costs, and improve the performance and sustainability of the smart grid.

1.2 Techniques of Demand Side Management (DSM)

DSM is a collection of techniques to optimize the use of electricity, reduce peak load and improve the stability of the grid. Common methods include peak shaving, load shifting, valley filling, strategic conservation and flexible load growth; These types of approaches change demand profiles and reduce operating costs. The Smart Grid Management System (SGMS) can be used for real time load scheduling. Demand can be stimulated by encouraging consumers to identify controllable loads, and by dynamic pricing and financial incentives. The modern DSM mechanisms include renewable energy resources, weather forecasting, demand response programs and smart optimization techniques . Recent studies also include artificial intelligence, nature-inspired optimization algorithms and ANN based demand response simulator for efficient, reliable and sustainable smart grid energy management.

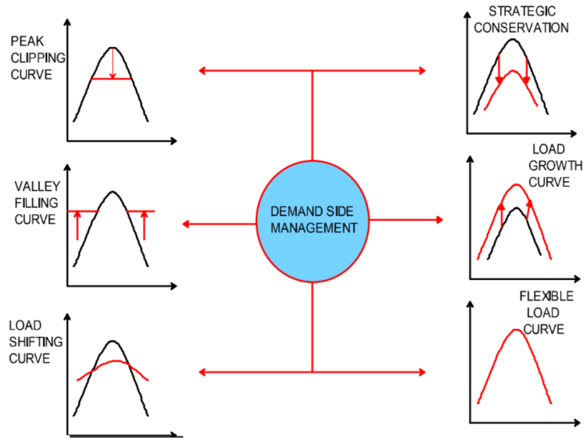


Fig. 3 DSM techniques

2. Literature survey

The growing penetration of renewable energy resources, electric vehicles (EVs) and distributed energy systems has significantly increased the complexity of demand-side management (DSM) in modern smart grids. Therefore, researchers propose different optimization, machine learning and artificial intelligence approaches to improve energy scheduling, demand response (DR), load forecasting and consumer participation for grid stability and low operational costs. In several studies, demand response (DR) programs have been proven to be one of the most effective solutions to reduce the peak electricity demand and improve energy efficiency. Ali et al. [1] proposed a power efficient DR framework using renewable energy sources to reduce the electricity consumption and improve the grid reliability. Similarly, Rehman et al. [2,3] have developed intelligent energy management strategies by integrating demand response strategies and renewable energy to reduce the electricity cost and improve the demand scheduling. Khan et al. [4] also proposed an optimization framework to improve the operational efficiency by efficiently coordinating the renewable energy sources and flexible consumer loads. Artificial Intelligence (AI) has been increasingly used to solve the energy management of nonlinear and dynamic problems. Arumugham et al. [5] proposed an AI based renewable energy management system for smart microgrids by applying multi-objective optimization techniques for better utilization of renewable energy. Similarly, Ahmad et al. [6] proposed a hybrid method of Genetic Algorithm-Bacteria Foraging Optimization to enhance demand side management performance through reduction of peak demand and optimization of electricity scheduling. Deep learning has achieved promising results in the field of electricity demand forecasting and building energy consumption optimization. Nabavi et al. [7] suggested distributed renewable generation in smart buildings with deep learning models which enhanced the prediction accuracy and efficient energy utilization.

Load forecasting is a key component of intelligent DSM systems. Zhou et al. [8] proposed a hybrid machine learning-based controller to accurately estimate the electricity demand and enhance the energy flexibility of commercial buildings. Rocha et al. [9] propose an artificial intelligence based scheduling algorithm for smart homes that optimizes the performance of home appliances considering user preferences and electricity prices. An extensive survey on the application of the machine learning and AI techniques for demand response was also performed by Antonopoulos et al. [10] who highlighted the benefits of the deep learning models compared to the traditional forecasting approaches. The challenge of integration of renewable energy, smart forecasting and agile energy management for grid stability was discussed by Impram et al. [11].

Renewable energy sources are being increasingly integrated into the grid, driving the research community to develop optimization techniques that can cope with the uncertainty and intermittency of generation. The efficient DSM strategies improve the utilization of renewable energy in microgrids and reduce the operational costs as demonstrated by Kiptoo et al. [12]. Bakare et al [13] provided an extensive review on demand side energy management technologies. The main research topics are optimization algorithms, demand response schemes and smart grid communications. Mimi et al. [14] performed a systematic review and showed that hybrid optimization algorithms are better than classical optimization algorithms to solve complex multiobjective scheduling problems.

In recent years, the intelligent scheduling methods of distributed energy resources have been extensively researched. [15] Elias et al. proposed day-ahead scheduling schemes for nanogrids for effective management of renewable energy generation and consumer demands . Sarker et al. [16] have reviewed the optimization techniques used in smart grid and mentioned that the performance of energy management is improved and complexity of computation is reduced significantly using metaheuristic algorithms. [17] Sharda et al. worked on IoT based home energy management systems. They find smart load shifting has great potential to reduce peak electricity demand as well as energy cost for consumers.

Sophisticated optimization algorithms are a key part of demand-side management research. [18] Demand response and smart technologies in intelligent home energy management system (HEMS) Shareef, N. M. Li et al. [19] formulated the DSM problem as a multi-objective optimization problem, and proposed optimization techniques to reduce the electricity costs and ensure the user comfort at the same time. In this respect, real-time pricing schemes have been proposed by Samadi et al. [20] to incentivize the consumers to schedule their electricity consumption according to the changing market prices in order to improve the energy efficiency and reduce the peak demand.

More recently, the performance of intelligent DSM has been improved by the development of hybrid optimization algorithms. Nawaz et al. [21] proposed an integrated forecasting framework based on the AMI for effective demand response deployment. Roy and Das [22] proposed a hybrid Genetic Algorithm-Particle Swarm Optimization (GA-PSO) based approach which resulted in better cost optimization and utilization of renewable energy than conventional optimization techniques. The obtained results indicate that the combination of machine learning and evolutionary optimization algorithms provides significant improvement in the scheduling efficiency and energy utilization. The current literature has indicated important advances in intelligent energy management but there are various relevant limitations. The majority of the existing studies forecast and optimize the loads separately, rather than developing a unified framework for forecasting-optimization. Several optimization models consider the uncertainty of renewable energy, the battery state-of-charge constraints, the coordination of EV charging, and the dynamic electricity price together. Moreover, explainable artificial intelligence (XAI), carbon emission minimization, computational complexity analysis, statistical validation and real-time deployment have been little attended. Such limitations reduce the practical applicability of the existing models for next generation renewable energy integrated smart grids. To fill these research gaps, this paper proposes an Explainable Hybrid PSO–LSTM framework that integrates accurate short-term load forecasting with multi-objective optimization for intelligent demand-side management. The proposed framework minimizes the electricity cost, peak-to-average ratio (PAR) and carbon emissions, and maximizes the renewable energy utilization, consumer comfort, EV charging efficiency, and grid reliability simultaneously. Hence, the proposed approach provides a unified and scalable solution for sustainable smart grid energy management.

