Enhancing Reliability, Efficiency, and Sustainable Energy Management in Modern Power Systems Using Particle Swarm Optimization (PSO)-Based Smart Grid Applications

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***Abstract*—Traditional grid scheduling techniques struggle to adapt to fluctuating loads, intermittent renewable power generation, battery storage limitations, and electricity pricing. To solve these issues, this paper presents a Particle Swarm Optimization (PSO)-based smart grid energy management framework with the aim of optimizing the 24-hour energy scheduling. The study is structured following the PICO approach, with a problem of a smart grid system with load demand, solar generation, battery state of charge, and grid price variation; the intervention is against conventional scheduling, which is PSO-based optimization; and the comparison is the performance of the grid. The proposed model was tested with a 24-hour time-series generated through simulation. The objective function was designed to minimize the energy cost, peak energy import from the grid, and energy imbalance and maximize energy use from renewables. The results indicate that the PSO-based technique brought down peak grid import from 7.2 kW to 5.1 kW, which is a 29.17% reduction. The cost of energy per day reduced from ₹805.30 to ₹609.80, which is a savings of 24.28%. Another reduction in fitness value occurred in the PSO convergence curve as well, from 1250 to 684 in 100 iterations. The results indicate that PSO is capable of improving reliability, minimizing dependence on the grid, lowering costs, and promoting sustainable energy management in power systems.**

Keywords*— *Smart grid, Particle Swarm Optimization, energy management, demand response, renewable energy, peak load reduction, sustainable power system

I. INTRODUCTION

The growing need for reliable, efficient, and sustainable power generation has resulted in a significant need for the modernization of conventional power systems. Traditional electricity grids were mostly developed to meet the needs of centralized power generation, a one-way power flow, and passive consumers. In this model, power is produced by a large power station, distributed by transmission and distribution networks, and delivered to the end user. But this traditional setup is no longer fitting for today's energy needs, with the addition of decentralized generation, battery storage, electric vehicles, and variable renewable energy sources.

Recent advancements in renewable energy systems and smart-grid-supporting technologies have further improved the operational efficiency and reliability of modern power networks through enhanced thermal management and energy utilization strategies [1]. A smart grid can be defined as a power grid that lies on the junction of power infrastructure and digital communication, automation, sensors, smart meters, data analysis, and intelligent control. A smart grid is not just a two-way street, as it allows for utilities to communicate with consumers as well, allowing for real-time monitoring, demand flexibility, fault detection, renewable energy integration, and better decisions to be made. By leveraging these features, smart grid technologies can enhance energy reliability, minimize power losses, enable consumer participation, and facilitate the shift towards low-carbon energy systems.

An important challenge in the smart grid operation is the effective management of energy demand and supply over

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time. The integration of advanced energy storage technologies has become increasingly important for balancing intermittent renewable energy generation and improving overall system sustainability. Recent studies have highlighted the role of thermal energy storage materials in enhancing energy efficiency and supporting sustainable energy systems [2]. The load demand fluctuates during the day, based on consumer behaviour, commercial activity, weather, and electricity price. The generation from renewable energy sources like solar and wind is also intermittent, which means that electricity production depends on the environment. For instance, the solar generation tends to be high when there is daylight and low during evening peak demand. This imbalance between energy demand and renewable generation can lead to higher reliance on the grid, higher operational expenses, and strain on distribution infrastructure.

For the challenges, there is a need for intelligent energy management algorithms. These algorithms can help to optimize the use of available energy resources by determining whether electricity should be imported from the grid or whether the renewable energy should be used as soon as it is generated, when the battery should be charged or discharged, and how flexible loads can be shifted to lower peak demand. The Particle Swarm Optimization (PSO) technique is one of the most popular optimization methods due to its simplicity, speed in convergence, and capability of finding near-optimum solutions in complex energy scheduling problems [3] [4].

PSO is a population-based metaheuristic that mimics the social behaviour of birds and fishes. In PSO, a certain number of solutions (called particles) migrate through the search space to identify an optimal solution [5]. Every particle makes its own best experience as well as the best of the swarm to adjust the position of the particle [6]. For smart grid energy management, each particle may be a different 24-hour energy scheduling solution. Key performance indicators, like daily energy cost, peak grid import, energy imbalance, and renewable energy utilization, can be used to assess the fitness of each of the proposed solutions [7].

