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Optimized DSM in SG with EV using Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO)

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Abstract— Demand-side management (DSM) has become an essential mechanism for improving the efficiency and flexibility of modern smart grid systems. The increasing use of electric vehicles (EVs) and use of renewable resources require proper co-ordination between electricity demand and supply for stability and economic reasons. In this paper, a review of the existing literature on demand side management strategies in a smart grid environment with a focus on the role of electric vehicles and their effects has been conducted. Research conducted on the co-ordination of EV charging, load shifting techniques and optimization-based demand scheduling has been studied. In addition to reviewing prior studies, this work introduces a conceptual optimization framework designed for DSM in smart grids that incorporate EV charging loads, renewable generation, and battery storage systems. The framework considers operational constraints such as generation limits, battery state-of-charge boundaries, and demand flexibility under time-of-use electricity pricing. It also provides an evaluation viewpoint for applying meta-heuristic optimization approaches like Particle Swarm Optimization (PSO) and Grey wolf Optimizer (GWO) to the problem of demand scheduling. Programming output simulated in MATLAB indicated the supremacy of GWO algorithm over PSO method in the aspects of reduced cost, computation time and efficiency. The proposed approach provides a foundation on which to conduct further investigation in enhancing energy management solutions to accommodate the increased penetration of EVs within Smart Grid infrastructure.

Keywords— Demand Side Management (DSM), Electric Vehicles (EVs), Distributed Generators (DGs), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO)

I. Introduction

Worldwide energy transition towards reliable, flexible and sustainable electricity supply is at forefront of change today. Traditional power system which has limited flexibility due to centralized architecture and fossil dependency is facing tough competition with new generation smart grid paradigm. Smart Grids (SGs) are future power systems which integrate monitoring, control and communication technologies throughout transmission and distribution system intelligently. SGs operate on two-way communication between utility and customer for monitoring, control, optimization of power flow anytime anywhere. They intend to provide power that is delivered in most efficient, reliable and consumer-centric manner.

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Demand Side Management (DSM) is integral part of SGs providing control knobs to actively manage and alter power consumption as per availability of resources, price signals and
network requirements. It increases flexibility of grid by efficiently managing generation and demand therefore helping in peak load shaving, operational cost reduction and providing impetus to clean energy integration. It changes consumer consumption pattern by motivating users to shift their load from peak to off-peak hours therefore flattening load curve and reducing requirement of additional generation and network capacity. Load management through DSM helps in incorporating uncertain renewable generation such as solar and wind power.

In recent years, the rise of Electric Vehicles (EVs) and distributed renewable energy sources has introduced both challenges and exciting opportunities for DSM strategies. Smart handling of EVs allows them to become adaptable energy storage systems that can participate in the V2G (Vehicle-to-grid) service to provide key support to grid stability and integration of renewable energy sources. Renewable energy sources provide high environmental and economic benefits but are erratic and hard to predict, requiring sophisticated forecast and control strategies.

Several computational methods have been proposed in literature to optimize DSM. Metaheuristic techniques which are nature inspired optimization methods are seen to be very efficient to solve highly non-linear, multi-objective and high-constrained optimization problems. GWO and PSO techniques are observed to be very efficient at exploring and exploiting the search space.

A. Problem Statement

DSM has become an indispensable mechanism of enabling this transition; however, the existing DSM approaches have several gaps:

- *Integration Gaps:* Most studies deal with either EV management or renewable integration or energy storage in isolation rather than in an integrated framework that simulates real grid operating conditions.
- *Market and Price Awareness:* Most existing models do not account for dynamic electricity pricing and/or time-of-use (TOU) tariffs, thereby limiting the cost-optimization capabilities.
- *Renewable Uncertainty:* Most work assumed deterministic renewable generation, disregarding the uncertainty of renewable solar and wind generations.
- *Separate Optimization:* Load shifting and generation scheduling are optimally done separately, which results in an overall suboptimal solution.

Accordingly, the consequent research problem for this study is to develop a monolithic DSM optimization framework that accommodates EVs, renewables, and storage systems integrated in a cost-effective manner, computationally efficient, and user satisfaction guaranteed, as presented in the problem formulation. The framework should be able to utilize metaheuristic algorithms such as PSO and GWO to offer a scalable and feasible solution for the current smart grid-related application.

B. Objectives

This research's all-encompassing objective is to develop a cost-driven DSM strategy that not only reduces total daily electricity costs but also guarantees grid reliability, ensures maximum renewables integration, and maintains user comfort.