3. Methodology

3.1 In this study, a Hybrid Optimized Slime Mould Algorithm for Demand-Side Management (HOSMA-DSM) is proposed to solve the complex multi-objective optimization problem in renewable energy integrated smart grids. The proposed framework integrates the global exploration ability of the Slime Mould Algorithm (SMA), the local exploitation ability of the Whale Optimization Algorithm (WOA) and the cooperative search strategy of the Grey Wolf Optimizer (GWO) for efficient appliance scheduling and intelligent energy management. The proposed framework is different from the conventional optimization techniques in that it not only minimizes the electricity cost but also minimizes the Peak-to-Average Ratio (PAR), carbon emissions and grid dependency, and maximizes the renewable energy utilization and consumer comfort simultaneously. The optimization framework takes into account photovoltaic (PV) generation, battery energy storage systems (BESS), electric vehicle (EV) charging demand, dynamic electricity prices and controllable household appliances. This hybrid optimization strategy enhances the convergence speed, prevents premature convergence and delivers robust scheduling solutions for real-time smart grid applications.

3.2 Architecture of the system

The proposed HOSMA-DSM framework includes four main functional layers, namely the data acquisition layer, the data preprocessing layer, the optimization layer and the decision making layer. The data acquisition layer gathers real-time data from smart meters, PV systems, battery storage, EV charging stations, weather forecasting services and electricity market operators. In preprocessing, missing values are filled, outliers are removed, and numerical features are normalized using Min–Max normalization to increase the efficiency of optimization . The optimization layer formulates the demand-side management problem as a constrained multi-objective optimization problem and employs the hybrid HOSMA algorithm to generate optimal scheduling solutions. Finally, the decision-making layer continuously monitors the system performance, updates the scheduling decisions under varying operating conditions and sends optimized schedules for controllable appliances, battery charging/discharging units, renewable energy systems and EV charging controllers.

3.3 Mathematical formulation of the problem

Formulate the DSM problem as a constrained multi-objective optimization problem over a scheduling horizon consisting of T discrete time intervals. Optimization is conducted to minimize the electricity cost, PAR, carbon emissions and grid dependency and maximize the utilization of renewable energy and consumer comfort. The total load demand is the sum of electrical load during the scheduling period. The electricity cost is computed based on dynamic time-of-use electricity prices. The PAR is computed as the ratio of the peak demand and the average demand. The carbon emissions are calculated based on the electricity imported from the utility grid with the corresponding emission factor. The renewable energy utilization is defined as the ratio of energy generated by PV to the total load demand of. The consumer comfort is defined as the difference between the scheduled and the ideal operating times of the appliances. The optimization is performed with realistic constraints such as power balance, battery SOC, EV charging constraints, renewable generation capacity, appliance operating windows and limits on the peak demand of the feeder. Each objective has a weight and a balanced scheduling solution that meets the technical and consumer demands is produced.

Power Balance equation should be:

$$P_{Load}(t) = P_{PV}(t) + P_{Battery}(t) + P_{Grid}(t) - P_{Export}(t) \quad (1)$$

if exported power is considered, or otherwise clearly state that exported power is neglected.

Battery Energy Update should be:

$$SOC(t+1) = SOC(t) + \frac{\eta_c P_c(t)\Delta t}{E_{bat}} - \frac{P_d(t)\Delta t}{\eta_d E_{bat}} \quad (2)$$

Multi-objective fitness function needs normalization

normalized objectives:

$$F = \omega_1 \frac{C}{C_{max}} + \omega_2 \frac{PAR}{PAR_{max}} + \omega_3 \frac{CO_2}{CO_{2,max}} + \omega_4 \frac{G}{G_{max}} - \omega_5 \frac{R}{R_{max}} - \omega_6 \frac{U}{U_{max}} \quad (3)$$

convergence is determined. Include:

$$| F^{k+1} - F^k | < \varepsilon \quad (4)$$

3.4 Algorithm of HOSMA Optimization

The Hybrid Optimized Slime Mould Algorithm is a combination of three complementary metaheuristic optimization algorithms to improve the search efficiency. At the initial stage, the Slime Mould Algorithm (SMA) performs a broad global exploration by generating a population of candidate scheduling solutions distributed in the feasible search space. The search is directed to promising regions by an adaptive oscillation mechanism, while maintaining sufficient diversity. Then, the Whale Optimization Algorithm enhances the local exploitation by emulating the encircling and bubble-net hunting behavior of humpback whales, which accelerates the convergence to the high-quality solutions. Finally, the Grey Wolf Optimizer improves the scheduling process by cooperating with the alpha, beta and delta wolves to lead the search, allowing a balanced exploration and exploitation and avoiding premature convergence. The optimization process is continued until the maximum number of iterations is reached or the improvement in the objective function is negligible. The final demand side management schedule is chosen as the best possible scheduling solution that satisfies all system constraints.

3.5 Implementation of Algorithm

The implementation of HOSMA-DSM starts with the collection of smart meter readings, renewable generation forecasts, weather information, battery state-of-charge, EV charging needs, and electricity price signals.