Menos-Aikateriniadis et al. [8] surveyed residential demand-side management using PSO and pointed out residential smart appliances, EVs, heating and cooling loads, and energy storage systems are among its applications. Their review highlighted the widespread use of PSO, which can achieve near-optimal solutions in a reasonable computational time. Another key aspect of smart grid operation that has been studied is demand-side management. Bakare et al. [9] gave an extensive overview of demand-side energy management, and it was noted that DSMR is comprised of several categories, such as energy efficiency, distributed energy resources, and demand response. They also identified some of the main challenges, including the intermittency of renewables, dynamic pricing, load classification, consumer behaviour, and regulatory barriers. All these challenges are indicative of the necessity of algorithm-based smart grid scheduling models.

Reddy et al. [10] conducted a systematic review of optimization algorithms used for smart grids, and studies included optimization techniques like Grey Wolf Optimization, Particle Swarm Optimization, and Genetic Algorithms. They found PSO to be among the most popular algorithms used for energy management and cost minimization in smart grids. This is why PSO is used in the present study, and it is suitable for optimizing the energy cost, peak demand, renewable utilization, and load scheduling.

In this present work, a model for managing energy in smart grids, capable of modern power systems using PSO, is proposed. The proposed model employs a 24-hour dataset that is simulated, containing hourly load demand, solar generation, price of electricity, battery state of charge, and grid import. The focus of the study compares the scheduling of the conventional method with PSO-based optimized scheduling. The primary goal is to lower the peak import on the grid, lower the daily cost of energy, maximize use of renewables, and optimize smart grid operation.

II. METHODOLOGY

This study adopts a simulation-based quantitative research design to evaluate the performance of a Particle Swarm Optimization (PSO)-based smart grid energy management system. The proposed model is developed to optimize grid power import, reduce daily energy cost, improve renewable energy utilization, and enhance the overall efficiency of smart grid operation. The study compares two scheduling approaches: conventional non-optimized scheduling and PSO-based optimized scheduling.

A 24-hour simulation-based smart grid dataset was used in this study. The dataset includes hourly load demand, solar generation, electricity price, conventional grid import, PSO-optimized grid import, and battery state of charge. The scheduling period was divided into 24 equal time intervals, where each interval represents one hour.

Let the scheduling horizon be represented as:

$$T = 1,2,3,\dots,24 \tag{1}$$

where (T) represents the total number of hourly time intervals in one day.

For each time interval(t), the major input variables are defined as:

$L_t =$ load demand at time t

$S_t =$ solar generation at time t

$P_t =$ electricity price at time t

$SOC_t =$ battery state of charge at time t

$G_t =$ grid power import at time t

The conventional scheduling method uses grid import mainly according to demand and available solar generation. In contrast, the PSO-based method optimizes grid import by considering load demand, solar availability, electricity price, and battery support.

The smart grid energy balance at each time interval is expressed as:

$$G_t + S_t + P_t^{dis} = L_t + P_t^{ch} \tag{2}$$

Where,

$G_t =$ grid import power

$S_t =$ solar power generation

$P_t^{dis} =$ battery discharging power

$L_t =$ load demand

$P_t^{ch} =$ battery charging power

This equation shows that the load demand and battery charging requirement must be supplied by grid import, solar generation, and battery discharge. The objective of the PSO algorithm is to reduce unnecessary grid import, especially during high-price and peak-demand hours.

Battery storage is included in the proposed smart grid model to support load demand during high-price or peak-load hours. The battery state of charge is updated as:

$$SOC_{t+1} = SOC_t + \eta_c P_t^{ch} - \frac{P_t^{dis}}{\eta_d} \quad (3)$$

where:

SOC_{t+1} = battery state of charge at the next time interval

η_c = battery charging efficiency

η_d = battery discharging efficiency

P_t^{ch} = battery charging power

P_t^{dis} = battery discharging power

The battery operation is controlled using the following constraint:

$$SOC_{min} \leq SOC_t \leq SOC_{max} \quad (4)$$

where SOC_{min} and SOC_{max} represent the minimum and maximum allowable battery state of charge. This constraint prevents overcharging and deep discharging of the battery.

