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Intelligent Load Management System Development with Renewable Energy for Demand Side Management

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Abstract

Electric smart grid reliability and stability could be increased by the application of demand response initiatives and renewable energy resources. This study provides a brand new demand side management paradigm for smart grids with renewable energy integration that is based on intelligent optimisation. The suggested system combines real-time demand response programmes from electric utility companies and makes use of fuzzy logic to forecast consumer energy consumption patterns. Using demand response programmes, a smart energy management controller adjusts consumer energy usage forecasts to produce an operation schedule. Using simulations employing real-world data, we assess the efficacy of the suggested intelligent demand side management framework. According to the findings, compared to the load management-free method, total electricity costs and carbon emissions have significantly decreased. A potential strategy for demand side management with the integration of renewable energy, the proposed intelligent hybrid optimisation method of load management achieves superior performance in regulating energy consumption, peak loads, and carbon emissions. By presenting a useful and effective paradigm for demand-side management with renewable energy integration, this research makes a contribution to the field of energy management.

Keywords: load management system, demand side management, demand response, renewable energy integration, hybrid optimization

1. Introduction

Our energy needs are rising quickly as a result of population growth and advanced technologies. Presently, fossil fuels are used extensively in the production of power, and in the India, electricity production is responsible for 44% of all greenhouse emissions (Akhtar et al., 2021). Researchers are looking for renewable energy sources to replace conventional power plants that predominantly use fossil fuels in order to limit emissions of greenhouse gases that cause global warming (O. Siddiqui et al., 2022). The installation of numerous RES, however, raises the

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possibility of power system instability or energy waste. The need to upgrade traditional electricity networks to smart grids (SG) is necessary to address these issues and effectively manage the renewables(Bashir et al., 2021).

Electric utility companies (EUCs) and consumers can take an active role in the power market thanks to a smart grid, which is an intelligent electricity network. The objective is to provide consumers with a reliable, secure, and inexpensive source of electricity while preserving the stability of the power system. The smart grid includes a variety of devices, including energy storage systems, smart home appliances, smart meters, and renewable energy sources (RES). Modern management methods are used by the smart grid to control power plants, transmission systems, and distribution networks (Paul et al., 2020). It has an advanced monitoring infrastructure (AMI) that gathers and shares information with consumers and EUCs on energy demand, supply, and pricing. By using the least amount of energy necessary in accordance with the pricing information provided by AMI, users can lower their electricity bills thanks to the smart grid's two-way information transmission capabilities. On the other hand, by modifying the timing of power generation, EUCs can achieve the best demand-side management (DSM) and lowest generation costs (Paul et al., 2022a; Sarwar & Siddiqui, 2016a).

Recent literature has developed a number of demand-side management (DSM) solutions to assist consumers in reducing their energy use by incorporating RES or running their loads off-peak. The heat storage capabilities of thermostatic devices and energy storage systems (ESS) coupled with photovoltaic (PV) panels were taken into account by the authors in (Golmohamadi et al., 2019). To lower the cost of thermal appliances, they provided a heuristic forward-backward algorithm. To stop power system peaks, they suggested a peak flattening method (Paul et al., 2022b). The importance of optimal energy algorithms in enhancing EUC performance, attaining consumer energy savings, and promoting environmental advantages was covered by the authors in (Hubert & Grijalva, 2011). They suggested using evolutionary algorithms (GAs) to solve these challenges in two stages, minimizing both electricity costs and customer discomfort. The first step of optimisation focuses on lowering power costs, while the second stage builds on the first stage optimisation without raising the price of electricity that is purchased (Kong et al., 2020).