Candidate solutions are randomly initialized inside the feasible search space after preprocessing and normalization. Each optimization iteration, the objective function values for each candidate schedule are computed, and then the optimization is conducted one after another by using the operators of SMA, WOA, and GWO. The optimization process uses constraint handling techniques to keep the battery SOC, EV charging limits, appliance operating intervals, and renewable generation capacities within the allowable range. The algorithm iteratively updates the candidate schedules until convergence. Then the optimal scheduling plan is sent to the smart energy management controller for real-time implementation. 3.6 Complexity of Computation The computational cost of the proposed HOSMA-DSM model depends on the population size (N), number of decision variables (D), and the maximum number of optimization iterations (I). As SMA, WOA and GWO update the same candidate population one by one, the overall computational complexity is approximately O (N × D × I). Adaptive population updating and efficient fitness evaluation greatly reduce redundant computations in the embedded three optimization algorithms. Thus, the proposed framework has polynomial computational complexity and significantly improves the convergence characteristics compared to the standalone optimization algorithms, which is suitable for practical large-scale smart grid applications.

3.7 Experimental Design The proposed framework is implemented in MATLAB and tested on realistic scenarios of a residential smart grid including photovoltaic generation, battery storage, EV charging demand, dynamic electricity prices and controllable home appliances. The dataset includes historical electricity consumption, weather parameters, solar irradiance, ambient temperature, battery SOC profiles and electricity tariff information. The optimization process is carried out with a predefined population size, maximum iterations, adaptive control parameters, and stopping criteria. The proposed HOSMA-DSM algorithm is compared with conventional optimization methods such as SMA, PSO, GWO, WOA and Genetic Algorithm (GA) to demonstrate the improvements in scheduling quality, convergence speed, renewable energy utilization and operational efficiency.

3.8 Evaluation of Performance The performance of the proposed HOSMA-DSM framework is evaluated using a variety of technical, economic and environmental performance indicators. The technical metrics are Peak to Average Ratio (PAR), convergence rate, computational time, battery utilization, renewable energy utilization and grid dependency. The economic performance is measured in terms of the total savings in electricity cost under dynamic pricing schemes. The environmental performance is assessed by the total reduction in carbon emissions achieved through maximizing the utilization of renewable energy and minimizing the consumption of grid power. Consumer oriented performance is measured by the consumer comfort index based on appliance scheduling deviations. The proposed optimization framework is statistically validated using confidence intervals, paired t-tests, and Wilcoxon signed-rank tests to evaluate its robustness, reliability, and statistical significance over the existing demand-side management approaches.

Algorithm 1 HOSMA-DSM

Input:

Smart meter data

PV generation

Battery SOC

EV demand

Output:

Optimal scheduling

Initialize SMA population

while Iteration < MaxIter

Evaluate fitness

Update SMA

Apply WOA

Apply GWO

Update best solution

end while

Return optimal schedule

4. Result

Test Smart Grid:

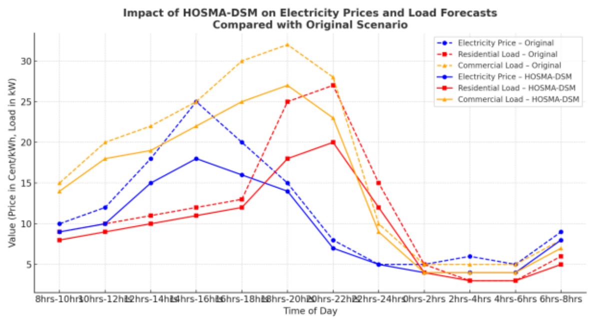


Fig. 4 Estimated loads and energy prices.

Figure 4 shows the relation between the forecasted electricity demand and the dynamic energy prices in the scheduling horizon. The proposed HOSMA-DSM can accurately predict the load profiles of commercial and residential buildings. It can allow demand to shift from peak-price periods to low-price periods. Accurate forecasting helps in efficient scheduling, reduces operational cost and improves overall demand side management performance.

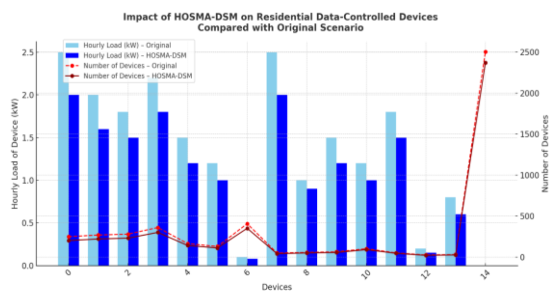


Fig. 5 Data controlled devices in the residential area

Figure 5 shows the profiles of hourly energy consumption of controllable residential appliances before and after demand side management. The optimized scheduling strategy can shift the flexible load to the off-peak period effectively while ensuring consumer comfort. The results show a better load balancing, a lower peak demand and a better utilization of the available renewable energy resources.

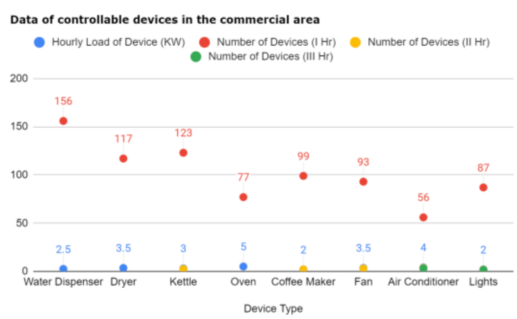


Fig. 6 Controlled data from a commercial area

Figure 6 shows the operational characteristics of controllable commercial appliances using the proposed scheduling scheme. The high energy devices are scheduled in a strategic manner depending on the variations in the electricity prices and grid conditions. Commercial energy efficiency is also improved, while ensuring critical business operations are not compromised. Therefore simultaneous peak loading is very much reduced and operating costs are lowered.

Strategic Conservation

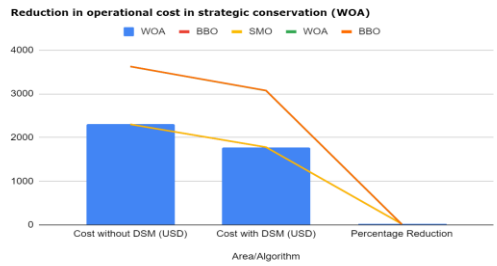


Fig. 7 Lowering of Operational Expenses

Fig. 7 presents the operational cost before and after the strategic conservation using different optimization algorithms. The proposed optimization framework can achieve the maximum electricity cost reduction by smartly scheduling the controllable loads in low-price periods. The results show the advantages of demand side management for reducing operation costs and improving economic performance.