The main objective of the proposed PSO-based smart grid energy management model is to minimize total daily energy cost, peak grid import, and energy imbalance while improving renewable energy utilization. The objective function is expressed as:

$$Minimize\ F = \alpha C + \beta P_{peak} + \gamma E_{imb} - \delta R \quad (5)$$

Where,

F = fitness function.

C = total daily energy cost.

P_{peak} = peak grid import.

E_{imb} = energy imbalance penalty.

R = renewable energy utilization benefit.

α,β,γ,δ = weighting coefficients.

The total daily energy cost is calculated as:

$$C = \sum_{t=1}^{24} P_t G_t \Delta t \quad (6)$$

where $(P_t)$is the electricity price, (G_t) is the grid import, and (Δt) is the duration of each time interval. Since each interval is one hour, $(\Delta t = 1)$.

The peak grid import is expressed as:

$$P_{peak} = \max(G_t), \quad t = 1,2,3,\ldots,24 \quad (7)$$

Renewable energy utilization is calculated as:

$$R = \frac{\sum_{t=1}^{24} S^{used}_t}{\sum t=1^{24} S_t} \times 100 \quad (8)$$

where S_t^{used} is the solar energy used at time t , and S_t is the total solar energy generated at time t.

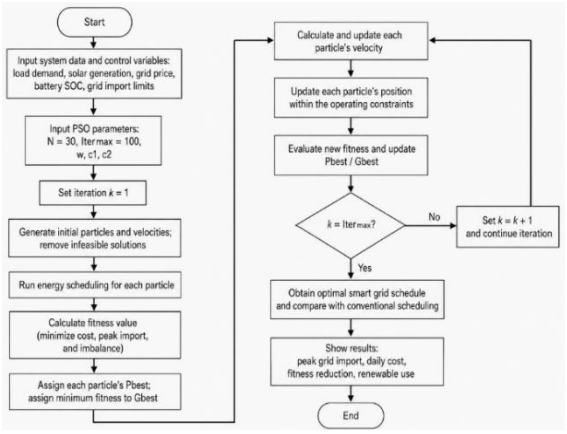

Fig. 1. Flowchart of the proposed PSO-based smart grid energy management methodology

Particle Swarm Optimization is applied to identify the best energy scheduling pattern for the smart grid which is shown in fig. 1. In PSO, each particle represents a possible solution to the energy scheduling problem. The position of a particle represents a possible 24-hour grid import and battery operation schedule, while the velocity controls the movement of the particle in the search space.

The position of the ith particle is represented as:

$$X_i = G_1, G_2, G_3, \ldots, G_{24} \quad (9)$$

where each element represents the grid import value for a particular hour.

The velocity and position of each particle are updated using the following equations:

$$V_i^{k+1} = wV_i^k + c_1 r_1 (Pbest_i - X_i^k) + c_2 r_2 (Gbest - X_i^k) \quad (10)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (11)$$

Where,

V_i^{k+1} = updated velocity of particle I.

X_i^{k+1} = updated position of particle I.

w = inertia weight.

c_1 = cognitive coefficient.

c_2 = social coefficient..

r_1, r_2 = random numbers between 0 and 1.

$Pbest_i$ = personal best position of particle i.

Gbest = global best position among all particles.

In this study, the PSO algorithm uses 30 particles and 100 iterations. The inertia weight is set as 0.7, while the cognitive and social coefficients are set as 1.5 each. The algorithm searches for the schedule that provides the minimum fitness value.