The authors of (Lim et al., 2020) took into account the situation of residential consumers who had integrated ESS and PV to address energy management issues. By arranging the use of various appliances, they presented an algorithm to reduce electricity bills and the peak-to-average ratio (PAR). The authors of (Cheng et al., 2020)involved customers from both residential and commercial locations in order to address scheduling issues with electricity usage. By incorporating RES and electric vehicles, they devised the particle swarm optimisation (PSO) algorithm to lower peak-to-average ratio and electricity costs (EVs)(Kirmani et al., 2023). In (Sharifi & Maghouli, 2019), the authors looked at peak-to-average ratio and electricity cost saving while also maximizing user comfort. They blended inclining block rate (IBR) tariff with real-time pricing (RTP) to reduce high power use during cheap periods and boost PAR. Similar to this, in (Cheng et al., 2020), the authors integrated artificial intelligence to the system architecture, offering different energy-saving options based on prior experience. They also added a user feedback link to offer tailored services for energy conservation. Similarly, to increase efficiency, the authors presented an upgraded version of the automation system for commercial apartments in (Aurangzeb & Alhussein, 2020). With the help of this technology, users can keep an eye on, manage, and pinpoint their potential for energy savings (Prashant et al., 2022; Sarwar & Siddiqui, 2015).

The suggested system combines intrinsic models with genetic algorithm (GA) and particle swarm optimisation (PSO) optimisation algorithms to solve DSM problems. It is anticipated that combining these two strategies will offer a more efficient way to address numerous goals at once, including lowering carbon emissions while reducing peak energy use, user discomfort, and electricity costs (Sarwar & Siddiqui, 2016b; A. S. Siddiqui & Prashant, 2022). The proposed hybrid optimisation algorithm's hybridization method combines the advantages of PSO optimisation and genetic algorithms to overcome their respective weaknesses and provide superior outcomes (D. Ali et al., 2021; Md. S. Ali et al., 2023). By offering a more all-encompassing approach to DSM in SG, the suggested framework is anticipated to address the shortcomings of the existing literature. By offering a more practical and comprehensive solution to the DSM issue, our work intends to support the development of sustainable and effective energy management systems.

To sum up, the proposed DSM framework employs an integrated strategy that combines several aspects such a forecasting model, distributed energy resources, price signals, and a hybrid optimisation algorithm to reduce electricity costs, carbon emissions, peak-to average ratio, and enhance user comfort. In order to increase flexibility and involvement in demand response programmes, the framework also contains a classification of consumer loads. The suggested hybrid GA-PSO optimisation method performs better than other intrinsic optimisation techniques, according to simulation results.

This paper is discussed as follows. The introduction along with literature review is given in section 1. The architecture of the proposed DSM model is given in section 2. The proposed hybrid optimization technique is described in section 3 and the results of the work are given in section 4. The conclusion is given in section 5 followed by references at the end.

2. Architecture of proposed model

In this section, we present the suggested system model for a smart power grid (SPG), which, as shown in Figure 1, consists of an energy management controller (EMC) for monitoring and managing all activities, distributed generation (DGs), various types of loads in smart homes, and a fuzzy logic-based forecaster. All communication messages between smart appliances and the EMC must be securely transmitted through the wireless communication infrastructure in order to guarantee secure energy management and delivery.

The suggested system model is a comprehensive framework that combines a model of household energy demand, a model of energy supply made up of RES and the power grid, and a model of load scheduling to fulfil consumer energy needs (Ahmad et al., 2023). A fuzzy logic-based forecaster is trained using historical load and DR data to forecast real-time pricing and power usage patterns of consumers. The fuzzy logic learning based forecaster was chosen because it can manage consumers' uneven behavior.