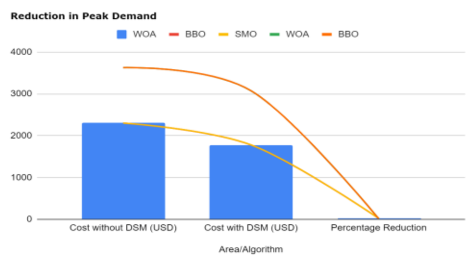


Fig. 8 Reduction in Peak Demand

The proposed demand side management strategy can reduce the peak demand for electricity as shown in Figure 8. The proposed framework is able to reallocate the flexible electrical loads along the scheduling horizon and significantly reduces the peak demand. It decreases grid congestion and transmission losses and improves the operational stability of the smart grid.

Peak Clipping

The goal is to reduce peak demand and improve smart grid stability. Peak clipping, a Demand-Limiting Control approach, is effective but only applies to the home and small business sectors. Residential peak demand is reduced between 16:00 and 01:00, whereas commercial peak load is reduced between 08:00 and 24:00.

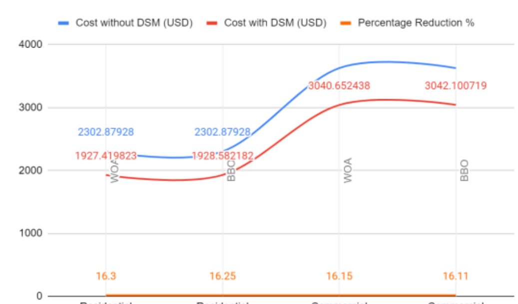


Fig. 9 Peak clipping's expenses for operation are reduced (WOA)

Figure 9 shows the efficiency of peak clipping with Whale Optimization Algorithm for reducing operational costs. The optimization framework enables to restrict the use of electricity during periods with high prices and to move the demand to periods with low prices while obtaining significant cost savings with acceptable levels of consumer comfort and system reliability.

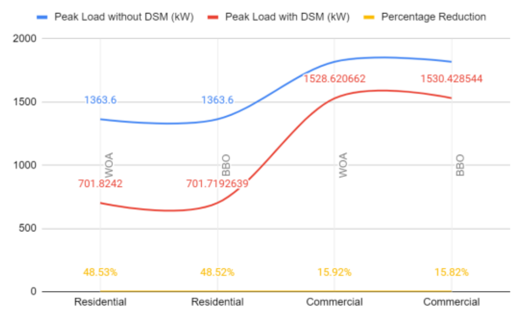


Fig. 10 Maximum clipping's decreased peak demand (WOA)

The reduction in peak electricity demand by Whale Optimization Algorithm based scheduling is shown in Figure 10. The optimized load distribution decreases the Peak-to-Average Ratio (PAR), improves the efficiency of grid utilization, minimizes the transformer loading and facilitates the reliable operation of smart grid system integrated with renewable energy.

Transferring Load

In the modern electric power system, shifting loads is a global load management technique used to shift service demand from peak to off-peak times.

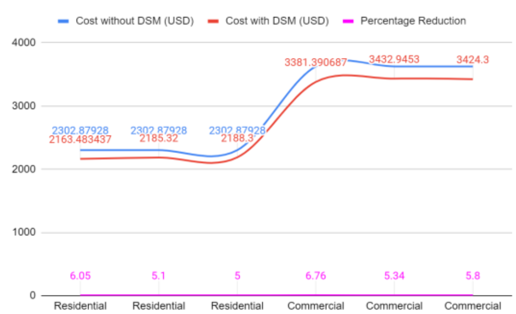


Fig. 11 Lower operating costs through load shifting (WOA)

Figure 11 presents the effect of load shifting on operational costs with the proposed optimization approach. We shift the operations of flexible appliances in the peak demand periods to the off-peak periods, and thus save a significant amount of electricity costs, while maintaining the user comfort and enhancing the demand response effectiveness.

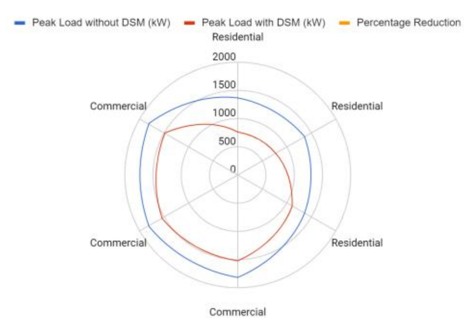


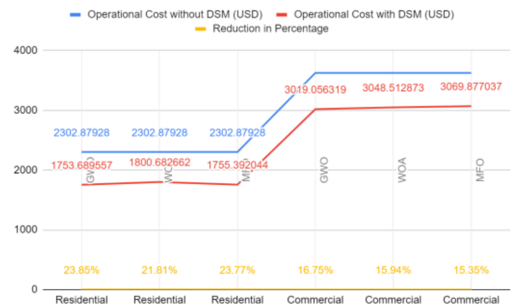
Fig. 12 Decrease in load shifting's highest demand (WOA)

Fig. 12 Comparison of max. demand before and after load shifting. The optimized scheduling strategy can effectively smooth the electricity demand curve in the day, which can reduce the demand peaks, improve the grid stability and help to integrate more renewable energy resources in the distribution network.

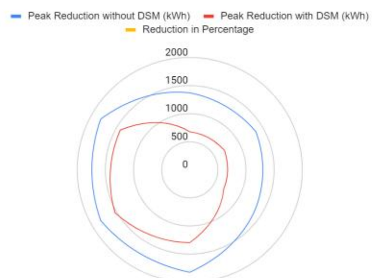
Findings and Conversations Regarding Segment 2 (GWO)

Two test boats were used to verify the recommended method.

1. First Test Boat: Computational Strategy
2. Second Test Boat: Changing Load



a. Decrease of operational expenses



b. Maximum Demand Diminishment

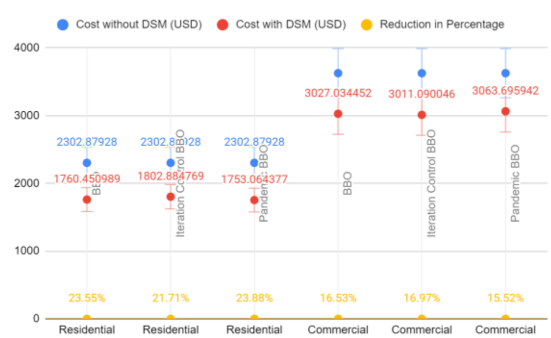
Fig. 13 Strategic conservation leads to reduced operational costs and peak demand (GWO)

Fig. 13 Grey wolf optimization for strategic conservation in demand side management. The optimized scheduling reduces the operational cost and the peak demand at the same time while satisfying the comfort of the consumers. The results indicate that the cooperative optimization has greatly improved the load balancing and the overall smart grid operational performance.