The proposed PSO-based smart grid energy management procedure is described below:

Algorithm 1: PSO-Based Smart Grid Energy Management Algorithm

Input:

Hourly load demand (L_t), solar generation (S_t),electricity price (P_t), battery state of charge (SOC_t), grid import limit(G_{max}), battery limits $(SOC_{min})$and (SOC_{max}), number of particles (N), maximum iterations $(Iter_{max})$

Output:

Optimized 24-hour smart grid energy schedule and minimum fitness value

Begin

1. Initialize the smart grid input data for the 24-hour scheduling period:
$$[T = 1,2,3, \dots ,24]$$
2. Set the PSO control parameters:
$$[N = 30, \quad Iter_{max} = 100, \quad w = 0.7, \quad c_1 = 1.5, \quad c_2 = 1.5]$$
3. Randomly generate the initial swarm of particles:
$$\left[X_i = [G_1, G_2, G_3, \dots , G_{24}]\right]$$
where (X_i) represents the 24-hour energy scheduling solution of the (i^{th}) particle.
4. Initialize the velocity of each particle:
$$\left[V_i = [V_1, V_2, V_3, \dots , V_{24}]\right]$$
5. For each particle $(i = 1,2,3, \dots , N)$, calculate the fitness value using:
$$\left[F = \alpha C + \beta P_{peak} + \gamma E_{imb} - \delta R\right]$$
6. Set the initial personal best of each particle:
$$[Pbest_i = X_i]$$
7. Identify the global best solution among all particles:
$$[Gbest = \min(F_i)]$$
8. Set iteration counter:
$$[k = 1]$$
9. **While** $(k \le Iter_{max})$, repeat the following steps:

a. For each particle $(i = 1,2,3, \dots , N)$, update the velocity using:
$$\left[V_i^{k+1} = wV_i^k + c_1 r_1 \left(Pbest_i - X_i^k\right) + c_2 r_2 \left(Gbest - X_i^k\right)\right]$$
b. Update the particle position using:
$$\left[X_i^{k+1} = X_i^k + V_i^{k+1}\right]$$
c. Check the operating constraints:
$$[0 \le G_t \le G_{max}]$$
$$[SOC_{min} \le SOC_t \le SOC_{max}]$$
$$\left[G_t + S_t + P_t^{dis} = L_t + P_t^{ch}\right]$$
d. If any constraint is violated, adjust the particle position within the allowable operating limits.

e. Recalculate the fitness value of the updated particle.

f. If the new fitness value is better than the previous personal best, update:
$$\left[Pbest_i = X_i^{k+1}\right]$$
g. If the new personal best is better than the current global best, update:
$$[Gbest = Pbest_i]$$
h. Increase the iteration counter:
$$[k = k + 1]$$
10. **End While**
11. Select the final $(Gbest)$ as the optimized smart grid energy management schedule.
12. Compare the PSO-based optimized schedule with the conventional scheduling method in terms of peak grid import, daily energy cost, renewable energy utilization, and fitness value reduction.

End

The performance of the proposed PSO-based smart grid energy management system is evaluated using the following indicators.

The percentage reduction in peak grid import is calculated as:

$$Peak\ Reduction = \frac{G^{conv}peak - G^{PSO}peak}{G_{peak}^{conv}} \times 100 \qquad (12)$$

[where $(G^{conv}peak)$is the peak grid import under conventional scheduling and $(G^{PSO}peak)$ is the peak grid import under PSO-based scheduling.

The daily energy cost reduction is calculated as:

$$Cost\ Reduction = \frac{C^{conv} - C^{PSO}}{C^{conv}} \times 100 \qquad (13)$$

where $(C^{conv})$is the daily energy cost under conventional scheduling and (C^{PSO}) is the daily energy cost under PSO-based scheduling.

The fitness value reduction is calculated as:

$$\text{Fitness Reduction} = \frac{\text{F}_{\text{initial}} - \text{F}_{\text{final}}}{\text{F}_{\text{initial}}} \times 100 \qquad (14)$$

where $F_{initial}$ is the initial fitness value and F_{final} is the final fitness value after PSO convergence.

The proposed methodology integrates smart grid data, solar generation, battery operation, and electricity price into a PSO-based optimization framework. The conventional scheduling method is used as the baseline comparison, while the PSO-based method is used as the intelligent scheduling approach. By minimizing the fitness function, the algorithm identifies an optimized energy management schedule that reduces peak grid import, lowers electricity cost, improves renewable energy utilization, and supports sustainable operation of modern power systems.