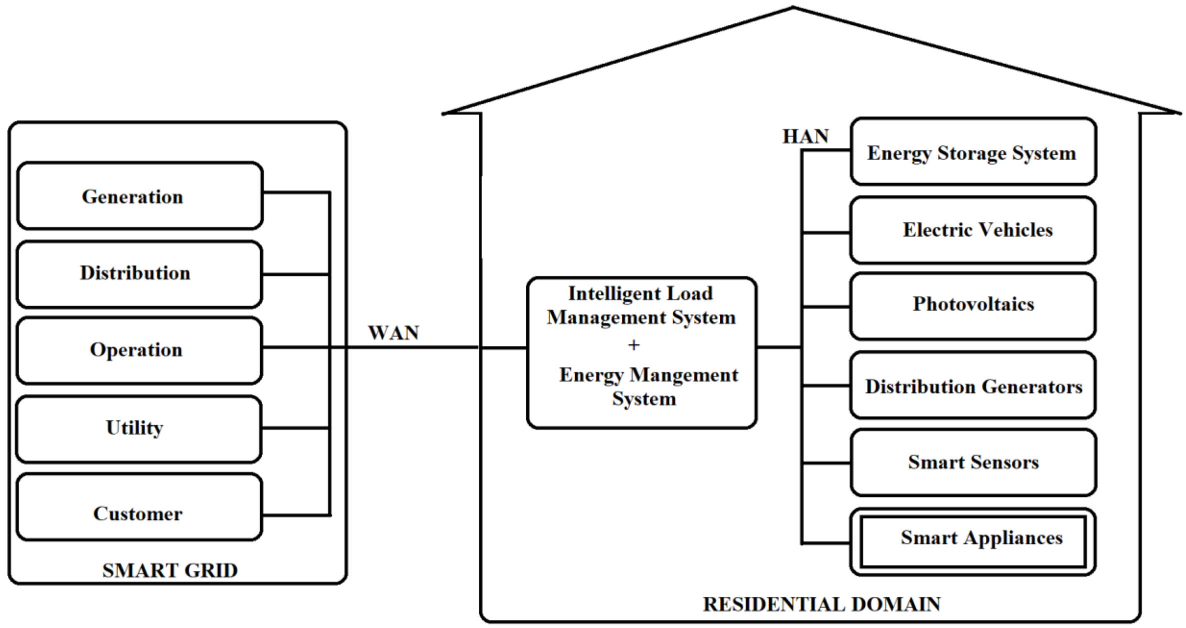

Figure 1. Architecture of proposed intelligent load management system model

The consumer appliances have been divided into categories in the following section based on factors including power rating, environmental factors, and customer preferences.

2.1. Non schedulable appliances

These devices cannot be controlled, and their need can be met immediately, regardless of the cost factor. These appliances' combined total power usage is listed as follows in eq. 1.

$$\tau_v^t = \sum_{t=1}^{T} \sum_{q \epsilon Q} (\rho_{qc}(t) x_{qc}(t)) \tag{1}$$

Where C is the total number of fixed appliances q_1, q_2, q_3, q_4 etc. Each appliance's power rating for a specific time period is denoted by the symbol q_c.

This is subject to the constraint of upper and lower power consumption limit given in eq. 2.

$$\tau_v^{min} \leq \tau_v^t \leq \tau_v^{max} \tag{2}$$

2.2. Schedulable appliances

Shiftable or schedulable appliances are those that can be scheduled to run on a specific schedule. To reduce electricity costs and PAR, such appliances' timing and power usage can be controlled. Based on these attributes, these appliances are divided into three classes i.e., rechargeable, interruptible, and uninterruptible devices. The respective power consumption equations of these kinds of devices are given as under in eq. 3, eq. 4 and eq.5.

$$\tau_w^t = \sum_{t=1}^{T} \sum_{W_r \epsilon W} (\lambda W_R(t) \rho W_r(t) x W_r(t)) \tag{3}$$

$$\tau_\phi^t = \sum_{t=1}^{T} \sum_{L_m \epsilon L_M} \lambda L_m (\rho L_m(t) x L_m(t)) \tag{4}$$

$$\tau_s^t = \sum_{t=1}^{T} \sum_{S_r \epsilon S_R} (\rho_{qc}(t) x_{qc}(t)) \tag{5}$$

2.3. Photovoltaic sources

Photovoltaic energy is widely available, cheap to produce, and available to all customers. In order to reduce electricity costs, PAR, and carbon emissions, solar energy is taken into account in this study as a source of power for homes and power grids. The formula shown in eq. 6 can be used to calculate the solar energy system's output power.

$$P^{pv}(t) = \eta^{pv} \times A^{pv} \times Irr.(t) \times (1 - 0.005(tem(t) - 25)) \tag{6}$$