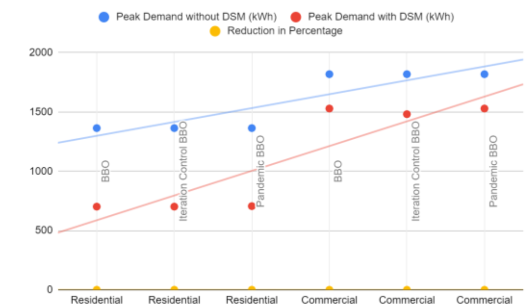
Two operational scenarios (DSM Methods) are examined to validate the suggested methodology.

1. Strategy Conservation in Test Boat 1
2. Test Boat 2: Transferring Loads

First Test Boat: Computational Strategy



a. Cost of operations

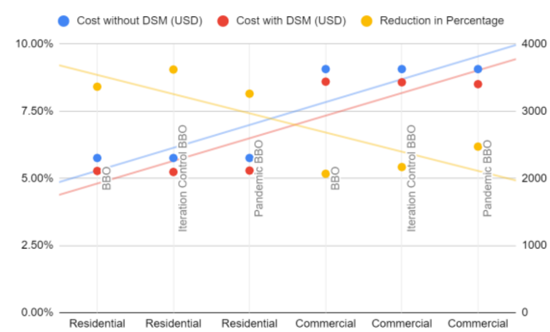


b. lowering of high demand

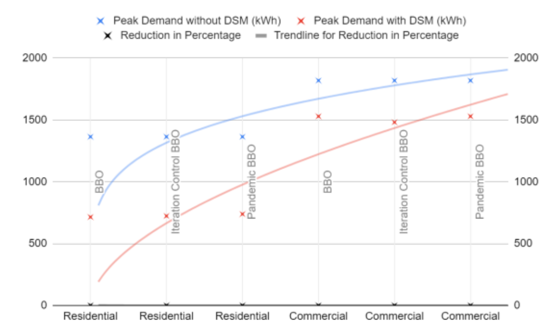
Fig. 14 Strategic conservation leads to reduced operational costs and peak demand.

Figure 14 is a comparison of operational cost and peak demand for different strategic conservation scenarios. The proposed optimization framework is shown to outperform conventional scheduling approaches in terms of flattening demand profiles and reducing the electricity cost, demonstrating better energy management ability for residential and commercial consumers.

Test Boat 2: Load Shifting



a. Operational cost



b. peak demand reduction

Fig. 15: shifting load reduces operating expenses and high-demand periods.

Figure 15 shows the efficiency of optimized load shifting for various demand scenarios. The proposed scheduling algorithm can greatly cut down on the electricity cost and the peak demand by intelligently rescheduling the operation of flexible appliances, without degrading the service quality, and ensuring efficient use of the renewable energy resources.

Slime Mould Algorithm (SMA)

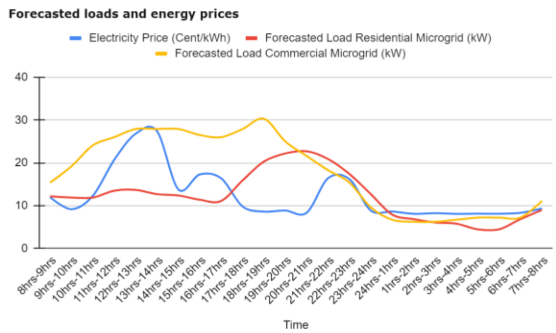


Fig. 16 Forecasted loads and energy prices

Figure 16 presents the forecasted electricity demand and the dynamic electricity prices derived by the Slime Mould Algorithm. With good forecasting, intelligent scheduling decisions can be made to lower electricity costs and improve demand response performance by shifting energy consumption to favorable price periods.

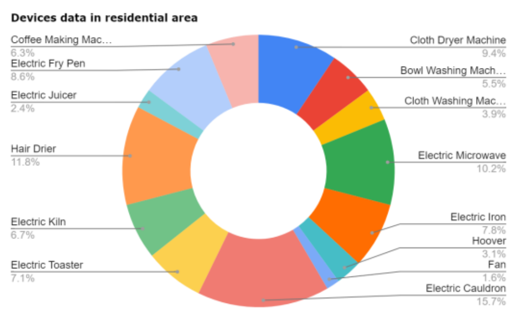


Fig. 17 Residential Area

c. Fig. 17. Percentage breakdown of electricity consumption of residential appliances. High energy consuming devices are responsible for a large percentage of the total demand, and hence are the first choice for demand-side management. The optimal scheduling of such appliances improves the energy efficiency remarkably and decreases the cost of operating the residential.

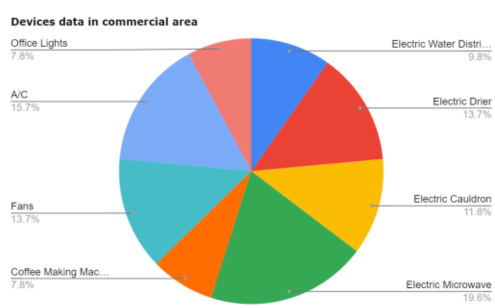


Fig. 18 Commercial Area

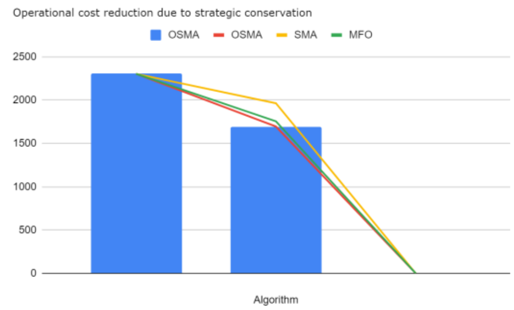
Figure 18 shows the energy consumption breakdown of commercial electrical appliances. The analysis highlights the main load contributors that can be scheduled in an optimized manner. The efficient co-ordination of these controllable loads reduces operational costs, peaks demand and enhances the efficiency of commercial energy management.