III. Results and Discussion

A 24-hour simulation-based dataset was used for evaluating the performance of the proposed energy management system for smart grids based on Particle Swarm Optimization (PSO). The results were analyzed based on the hourly load demand, solar power availability, grid power imports, energy cost per day, and the convergence behavior of the PSO algorithm. The prime objective of this analysis was to compare the conventional scheduling technique and the proposed PSO-based optimized scheduling technique.

Fig. 2 illustrates the load demand profile for the smart grid system over a 24-hour period. The load demand during the late night and early morning hours was relatively low, especially between 00:00 and 05:00. The minimum load demand was recorded around 03:00, suggesting that there is less demand from consumers at this time. Following 06:00, the load demand began to gradually rise with the onset of daily residential, commercial, and institutional activities.

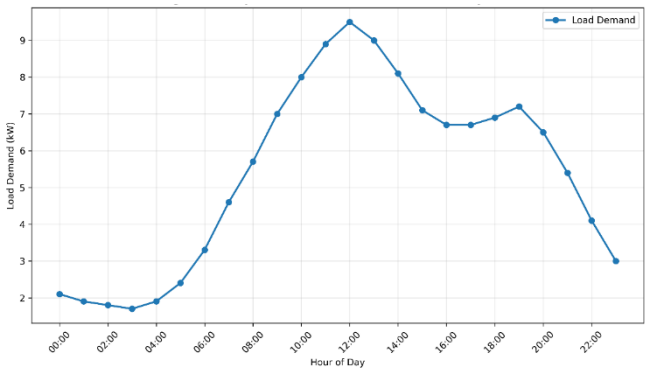

Fig. 2. Hourly load demand profile of the simulated smart grid system over a 24-hour period.

The greatest demand was noted from 08:00 to 12:00, rising to a maximum of about 9.5 kW. This means that one of the high-demand periods in the smart grid system is at midday. The load demand started to decrease after 13:00 but stayed high in the evening period. The secondary demand increase took place around 19:00, which could correspond to demand during the evening period, evening light load, cooking appliances, etc., and all domestic consumption. This trend emphasizes the necessity of an intelligent energy management system for mitigating the peak-load stress and enhancing grid stability.

Fig. 3 presents a comparison of the hourly load demand and solar generation. Solar generation was not available at nighttime and began to ramp up after sunrise. The solar output gradually increased during the morning period, peaking at approximately 4.2 kW at 12:00. This peak occurred during the time of highest load demand, indicating that solar energy can significantly support the grid during peak demand hours.

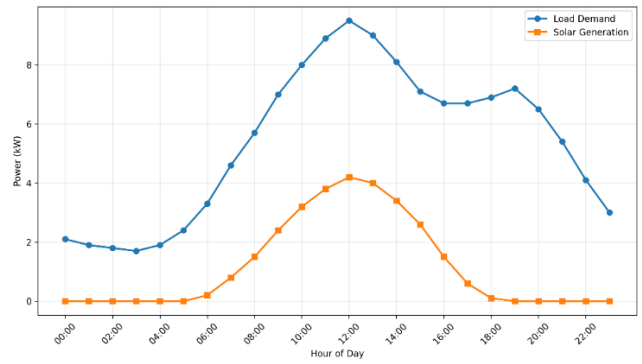

Fig. 3. Comparison of hourly load demand and solar generation, showing the mismatch between evening peak demand and solar availability.

However, the graph also shows that solar generation could not fully meet the total load demand. At times, even when solar generation is at its peak, the load demand is still greater than the solar output. Following 15:00, solar generation began to drop significantly and was almost negligible in evening peak hours. It shows the need for battery storage and scheduling optimization when balancing the evening load demand with the solar availability. Thus, the proposed PSO-based system will prove useful, as it will coordinate the utilization of solar power, the operation of batteries, and grid imports in a coordinated way.