A bi-modal distribution, which is a linear blend function of two uni-modal distributions, is typically used to represent the distribution of solar irradiation throughout an hour. Probability density function is used to model the uni-modal distribution, as indicated in eq. 7.

$$F(Irr.(t)) = \omega \left(\frac{\psi 1}{\lambda 1}\right) \left(\frac{Irr.(t)}{\lambda 1}\right)^{\left(\psi 1 - 1)^{e^{-\left(\frac{Irr.(t)}{\lambda 1}\right)^{\psi 1}}}\right)} + \omega \left(\frac{\psi 2}{\lambda 2}\right) \left(\frac{Irr.(t)}{\lambda 2}\right)^{\left(\psi 2 - 1)^{e^{-\left(\frac{Irr.(t)}{\lambda 2}\right)^{\psi 2}}}\right)} \tag{7}$$

2.4. Energy Storage Systems

Batteries are employed in this study as Energy Storage Systems (ESS) to store excess solar energy during off-peak hours or when the battery charge level falls below a predetermined lower cut-off. The following eq. 8 is a model for the storage equation.

$$SE(t) = SE(t-1) + k.\eta^{ESS}.ES^{ch}(t) - k.\frac{ES^{dis}(t)}{\eta^{ESS}} \tag{8}$$

2.5. Energy cost

The price of energy per unit, which fluctuates with respect to time interval t, is calculated in this section. To determine the price of energy, a Real-Time Pricing (RTP) tariff is employed. The following eq. 9 is used to determine the hourly energy cost.

$$\zeta(T) = \sum_{t=1}^{T} (\tau_F^t(T) + \tau_v^t(T)) \times EP(t) \tag{9}$$

2.6. Peak to average ratio

The ratio of the maximum power consumed by the customer at a given moment to the average power consumed throughout the scheduled time is known as the peak-to-average ratio. It demonstrates the causal link between consumer peak energy use and the EUC peak power plants (Electricity Utility Company). Indicating a more consistent and predictable energy demand, a lower peak-to-average ratio value enables EUCs to run fewer peak power plants, resulting in a more constant supply of electricity for consumers. With the use of eq.10 the peak-to-average ratio for N consumers may be determined.

$$\delta(T) = \frac{max\left(E_{total}(t)\right)}{\frac{1}{T}\sum_{t=1}^{N}\left(\sum_{t=1}^{N} E_{total}(t)\right)} \tag{10}$$

2.8. Greenhouse emissions

The greenhouse emissions from electricity consumption are shown in eq.11. Where EP_{avg} and m stand for, respectively, the average monthly energy consumption, the price per kWh and the electricity emission factor is considered as per standards, and the number of months annually.

$$\theta(t) = \frac{EP_{avg}}{\eta \times \gamma \times m} \tag{11}$$

2.9. Comfort of consumer

In this study, the comfort of user is connected to the price of electricity and the delay in an appliance's operation over the planned time frame. Actually, UC may be measured in terms of waiting time, which refers to how long a user must wait until an appliance turns on. The user must run their appliances in accordance with the timetable established by the suggested strategy in order to receive cheaper electricity costs. This is expressed mathematically as in eq. 12.

$$User\ delay = \frac{EP_{avg}}{\eta \times \gamma \times m} \tag{12}$$

2.10. Objective function of the optimization problem

The objective function, represented by eq. 13 is shown below. The objective function focuses on minimizing the cost of energy, lowering peak-to-average ratio, and following the restrictions listed in eqs. 14 to 20. Following is the objective function.

$$min \sum_{t=1}^{T} \left(\zeta(t) + \delta(t) + \theta(t)\right) \tag{13}$$

$$\tau_v^t(t) + \tau_F^t(t) = E(t) + ESS(t) + \phi(t) \tag{14}$$

$$E(t) = P^{pv}(t) \tag{15}$$

$$\sum_{a=1}^{n} \eta = LOT(a) \tag{16}$$

$$\sum_{a=1}^{n} \alpha \leq \eta \leq \beta \tag{17}$$

$$ESS_{max} > ESS_{max} > 0 \tag{18}$$

$$K_c > Irr(t) > 0 \tag{19}$$

$$KI > \phi_I \tag{20}$$

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3. Proposed Hybrid GA-PSO Algorithm

The use of intelligent techniques is one of the key elements in solving various engineering challenges. These methods seek to specify a function's or a task's features in order to produce the best results within the available constraints. They make it possible to cut costs and increase production capacity. While simple optimisation issues can be solved using conventional analytical methods, many problems may be more complex and contain elements like noise that present techniques cannot properly handle.