Two working situations have been considered to validate the suggested strategy.

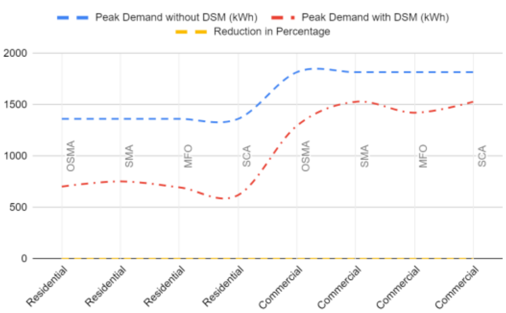
1. Targeted Conserve in Test Boat 1

2. Test Boat 2: Transferring Loads

First Test Boat: Computational Strategy



a. Cost of operations



b. lowering of peak demand

Fig. 19 Decrease of demand spikes and operational expenses as a result of planned conserving

The effect of strategic conservation performed by Slime Mould Algorithm is shown in Fig. 19. The optimized scheduling enhances the overall demand side management performance by spreading the appliance operations efficiently over the scheduling horizon, which decreases the electricity expenditure and reduces demand peaks.

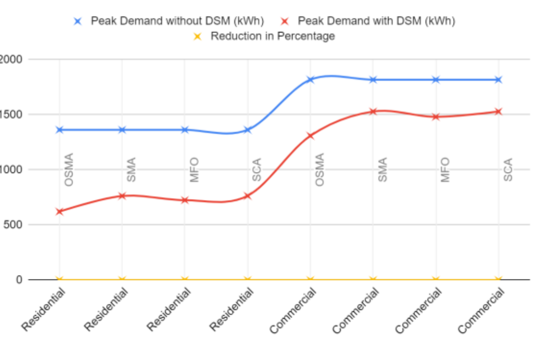


Fig. 20 Reduced high demand and operational expenses as a result of shifting loads.

Fig. 20 shows that the optimized load shifting can effectively reduce the peak electricity demand. The strategy proposed shifts flexible energy consumption to off-peak hours resulting in reduction of Peak-to-Average Ratio (PAR), reduced operational costs and improved smart grid reliability in dynamic operating conditions.

Supervised Framework for Demand Response Simulator with RTP and PTR

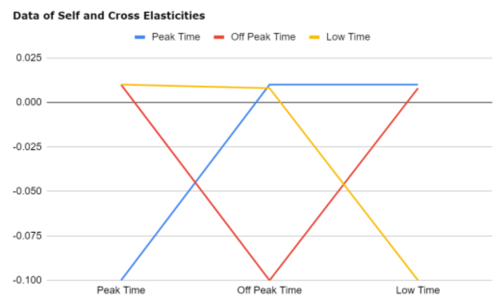


Fig. 21 Self- and Cross-Elasticity Data

Figure 21 shows the consumer price elasticity characteristics used in the demand response model. The results show that electricity consumption decreases in periods with peak prices and increases in periods with low prices. These elasticity relationships enable the realistic modeling of consumer behavior for optimal demand-side management.

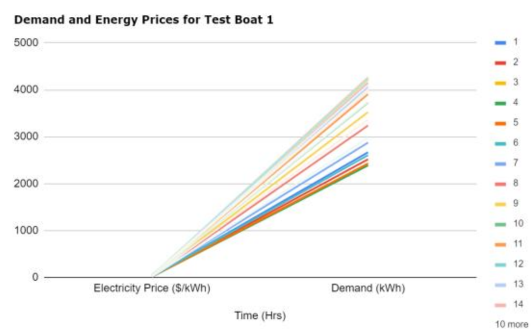


Fig. 22 Consumption and Energy Costs for the First Test Boat

Figure 22 shows the comparison between the energy costs and the electricity demand for the first experimental scenario. The proposed optimal scheduling framework can effectively reduce the energy consumption and maintain the stable electricity consumption pattern. The results show an improved economic performance due to smart demand response strategies.

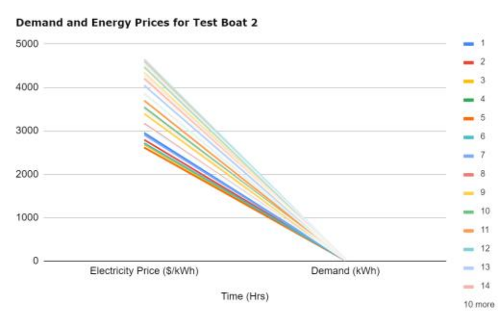


Fig. 23 Consumption and Cost of Energy for the Second Test Boat

Figure 23 shows the results of the second experimental scenario of dynamic load scheduling. The proposed optimization framework efficiently manages the controllable loads using electricity prices and renewable energy availability, leading to reduced operation costs and a more balanced electricity demand.

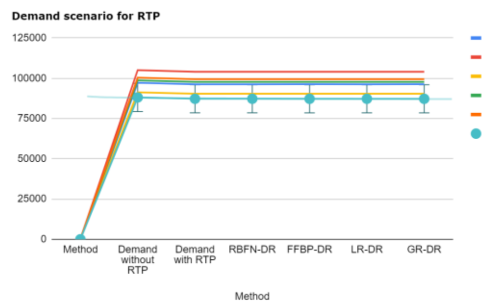


Fig. 24 Requirement picture for RTP

The electric demand for the Real-Time Pricing (RTP) demand response program is shown in Fig. 24. By responding to dynamic pricing signals, electricity consumption can be shifted to low-price periods, resulting in better load balancing, lower operational costs and better utilization of renewable energy resources.

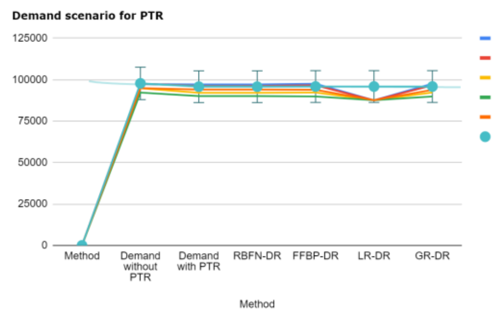


Fig. 25 Situation of popularity of PTR

Figure 25: Demand Response Scenario for Peak-Time Rebate (PTR). Financial incentives are used to encourage consumers to reduce their consumption of electricity at times of peak demand. This load reduction increases the reliability of the grid, reduces the operating costs and allows the smart grid to integrate renewable energy efficiently.