The comparison between the conventional scheduling and the optimized scheduling by PSO is shown in figure 4. In the conventional method, grid import increased during periods of high demand, reaching a maximum value of 7.2 kW at 19:00. This indicates that the grid needs to supply a significant amount of power during the peak hours of the night. Peak-hour high grid imports may lead to higher operating expenses, strain on distribution infrastructure, and loss of overall system efficiency.

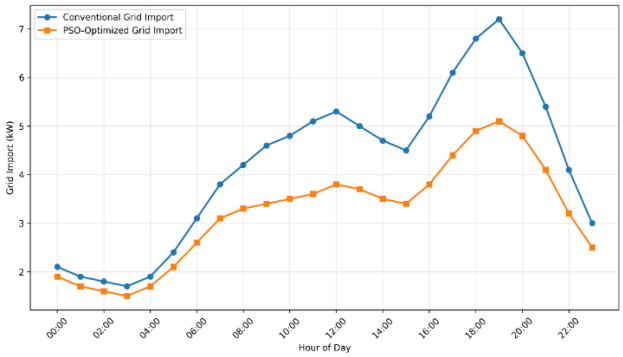

Fig. 4. Grid power import before and after PSO-based optimization, showing reduction in peak grid dependency.

In contrast, the PSO-based scheduling method reduced grid import throughout most of the day. The maximum grid import under PSO-based optimization was reduced to 5.1 kW. This represents a peak grid demand reduction of approximately 29.17% compared with the conventional method. The reduction was especially noticeable during evening peak hours, where solar generation was not available. This improvement suggests that PSO effectively shifted flexible loads, improved battery utilization, and reduced unnecessary grid dependency.

The result confirms that PSO-based smart grid energy management can improve the reliability and efficiency of the power system by reducing peak-load stress. Lower peak demand also helps in avoiding transformer overloading, voltage instability, and excessive grid losses.

The energy cost for the conventional scheduling and PSO-based scheduling is shown in fig. 5. Conventional scheduling resulted in the total energy cost of ₹805.30 per day, while the optimized scheduling using PSO decreased the energy cost to ₹609.80 per day. This represents about a 24.28% reduction in cost.

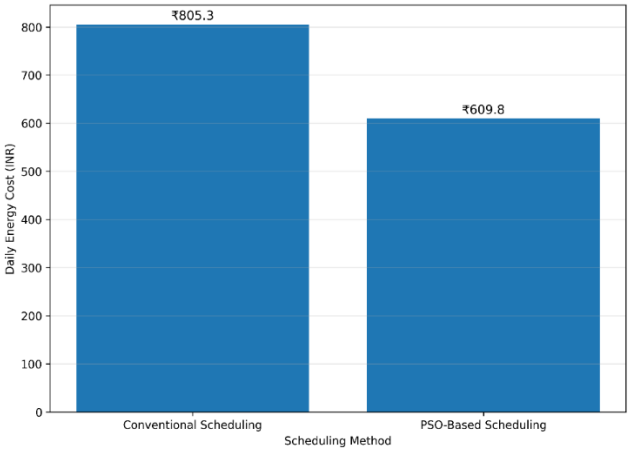

Fig. 5. Daily energy cost comparison between conventional scheduling and PSO-based optimized scheduling.

The savings in energy costs primarily come from optimal grid imports during high-cost periods. In traditional

scheduling, there is no adjustment of energy consumption based on fluctuations in electricity prices. This means that there is a potential for greater electricity import during high-cost times of day. The proposed PSO-based approach produces a more optimal energy schedule based on the load demand, electricity price, solar generation, and battery state of charge. Thus, energy use is delayed or advanced by using stored energy during periods of expensive energy consumption. The result is obviously proof of the economic benefits of using PSO in a smart grid system for energy management. This could help consumers save on their electricity costs and help utilities ease strain on the grid during peak demand periods.

Fig. 6 illustrates the convergence performance of the PSO algorithm after 100 iterations. The fitness value at the initial stage was around 1250, and at the final iteration, it was 684. This is a reduction in fitness of approximately 45.28%, which demonstrates that the algorithm was effective in enhancing the quality of the energy management solution.