Specific measurable objectives:

1. *Cost Optimization:* Set a single optimization framework to minimize cost over a 24-hour horizon with the coordination of schedules of loads, generation and energy storage system. It will consider dynamic pricing, renewables availability, and user-specific requirements.
2. *Load Shifting Strategy:* Develop and operate effective load-shifting management strategies geared towards shifting household and industrial consumptions from the high-cost to low-cost periods to flatten the load curves and eventually balance the grid.
3. *Efficient Generator Scheduling:* Schedule the operation of renewable and conventional generators to achieve economic dispatch and reduce fuel consumption and greenhouse gas emissions.
4. *Control Grid Interactions:* Smart grid pricing strategies-when to buy or sell excess power to the main utility grid based on real-time price fluctuations and available renewable energy production.
5. *Reduce Peak Demand:* By reducing the peak-to-average load ratio, grid congestion is avoided, the system's operational efficiency is improved, and the need for infrastructure expansion is minimized.

II. LITERATURE STUDY

There have been numerous literatures on DSM and EV integration over the last decade. There are a number of optimization approaches that have been proposed over the years to improve energy scheduling, renewable integration, and cost minimization.

Research on DSM with EV integration is progressive in recent years. Bashash and Fathy [1] suggested a cost-optimal charging framework for plug-in hybrid EVs based on time varying electricity prices. The authors proved that optimized schedules of charging have the potential to reduce the cost of electricity bills reasonably. López et al. [2] investigated DSM strategies with EV load shifting and V2G support. This is evidenced by enhanced system profitability, reduced peak loads on the distribution network. Likewise, Bharathi et al., [3] developed genetic algorithm-based DSM method to reduce peak demand in industrial and residential sectors.

Vehicle-to-grid technologies have also been extensively studied. Erdogan et al. [4] came up with a coordinated V2G control scheme that led to significant distribution systems peak shaving. Liu and Hsu [5] developed a robust DSM framework with due consideration of uncertain renewable generation and bidirectional energy trading. Microgrid energy management is also an extensively studied area. Yang et al. Abid et al. [7] presented a bat optimization algorithm-based microgrid energy management strategy.

Optimization algorithms have been emphasized in recent review studies of the importance in DSM applications. Sarker et al. [13] analysed different DSM optimization techniques and concluded that hybrid metaheuristic provide improved solution quality. In the same way, Mohanty et al., [19] reviewed EV-based DSM strategies, pointing to the difficulty in dealing with uncertainties in renewable energy generations and load predictions. The Grey Wolf Optimizer presented by Mirjalili et al. [24] has shown robust performance in addressing complex engineering optimization problems such as energy management systems.

Nevertheless, some challenges are still available regarding the integration of EVs, renewable resources, and storage systems in a unified DSM framework. This study deals with these challenges by proposing an integrated optimization framework.

III. Mathematical Modelling

A. Objective Function Formulation

This research objective is to minimize the overall cost operation for the system. System hourly electricity demands over 24-hour periods have to be satisfied. Distributed generation sources and battery storage units are available along with the main grid. It should work with a minimum cost, still satisfying technical constraints such as generation limits, SOC constraints for battery, and load balancing constraints.

Mathematical form of the objective function:

Let: $P_{grid,t}$: Power transferred to or from grid at time t (positive if buying, negative if selling)

$C_{buy,t}(t)$: Buying rate at time t (₹/kWh)

$C_{sell,t}$: Selling rate at time t (₹/kWh)

$Penalty_t$: Penalty cost at hour t for constraint violations (₹)

Then, the total cost over 24 hours is given by:

$$Minimize\ Cost\ \sum_{t=1}^{24}\left(\begin{cases} C_{buy,t}(t)\cdot P_{grid,t}, & P_{grid,t}>0 \\ C_{sell,t}(t)\cdot P_{grid,t}, & P_{grid,t}<0 \end{cases} + Penalty_t\right) \quad (1)$$

This objective function is checked every hour for each solution. the optimization algorithm adjusts the generation and storage operation incrementally, considering all system constraints to determine the minimum total cost.

B. Operational Constraints

To keep the system technically sound and practical, several constraints are applied.

1) Power Balance Constraint: This means that at every hour, supply (from all generators and the grid) must be equal to total demand. This balance helps in reducing power losses and ensuring that the load requirements are smoothly met. The function to minimize the error between actual and desired load profiles is given by:

$$MINIMIZE\ (\gamma) = \sum_{t=1}^{T}\left(P_{Load,t} - P_{target,t}\right) \quad (2)$$

where, T represent the number of time periods (T=24), $P_{Load,t}$ represent the load demand and $P_{target,t}$ represent the desired load profile at time period t.

2) Generation Limits: Each generation unit has fixed operating limits that cannot be crossed. These limits are based on the system's technical ratings, environmental conditions, and operational safety.

$$P_{Gi,min} \le P_{Gi} \le P_{Gi,max} \quad (3)$$

Where, $P_{Gi,min}$ and $P_{Gi,max}$ represent the minimum and maximum power generation limits for unit i.