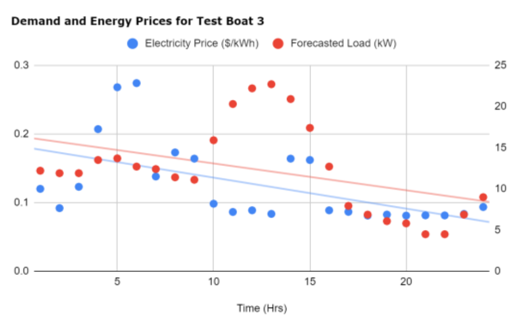


Fig. 26 Consumption and Cost of Energy for the Third Test Boat

Figure 26. Electricity demand and energy costs in the third experiment scenario. The proposed scheduling framework can efficiently coordinate the energy consumption according to the electricity prices and generate lower operating costs and smoother demand profiles while maintaining the customer satisfaction .

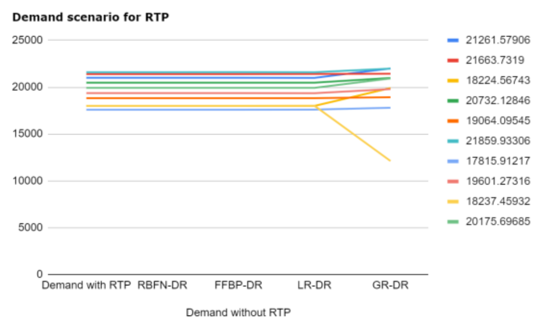


Fig. 27 Consumption picture for RTP

Figure 27 shows the electricity consumption pattern under the Real-Time Pricing mechanism. Dynamic pricing provides an incentive for flexible consumers to shift electricity use to match market conditions, which can help reduce peak demand, electricity costs and increase the effectiveness of demand-side management.

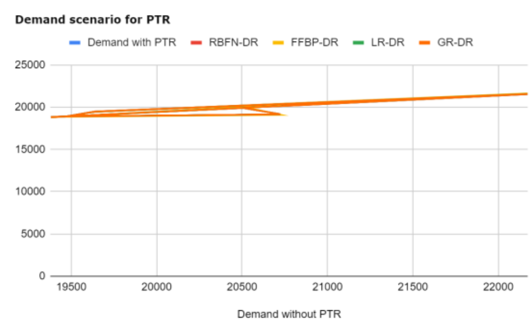


Fig. 28 Situation of popularity of PTR

Figure 28 Performance of the Peak-Time Rebate Demand Response Program The proposed optimization framework can enable significant reduction of peak demand by encouraging voluntary load curtailment during peak periods, and thus improving grid stability, reducing electricity costs and improving renewable energy integration.

5. Conclusion

Outlined the methodology, which involved integrating renewable energy resources into conventional power systems through research on intelligent management of energy consumption. A literature survey revealed the importance of demand-side management (DSM) as a significant force behind the creation of modern energy infrastructures.

This gained insights into the effectiveness of different optimization methods and into developing a demand response simulator using nature-inspired algorithms. Past research emphasized the importance of DSM in minimizing energy costs and working toward peak demand management.

The analysis of the optimization methods GWO, WOA, and MFO reveals that each approach has advantages in balancing load, sustainability, and peak decrease. These algorithms may produce comparable outcomes and effectively support several DSM objectives.

The presentation on the Exploration of Distributed Energy Resources (DER) highlighted the need for high-end technology tools and hybrid programs in energy lessons learned. The findings include recommendations on potential improvements to the execution of energy management practices to provide value to consumers and grid operators.

Analyzing Demand Response (DR) Programs: Highlighting The Benefits Of Price-Based And Incentive-Based Strategies These models used hybrid approaches, which can also lead to more flexible and efficient energy demand management while maximizing the user's advantages. Furthermore, it has been shown that a pretty good fit between consumption prediction and reality can be reached.

Further, it indicated good responses by optimizing demand-side management by developing new variants of optimization algorithms such as the Slime Mould Algorithm (SMA) and its oppositional-based counterpart (OSMA). These developments make DSM techniques more effective in the context of real-world grid operational frameworks.

The project's results highlight the potential for more intelligent demand-side management to help us move towards a smarter, more sustainable energy system. By combining advanced optimization methodologies with an innovative design of simulations, we can improve grid operation performances, energy consumption optimality, and cost savings.