Minimizing the chance of early convergence in local minima is one potential tactic for enhancing the efficiency of the traditional particle swarm technique. This can be done by modifying a few particles using the genetic algorithm's mutation and crossover operators(Paul et al., 2023b). The state of each individual swarm particle should be taken into account by these operators because it has a big impact on the optimisation process. The performance of the particle swarm technique can be improved by including genetic algorithm operators(Paul et al., 2023a).

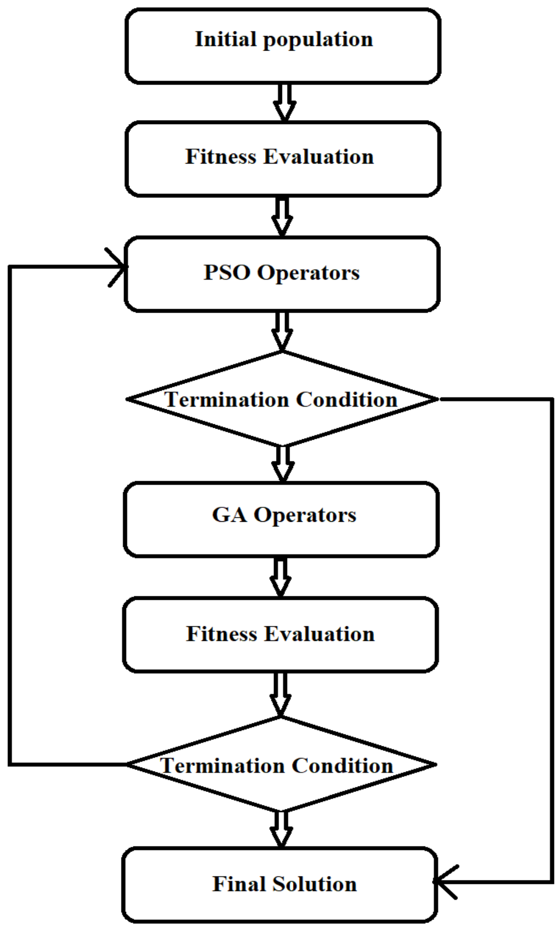

Figure 2. Flow chart of proposed hybrid GA-PSO optimization technique

The suggested strategy combines GA and PSO techniques, maximizing each method's advantages. A baseline population of particles is created in the first phase, and as needed, the algorithm is used to modify the placements and velocities of the particles. The number of times the genetic algorithm crossover and mutation operations are applied is determined by $[p_e . N]$, where N is the size of the PSO swarms (N = size of swarms $S(t)$), and $P_e \epsilon [0,1]$ is the number of times the GA's influence on the search phase is felt. The GA operators change their choice of the particle during the competition from the swarm S to the particle with the best practical individual solution, $\Delta P(t)$. The solution $S(t)$ obtained by the GA operators is then added to the provisional population $CH(t)$. Using the i value, the paternal particle $P_i(t)$ of O_i. is located. The provisional population and the PSO algorithm's swarm $S(t)$ are then combined, with the merging operation being a key component of the methodology suggested. The suggested fuzzy-based intelligent hybrid GA-PSO algorithm's flowchart is depicted in Figure 2.

The impact factor, which has a major impact on the convergence of the algorithmic process, heavily influences the choice of genetic operators. However, finding the best value can be difficult and is frequently problem specific. The procedure can also be improved by making changes as it is being carried out. The genetic algorithm operators should have a negligible impact on how new and better solutions are discovered via particle swarm optimisation in later iterations. The efficiency of the genetic algorithm operators must be improved when the particle swarm optimisation procedure is finished. This can aid in rerouting the search in a new route that might produce better outcomes. If the programme is stuck in a local optimum, the search can also be stopped.