3) Battery SOC Limits:

Let: $SOC_i(t)$ be the state of charge of battery i at hour t,

C_i be the total energy capacity of battery i,

SOC_{min} and SOC_{max} be the minimum and maximum allowable SOC levels.

Then, the SOC constraint for each battery is represented as:

$$SOC_{min} \le SOC_i(t) \le SOC_{max}, \forall t \in \{1, 2, \dots, 24\} \quad (4)$$

This ensure that the optimization algorithm maintains feasible and technically sound operating conditions for

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both energy storage units throughout the 24-hour schedule.

4) Battery Efficiency: Some energy is lost during both the charging and discharging of battery systems and are therefore not 100% efficient. Roundtrip efficiency sums the two energy losses to show these inefficiencies.

The roundtrip efficiency in this report is 95%. If 1 unit of energy is put into the battery then 0.95 unit will be able to be recovered. This has to be incorporated in to the energy balance equations to represent the actual system.

Let $P_i(t)$ be the power transferred to or from grid at time *t*. Then the battery SOC update equation considering efficiency is,

$$SOC_i(t+1) = \begin{cases} SOC_i(t) - \frac{P_i(t)}{\eta}, & P_i(t) > 0\ (discharging) \\ SOC_i(t) - P_i(t) \times \eta, & P_i(t) > 0\ (charging) \end{cases} \quad (5)$$

This means:

- When discharging, the battery must release a bit more energy than what the load receives.
- When charging, more energy is needed to store the same amount because of losses.

Using this condition gives a more accurate picture of how batteries really perform and avoids overestimating how much stored energy is available.

IV. Methodology

A. Role of Load Shifting

Load shifting is an important part of demand-side management (DSM). It means moving some electricity use from expensive peak hours to cheaper off-peak times. To keep the demand pattern realistic and avoid too much change, a limit is set on how much load can be moved in one day.

In this study, only 15% of the load or up to 4 hours can be shifted from high-cost hours to cheaper ones. The rule is meant to ensure the new demand shape remains little realistic and close to consumer behaviour. Four costly hours are thus shifted and four cheap hours are selected to absorb the demand load. This ensures that the curve remains overall balanced and smooth. As a result, only a small part of the peak demand (15%) is shifted to cheaper hours.

B. Optimization Techniques

Among the different metaheuristic techniques that have been adopted in electrical system optimization problems, Particle Swarm Optimization (PSO) and Whale Optimization Algorithm (WOA) have been highly acknowledged as simple but strong nonlinear optimizations.

1. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique inspired by the collective behaviour of biological systems such as bird flocking, fish schooling. A group of individuals, known as particles, move in a multidimensional search space to determine an optimum solution according to the simulated algorithm. A particle's current state is defined by its position and velocity vectors. A particle's movement is influenced by its own best experience and the best experience of the entire swarm.

Three components govern particle updating mechanism: inertia, cognitive learning, and social learning. The inertia component retains part of the previous velocity of the particle and allows for exploration of the search space. The cognitive component moves the particle toward the personal best position (p_{best}), which is the position where the best solution was encountered by a particle. The social component involves cognitive learning based on the social globalization g_{best}, which is the best solution obtained from all the particles in the swarm. This helps particles to search in better locations while keeping the diversity within potential solutions.

2. Whale Optimization Algorithm

Whale Optimization Algorithm (WOA) is a metaheuristic optimization approach inspired by nature, based on the bubble-net hunting mechanism performed by humpback whales, where whales circle below their prey, and producing a bubble-net that encircles and guides the fish toward them, before they attack the prey. WOA mathematically models this behaviour to perform optimization.

The algorithm begins with a population of candidate solutions representing whales. During each iteration, search agents update their positions relative to the best solution found so far or with respect to randomly selected individuals. The optimization process is modelled through three main behaviours: encircling the prey, bubble-net attacking, and random searching.

V. Results and Analysis

A. Results by PSO with Load Shifting

To maintain practical consumption patterns, load shifting is restricted to 15% of peak load over 4-hour windows.