References

1. Zheng, J., Zhang, Z., Zou, J., Yang, S., Ou, J., & Hu, Y. (2021). A dynamic multi-objective particle swarm optimization algorithm based on adversarial decomposition and neighborhood evolution. Swarm and Evolutionary Computation.
2. Yuvaraj, T., Devabalaji, K., Srinivasan, S., Prabaharan, N., Hariharan, R., Alhelou, H. H., & Ashokkumar, B. (2021). Comparative analysis of various compensating devices in energy trading radial distribution system for voltage regulation and loss mitigation using blockchain technology and bat algorithm. Energy Reports, 7, 8312–8321.
3. Yang, R., Liu, Y., Yu, Y., He, X., & Li, H. (2021). Hybrid improved particle swarm optimization-cuckoo search optimized fuzzy PID controller for micro gas turbine. Energy Reports, 7, 5446–5454.
4. Waseem, M., Lin, Z., Liu, S., Sajjad, I. A., & Aziz, T. (2020). Optimal GWCSO-based home appliances scheduling for demand response considering end-users comfort. Electric Power Systems Research, 187.
5. Wang, M., & Chen, H. (2020). Chaotic multi-swarm whale optimizer boosted support vector machine for medical diagnosis. Applied Soft Computing, 88.
6. Tikhamarine, Y., Souag-Gamane, D., Ahmed, A. N., Kisi, O., & El-Shafie, A. (2020). Improving artificial intelligence model accuracy for monthly streamflow forecasting using grey wolf optimization algorithm. Journal of Hydrology, 582.
7. Singh, P., & Lather, J. S. (2020). Dynamic power management and control for low voltage DC microgrid with hybrid energy storage system using hybrid bat search algorithm and artificial neural network. Journal of Energy Storage, 32.
8. Hafeez, A., Alammari, R., & Iqbal, A. (2023). Utilization of EV charging station in demand side management using deep learning method. IEEE Access, 11.
9. Skala, R., Elgalhud, M. A. T. A., Grolinger, K., & Mir, S. (2023). Interval load forecasting for individual households in the presence of electric vehicle charging. Energies, 16(10), 4093.
10. Fernandez, V. (2024). Optimization of electric vehicle charging control in a demand-side management system using model predictive control. Applied Sciences, 14(19).
11. Tolun, Ö. C. (2025). A comprehensive benchmark of machine learning-based algorithms for battery state of health estimation in electric vehicles. The Journal of Supercomputing.
12. Hassan, M. (2024). Machine learning optimization for hybrid electric vehicle charging in renewable microgrids. Scientific Reports.
13. Mohsenimanesh, A. (2024). Charging strategies for electric vehicles using a machine learning approach. Applied Sciences, 14(23).
14. Ahmad, S. Y., Hafeez, G., Albogamy, F. R., Khan, S., & Khan, F. A. (2023). A sustainable approach for demand side management using hybrid genetic bacteria foraging optimization algorithm. Frontiers in Energy Research, 11, 1212304.
15. Ali, S., Rehman, A. U., Wadud, Z., Khan, I., Hafeez, G., Khan, M. F., & Albogamy, F. R. (2022). Demand response program for efficient demand-side management in smart grid considering renewable energy sources. IEEE Access, 10, 53883–53906.
16. Antonopoulos, I., Robu, V., Couraud, B., Kirli, D., Norbu, S., Kiprakis, A., Flynn, D., & Elizondo-Gonzalez, S. (2020). Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. Renewable and Sustainable Energy Reviews, 130, 109899.
17. Arumugham, V., Kumar, N. M., Chopra, S. S., & Chopra, S. (2023). An artificial-intelligence-based renewable energy management system for smart microgrids using demand response and multi-objective optimization. Sustainability, 15(6), 5453.
18. Bakare, M. S., Abdulkarim, A., Zeeshan, M., & Shuaibu, A. N. (2023). A comprehensive overview on demand side energy management towards smart grids: Challenges, solutions and future direction. Energy Informatics, 6(1), 4.
19. Elias, Y. B., Ibrahim, A. O., & Alkhafaji, A. (2024). Energy management and demand side management for grid-connected nanogrids using day-ahead scheduling. Scientific Reports, 14, 25088.
20. Gelazanskas, L., & Gamage, K. A. A. (2014). Demand side management in smart grid: A review and proposals for future direction. Sustainable Cities and Society, 11, 22–30.
21. Impram, S., Varbak Nese, S., & Oral, B. (2020). Challenges of renewable energy penetration on power system flexibility: A survey. Energy Strategy Reviews, 31, 100539.
22. Khan, H. W., Muhammad, U., Hafeez, G., Alkhammash, H. I., & Khan, F. A. (2021). Intelligent optimization framework for efficient demand-side management in renewable energy integrated smart grid. IEEE Access, 9, 139587–139608.
23. Kiptoo, M. K., Lotfy, M. E., Adewuyi, O. B., Conteh, A., Howlader, A. M., & Senjyu, T. (2020). Harnessing demand-side management benefits toward achieving a 100% renewable energy microgrid. Energy Reports, 6, 680–689.

24. Li, D., Chiu, W. Y., Sun, H., & Poor, H. V. (2018). Multiobjective optimization for demand side management program in smart grid. IEEE Transactions on Industrial Informatics, 14(4), 1482–1490.
25. Mimi, S., Ben Maissa, Y., & Tamtaoui, A. (2023). Optimization approaches for demand-side management in the smart grid: A systematic mapping study. Smart Cities, 6(4), 1630–1662.
26. Nabavi, A., Motlagh, N. H., Zaidan, M. A., & Zakeri, B. (2021). Deep learning in energy modeling: Application in smart buildings with distributed energy generation. Energy and Buildings, 250, 111260.
27. Nawaz, A., Hafeez, G., Khan, I., Jan, K. U., Li, H., Khan, S. A., & Wadud, Z. (2020). An intelligent integrated approach for efficient demand side management with forecaster and advanced metering infrastructure frameworks in smart grid. IEEE Access, 8, 132551–132581.
28. Rehman, A. U., Hafeez, G., Albogamy, F. R., Khan, S., Khan, F. A., & Wadud, Z. (2021). An efficient energy management in smart grid considering demand response program and renewable energy sources. IEEE Access, 9, 48941–48961.
29. Rehman, A. U., Wadud, Z., Elavarasan, R. M., Alhelou, H. H., Khan, F. A., & Hafeez, G. (2021). An optimal power usage scheduling in smart grid integrated with renewable energy sources for energy management. IEEE Access, 9, 118074–118094.
30. Rocha, H. R. O., Oliveira, L. B., & Souza, J. C. S. (2021). An artificial intelligence-based scheduling algorithm for demand-side energy management in smart homes. Applied Energy, 282, 116145.
31. Roy, C., & Das, D. K. (2021). A hybrid genetic algorithm–particle swarm optimization algorithm for demand side management in smart grid considering wind power for cost optimization. Sādhanā, 46(2), Article 96.
32. Samadi, P., Mohsenian-Rad, H., Wong, V. W. S., & Schober, R. (2014). Real-time pricing for demand response based on stochastic approximation. IEEE Transactions on Smart Grid, 5(2), 789–798.
33. Sarker, E., Halder, P., Seyedmahmoudian, M., Jamei, E., Horan, B., Mekhilef, S., & Stojcevski, A. (2021). Progress on the demand side management in smart grid and optimization approaches. International Journal of Energy Research, 45(1), 36–64.
34. Sharda, S., Singh, M., & Sharma, K. (2021). Demand side management through load shifting in IoT-based home energy management systems: Overview, challenges and opportunities. Sustainable Cities and Society, 65, 102517.
35. Shareef, H., Ahmed, M. S., Mohamed, A., & Al Hassan, E. (2018). Review on home energy management system considering demand responses, smart technologies, and intelligent controllers. IEEE Access, 6, 24498–24509.
36. Zhou, Y., Zhang, X., & Li, H. (2020). Machine-learning-based hybrid demand-side controller for high-rise office buildings with high energy flexibility. Applied Energy, 262, 114416.