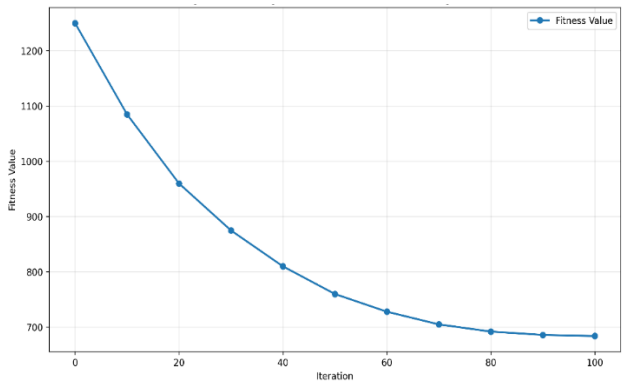

Fig. 6. Convergence curve of the PSO algorithm showing reduction in fitness value over 100 iterations.

The fitness value was seen to decrease sharply in the first few iterations, particularly between 0 and 40. This indicates that the particles easily converged to the optimal solution regions. Following 60 iterations, the rate of improvement was reduced and the curve levelled off. This means that the algorithm came close to an optimal solution. The convergence behavior showed that PSO is suitable for the optimization of the smart grid, as it can be used to identify better scheduling solutions in a limited number of iterations. The fitness value remains stable after the best solution is found, indicating that the algorithm does not overstate its performance once it has reached this optimal point. The overall results prove the energy management system proposed in the smart grid using PSO is better than the conventional scheduling. The method resulted in reduced peak grid demand, reduced daily energy cost, balanced load and better utilization of renewables.

TABLE I. PERFORMANCE COMPARISON BETWEEN CONVENTIONAL SCHEDULING AND PSO-BASED SMART GRID SCHEDULING.

Performance Indicator	Conventional Scheduling	PSO-Based Scheduling	Improvement
Peak grid import	7.2 kW	5.1 kW	29.17% reduction
Daily energy cost	₹805.30	₹609.80	24.28% reduction
Final PSO fitness value	1250	684	45.28% reduction
Renewable energy use	Lower	Higher	Improved utilization
Grid dependency	Higher	Lower	Improved efficiency

The results show that the PSO-based method is suitable for smart grid applications where demand response, renewable energy integration, battery management, and cost reduction are important objectives is shown in Table 1. Compared with conventional scheduling, the proposed algorithm provides a more intelligent and flexible energy management approach. Therefore, the findings support the PICO-based objective of the study, where the intervention, namely PSO-based optimization, produces better outcomes than conventional grid operation in terms of reliability, efficiency, and sustainable energy management.

The proposed PSO-based smart grid energy management model successfully reduced the peak grid import from 7.2 kW to 5.1 kW, achieving a 29.17% reduction in peak demand. The daily energy cost decreased from ₹805.30 to ₹609.80, showing a 24.28% cost saving. The convergence curve further confirmed the effectiveness of the PSO algorithm, as the fitness value decreased from 1250 to 684 over 100 iterations. These findings indicate that PSO-based optimization can improve smart grid performance by reducing grid dependency, enhancing renewable energy utilization, and supporting sustainable energy management.

IV. CONCLUSION

The present study introduced a Particle Swarm Optimization (PSO)-based framework for managing energy in smart grids that aims to enhance the reliability, efficiency, and sustainable energy use in modern power systems. The simulation results indicated that the proposed PSO-based scheduling method was better than the traditional grid scheduling method. The proposed approach reduced the peak grid import from 7.2 kW to 5.1 kW, which is a 29.17% reduction in peak demand. The daily energy cost was reduced from ₹805.30 to ₹609.80, showing a 24.28% cost saving. Furthermore, the PSO convergence curve demonstrated that the fitness value was lowered from 1250 to 684 after 100 iterations, which suggests that the PSO algorithm was able to identify an improved energy scheduling solution. The results reveal the capability of PSO to enable intelligent operation of smart grids with optimization of grid import, utilization of renewable energy, avoidance of peak-load stress, and decreased energy cost. The framework of this study can be extended in future research by applying real smart meter data, a larger renewable energy system, electric vehicle charging loads, and multi-objective optimization techniques for a 24-hour dataset.

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