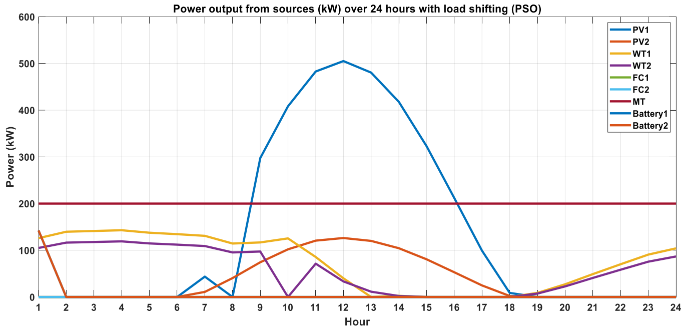

Figure 1. Power output (kW) from sources over 24-hours with PSO with load shifting

Fig. 1 illustrates the hourly power output (kW) for different generation sources and batteries over a 24-hour period with DSM by PSO. Microturbine provide a consistent base power of 200 kW, operating constantly throughout the day. PV_1 exhibits the highest variability, peaking sharply at approximately 505 kW around 12:00, dominating generation during midday (09:00 to 16:00). Conversely, the Wind Turbines (WT_1 and WT_2) generate maximum power during the night/morning hours, with WT_1 peaking near 145 kW (03:00–06:00) and WT_2 peaking near 120 kW (03:00-04:00), significantly dropping to near zero between 14:00 and 18:00. Notably, Battery 1 and Battery 2 show minimal to zero output, as they exhausted in first hour only from 80 to 20 % SOC.

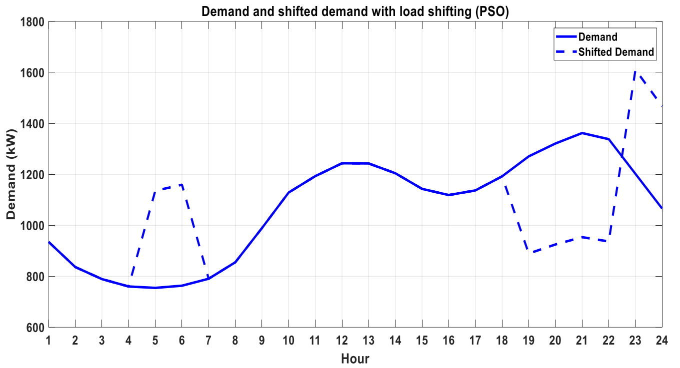

Figure 2. Demand and modified demand with load shifting (PSO)

Fig. 2 plots the original and adjusted load, registering DSM changes with demand shifted from high cost 18 to 22 hours to low-cost hours (23 to 24 and 4 to 7 hours), registering about 15% peak reduction with intelligent distribution with no adverse impact on the overall energy provided. The shifted (modified) demand column in DSM, measuring the modified demands that make economic optimization possible, having the same total generation capacity but lowering total cost of generation.

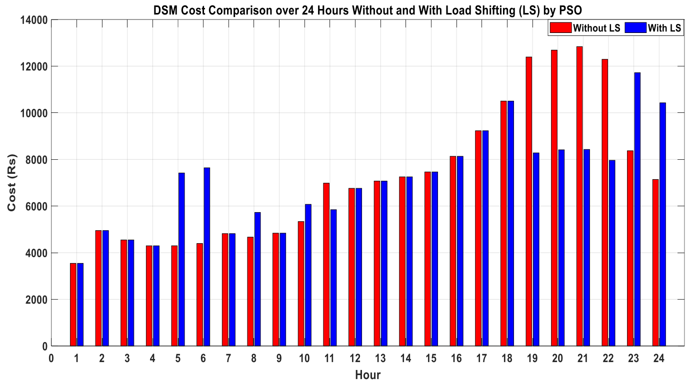

Figure 3. Hourly cost comparison with and without DSM powered with PSO

Fig. 3 uses a bar chart to compare the total hourly cost under various scenarios, focusing on cost reduction by DSM in high-cost periods (hours 19-22) by shifting loads to the renewable-surplus windows and low-cost periods with load shifting method of DSM.

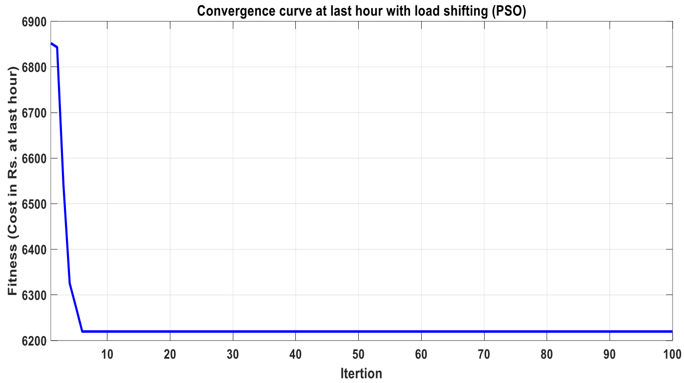

Figure 4. Convergence curve by PSO algorithm with load shifting

Fig. 4 shows slightly increased convergence time due to DSM load shifting constraints (execution time of 1.998558 sec) that introduce additional decision variables for modification of demands, exploring larger space and arriving at better solutions.

Performance measures of PSO on different scenarios is given in Table I, where the total cost for 24 hours is Rs.1,74,783.9 without DSM and 1.8167 sec as the running time (PSO algorithm and cost calculation time) compared to Rs. 1,71,316.5 for the scenario with DSM and a running time of 1.9985 sec, giving a computational overhead where the complexity of the load shift increases the running time by 10%, but the absolute saving here is of Rs. 3467.4 for 24 hours through enhanced resource utilization and DSM will result into a reasonable amount of 12,65,601 Rs. over a year.

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TABLE I
COMPARISON OF OPTIMUM COST AND SPEED BY PSO

PSO	**Total Cost in Rs. (24 Hours)**	**Time (sec)**
Without DSM	174783.9	1.816664
With DSM	171316.5	1.998558

A. Results by GWO with Load Shifting

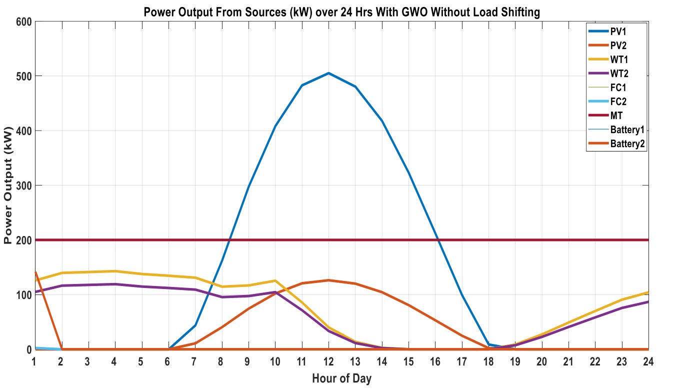

Figure 5. Power output (kW) from sources over 24-hours with GWO with load shifting

Fig. 5 illustrates the hourly power output (kW) for different generation sources and batteries over a 24-hour period with DSM by GWO. Microturbine provide a consistent base power of 200 kW, operating constantly throughout the day. PV_1 exhibits the highest variability, peaking sharply at approximately 505 kW around 12:00, dominating generation during midday (09:00 to 16:00). Conversely, the Wind Turbines (WT_1 and WT_2) generate maximum power during the night/morning hours, with WT_1 peaking near 145 kW (03:00–06:00) and WT_2 peaking near 120 kW (03:00-04:00), significantly dropping to near zero between 14:00 and 18:00. Notably, Battery 1 and Battery 2 show minimal to zero output, as they exhausted in first hour only from 80 to 20 % SOC.

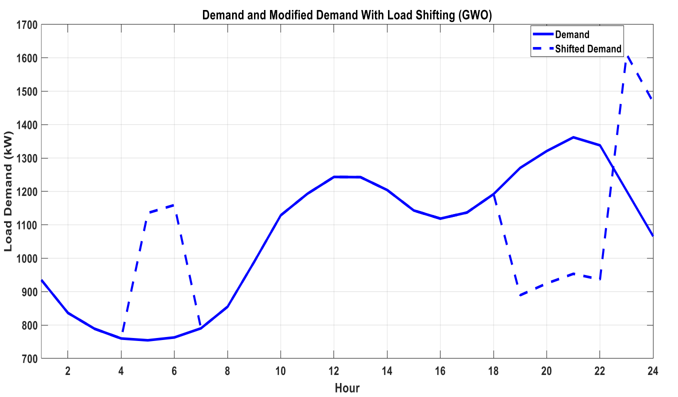

Figure 6. Demand and modified demand with load shifting (GWO)

Fig. 6 plots the original and adjusted load, registering DSM changes with demand shifted from high-cost hours to low-cost hours, registering about 15% peak reduction with intelligent distribution with no adverse impact on the overall energy provided. The shifted (modified) demand column in DSM, measuring the modified demands that make economic optimization possible, having the same total generation capacity but lowering total cost of generation.

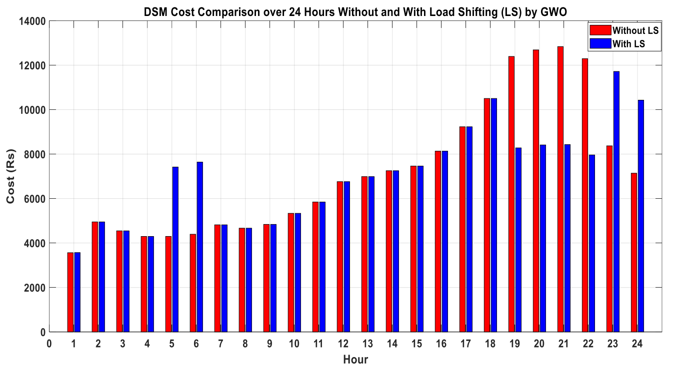

Figure 7. Hourly cost comparison with and without DSM powered with GWO

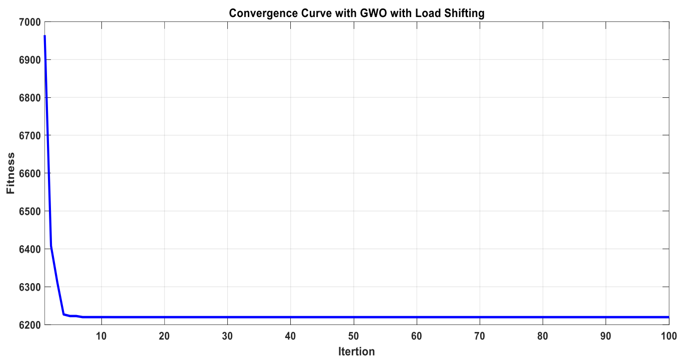

Figure 8. Convergence curve by GWO algorithm with load shifting

Fig. 8 shows slightly increased convergence time due to DSM load shifting constraints (execution time of 0.3249 sec) that introduce additional decision variables for modification of demands, exploring larger space and arriving at better solutions.

Performance measures of GWO on different scenarios is given in Table II, where the total cost for 24 hours is Rs.1,71,316 without DSM and 0.2977 sec as the running time (GWO algorithm and cost calculation time) compared to Rs. 169459 for the scenario with DSM and a running time of 0.3249 sec, giving a computational overhead where the complexity of the load shift increases the running time by 10%, but the absolute saving here is of Rs. 1857 for 24 hours through enhanced resource utilization and DSM which will result into a reasonable amount of 6,77,805 Rs. over 365 days.

TABLE II
COMPARISON OF OPTIMUM COST AND SPEED BY GWO

GWO	**Total Cost in Rs. (24 Hours)**	**Time (sec)**
Without DSM	171316 Rs. for 24 Hrs	0.2977 sec
With DSM	169459 Rs. for 24 Hrs	0.3249 sec

VI. CONCLUSIONS

DSM is becoming an important issue in smart grid operation with the aim to increase the usage efficiency of the resources while keeping the grid reliability. An overall optimization framework for DSM is addressed in terms of coordinated operation of generation, storage and load in economical way. The presented framework focuses on minimizing energy cost and improving the utilization of renewable sources, decreasing peak electricity demand and maintaining the stability of the system under diverse load and pricing scenarios. The utilization of metaheuristic optimization algorithms, specifically PSO and GWO algorithms, is assessed for addressing complicated DSM scheduling problems, with the capability to handle nonlinear objectives and numerous constraints and enabling effective utilization of distributed energy resources and EVs while considering the dynamic characteristics of renewable energy and the fluctuating nature of electricity price. It is shown that through coordinated DSM with efficient optimization algorithms, the smart grid can achieve high levels of efficiency and sustainability.

The proposed approach emphasizes 24-hour scheduling, dynamic electricity buying and selling prices, and DSM through load shifting by PSO. By shifting electricity demand to lower-cost periods, the strategy reduces overall operational costs while optimizing EV charging and discharging so that EVs function as flexible distributed energy resources, supporting both grid stability and energy storage. Integration of forecasts from renewable sources such as solar and wind maximizes clean energy utilization while reducing reliance on expensive grid power.

The total system cost is 1,74,784 Rs. for the day without DSM and 1,71,316 Rs. with optimized DSM by PSO. The system's operation is characterized by a reliance on microturbine to establish a reliable baseload, consistently supplying a total of 200 kW. Solar PV dominates midday generation, peaking at 505.09 kW at 12:00, while Wind Turbines supplement power during the night and morning, peaking around 143 kW at 04:00. The Battery system (Batt1/Batt2) is largely ineffective, rapidly discharging from an initial 80% SOC to the 20% minimum limit by hour 2 and remaining inactive thereafter, failing to mitigate peak demands. The load demand exhibits a pronounced evening peak, reaching its maximum of 1362 kW at 21:00. This peak demand, combined with the sharp decline in solar and wind generation during the evening, necessitates a maximum import of 1072 kW from the grid at the same hour. Consequently, the total cost of generation mirrors this load profile, spiking to its highest point of 12,835 Rs at 21:00, around three-fold increase from the morning minimum.

The total system cost is 1,71,316 Rs. for the day without DSM and 1,69,459 Rs. with optimized DSM by GWO. GWO execution time is very less as compared to PSO (0.3249 sec as compared to 2 sec by PSO), which makes it more suitable for real time implementation. Cost for a day with GWO is 1,69,459 Rs. Which is less as compared to 1,74,784 Rs. Per day with PSO with DSM. Yearly saving doesn't make PSO efficient because it is the cost saving on its higher base. Reduced daily cost matters most and which is obtained with GWO.

The proposed optimization work represents a significant step forward in microgrid management by combining advanced computational speed with practical energy system goals. Overall, this research contributes to the development of next-generation DSM frameworks that are cost-effective, reliable, and user-focused. By combining renewable energy integration, advanced scheduling, optimization techniques, and load-shifting strategies, the proposed approach prepares the grid to meet the challenges posed by growing electric mobility and renewable energy penetration, supporting a cleaner, smarter, and more efficient power system.

REFERENCES

[1] S. Bashash and H. K. Fathy, "Cost-Optimal Charging of Plug-In Hybrid Electric Vehicles Under Time-Varying Electricity Price Signals," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 5, pp. 1958-1968, Oct. 2014. doi: 10.1109/TITS.2014.2308283

[2] M.A. López, S. de la Torre, S. Martín, J.A. Aguado, "Demand-Side Management in Smart Grid Operation Considering Electric Vehicles Load Shifting and Vehicle-to-Grid Support," *International Journal of Electrical Power & Energy Systems*, Volume 64, Pages 689-698, ISSN 0142-0615, 2015. https://doi.org/10.1016/j.ijepes.2014.07.065

[3] C. Bharathi, D. Rekha, and V. Vijayakumar, "Genetic Algorithm Based Demand Side Management for Smart Grid," *Wireless Pers Commun* 93, pp. 481–502, 2017. https://doi.org/10.1007/s11277-017-3959-z

[4] N. Erdogan, F. Erden and M. Kisacikoglu, "A Fast and Efficient Coordinated Vehicle-to-Grid Discharging Control Scheme for Peak Shaving in Power Distribution System," in *Journal of Modern Power Systems and Clean Energy*, vol. 6, no. 3, pp. 555-566, May 2018. doi: 10.1007/s40565-017-0375-z

[5] Ren-Shiou Liu, Yu-Feng Hsu, "A Scalable and Robust Approach to Demand Side Management For Smart Grids with Uncertain Renewable Power Generation and Bi-Directional Energy Trading," *International Journal of Electrical Power & Energy Systems*, Volume 97, Pages 396-407, ISSN 0142-0615, 2018. https://doi.org/10.1016/j.ijepes.2017.11.023

[6] X. Yang, Y. Zhang, H. He, S. Ren and G. Weng, "Real-Time Demand Side Management for a Microgrid Considering Uncertainties," in *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 3401-3414, May 2019. doi:10.1109/TSG.2018.2825388

[7] Abid, S.; Alghamdi, T.A.; Haseeb, A.; Wadud, Z.; Ahmed, A.; Javaid, N., "An Economical Energy Management Strategy for Viable Microgrid Modes," *Electronics*, *8*, 1442, 2019. https://doi.org/10.3390/electronics8121442

[8] Nagata, Takeshi and Monde, Shogo, "A Multi-Agent Based Micro-Grid Operation Method Considering Charging and Discharging Strategies of Electric Vehicles," *International Journal of Smart Grid and Clean Energy*, vol. 8, no. 2, March 2019. pp. 149-155, 2019. doi: 10.12720/sgce.8.2.149-155

[9] Puttamadappa C., Parameshachari B. D., "Demand Side Management of Small Scale Loads in A Smart Grid using Glow-Worm Swarm Optimization Technique," *Microprocessors and Microsystems*, Volume 71, 102886, ISSN 0141-9331, 2019. https://doi.org/10.1016/j.micpro.2019.102886

[10] K. Prakash Kumar, B. Saravanan, "Day Ahead Scheduling of Generation and Storage in A Microgrid Considering Demand Side Management," *Journal of Energy Storage*, Volume 21, Pages 78-86, ISSN 2352-152X, 2019. https://doi.org/10.1016/j.est.2018.11.010

[11] S. Singh, P. Chauhan and N. J. Singh, "Feasibility of Grid-connected Solar-wind Hybrid System with Electric Vehicle Charging Station," *Journal of Modern Power Systems and Clean Energy*, vol. 9, no. 2, pp. 295-306, March 2021. doi: 10.35833/MPCE.2019.000081

[12] Badugu, J., Yeddula Pedda, O. & Choppavarapu, S.B., "Role of Demand Side Management in Residential Distribution Systems with the Integration of Electric Vehicles," *J. Electr. Eng. Technol.* 16, pp. 43-54, 2021. https://doi.org/10.1007/s42835-020-00566-8

[13] E. Sarker, P. Halder, M. Seyedmahmoudian, E. Jamei, B. Horan, S. Mekhilef, and A. Stojcevski, "Progress on The Demand Side Management in Smart Grid and Optimization Approaches," *Int. J. Energy Res.*, vol. 44, no. 13, pp. 11604-11632, 2020. doi: 10.1002/er.5631

[14] Duman, Hamza Salih Erden, Ömer Gönül, Önder Güler, "A Home Energy Management System with an Integrated Smart Thermostat for Demand Response in Smart Grids," *Sustainable Cities and Society*, Volume 65, 2021, 102639, ISSN 2210-6707. https://doi.org/10.1016/j.scs.2020.102639

[15] Tuo Xie, Yang Su, Gang Zhang, Kaoshe Zhang, Hua Li, Ruogu Wang, "Optimizing peak-shaving cooperation among electric vehicle charging stations: A two-tier optimal dispatch strategy considering load demand response potential," *International Journal of Electrical Power & Energy Systems*, Volume 162, 110228, ISSN 0142-0615, 2024. https://doi.org/10.1016/j.ijepes.2024.110228

[16] Swati Sharda, Mukhtiar Singh, Kapil Sharma, "Demand side management through load shifting in IoT based HEMS: Overview, challenges and opportunities," *Sustainable Cities and Society*, Volume 65, 2021, 102517, ISSN 2210-6707, 2021. https://doi.org/10.1016/j.scs.2020.102517

[17] S. Ali *et al.*, "Demand Response Program for Efficient Demand-Side Management in Smart Grid Considering Renewable Energy Sources," in *IEEE Access*, vol. 10, pp. 53832-53853, 2022. doi: 10.1109/ACCESS.2022.3174586

[18] Asmae Chakir, Meryem Abid, Mohamed Tabaa, Hanaa Hachimi, "Demand-Side Management Strategy in A Smart Home Using Electric Vehicle and Hybrid Renewable Energy System," *Energy Reports*, Volume 8, Supplement 9, Pages 383-393, ISSN 2352-4847, 2022. https://doi.org/10.1016/j.egyr.2022.07.018

[19] Sarthak Mohanty, Subhasis Panda, Shubhranshu Mohan Parida, Pravat Kumar Rout, Binod Kumar Sahu, Mohit Bajaj, Hossam M. Zawbaa, Nallapaneni Manoj Kumar, Salah Kamel, "Demand side management of electric vehicles in smart grids: A survey on strategies, challenges, modeling, and optimization," *Energy Reports*, Volume 8, Pages 12466-12490, ISSN 2352-4847, 2022. https://doi.org/10.1016/j.egyr.2022.09.023

[20] Nosratabadi, S.M., Moshizi, H.N., Guerrero, J.M., "Strategy for Demand Side Management Effectiveness Assessment via A Stochastic Risk-Based Bidding Approach in A Multi-Energy Microgrid Containing Combined Cooling, Heat and Power and Photovoltaic Units," *IET Renewable Power Gener*. 16(10), pp. 2036–2058, 2022. https://doi.org/10.1049/rpg2.12482

[21] Ghorpade Satish and Sharma Rajesh, "A Comprehensive Review of Demand-Side Management in Smart Grid Operation with Electric Vehicles," *Electrical Engineering*, 106, pp. 6495-6514, 2024. doi: 10.1007/s00202-024-02330-x

[22] Eissa, M.M., Swief, R.A.W. and Salam, T.S.A., "Demand Side Management with Electric Vehicles and Optimal Renewable Resources Integration Under System Uncertainties," *Sci Rep* 15, 18570, 2025. https://doi.org/10.1038/s41598-025-00752-6

[23] Ying Wang, Zhile Yang, Monjur Mourshed, Yuanjun Guo, Qun Niu, Xiaodong Zhu, "Demand Side Management of Plug-In Electric Vehicles and Coordinated Unit Commitment: A Novel Parallel Competitive Swarm Optimization Method," *Energy Conversion and Management*, Volume 196, pp. 935-949, ISSN 0196-8904, 2019. https://doi.org/10.1016/j.enconman.2019.06.012

[24] Seyedali Mirjalili, Seyed Mohammad Mirjalili, Andrew Lewis, "Grey Wolf Optimizer," *Advances in Engineering Software*, Volume 69, pp. 46-61, ISSN 0965-9978, 2014. https://doi.org/10.1016/j.advengsoft.2013.12.007

[25] A. Kumari and S. Tanwar, "A Reinforcement-Learning-Based Secure Demand Response Scheme for Smart Grid System," in *IEEE Internet of Things Journal*, vol. 9, no. 3, pp. 2180-2191, 1 Feb.1, 2022. doi: 10.1109/JIOT.2021.3090305