Our research suggests using a multiple input, single output neuro-fuzzy system to control the impact factor and reduce the objective function. Information can be saved in understandable IF-THEN fuzzy system rules by employing a neural fuzzy system. The properties of these regulations can be specified by a specialist or swiftly identified by artificial intelligence techniques.

The size of ΔP_e, is determined by the neural fuzzy framework, which can change how much of an impact the genetic algorithm has on how the suggested hybrid algorithm finds the best feasible outcome. Based on the current P_e value and the normalised effectiveness of the genetic algorithms to the particle swarm optimisation method, the intelligent fuzzy network decides what to do. Larger values of ΔE_{GA} suggest that genetic algorithm operators can produce solutions that are more efficient than PSO. This circumstance may be a sign that particle swarm optimisation is stuck in a local minimum or has achieved a deadlock if it continues after multiple rounds. The value of ΔE_{GA} is given by the equation below.

$$\Delta EN_{GA} = {\Delta E'}_{GA} \Big/ \left({\Delta E'}_{PSO} + {\Delta E'}_{GA}\right) \tag{21}$$

Where:

$$E'_{GA} = \sum_{t'=t-w_0}^{t} \Delta E_{GA}(t') \Big/ \sum_{t'=t-w_0}^{t} |CH(t')| \tag{22}$$

$$E'_{PSO} = \sum_{t'=t-w_0}^{t} \Delta E_{PSO}(t') \Big/ \sum_{t'=t-w_0}^{t} N \tag{23}$$

$$E_{GA(t')} = \sum_{j=1}^{|CH(t')|} \begin{cases} f\left(g(t') - f(o_j)\right) iff\left(g(t')\right) > f(o_j) \\ 0 \ otherwise \end{cases} \tag{24}$$

$$E_{PSO(t')} = \sum_{i=1}^{N} \begin{cases} f(g(t') - f(x_i(t')) iff\left(g(t')\right) > f(x_i(t') \\ 0 \ otherwise \end{cases} \tag{25}$$

$$\Delta EN_{PSO} = \Delta E'_{PSO} \Big/ (\Delta E'_{GA} + \Delta E'_{PSO}) \tag{26}$$

The ΔE_{GA} metric is a complement to the ΔE_{PSO} efficiency number and using any of these values has no impact on the method's precision or efficacy. The p_e component is modified based on the e estimate produced by the fuzzy logic method using the provided equation.

$$p_e = p_e + \Delta p_e = p_e + FS(\Delta EN_{GA}, p_e) \tag{27}$$

The results from the surveillance window or the final w_m repetitions of the loop function in the suggested technique are taken into consideration to calculate $\Delta E'_{PSO}$ and $\Delta E'_{GA}$ in order to ensure computational efficiency and reliability. To see how adjustments to the p_e variable affect the process of finding optimal solutions, this variable is also changed no more frequently than once every w_m iteration.

4. Results and discussion

The proposed hybrid GA-PSO optimization technique is used to apply the intelligent load management system in the smart grid. We have considered the integration of renewable resources in non-islanding mode and also the energy storage system is considered. The load has various kinds of appliances connected to the grid as discussed earlier. The simulations are carried out in Matlab 2021.

Figure 3 shows the different overall energy costs in dollars at different hours of the day. It can be seen that the energy costs are much higher when no load management system is applied and once the proposed method is applied, the total hourly electricity costs fall dramatically as evident from the plot. The same is quantitatively tabulated in Table 1, which gives statistical comparison of the proposed approach with the one without the load management.

The equivalent greenhouse emission energy costs in dollars at different hours of the day are again given in Figure 4. The price per kWh and the electricity emission factor is considered as per standards, and the number of months annually. The greenhouse emission energy costs are much higher when no load management system is applied and once the proposed method is applied, the total hourly electricity costs also decrease significantly as apparent from the plot. This again is quantitatively tabulated in Table 1, which gives us the comparison of the proposed approach with the one without the load management.

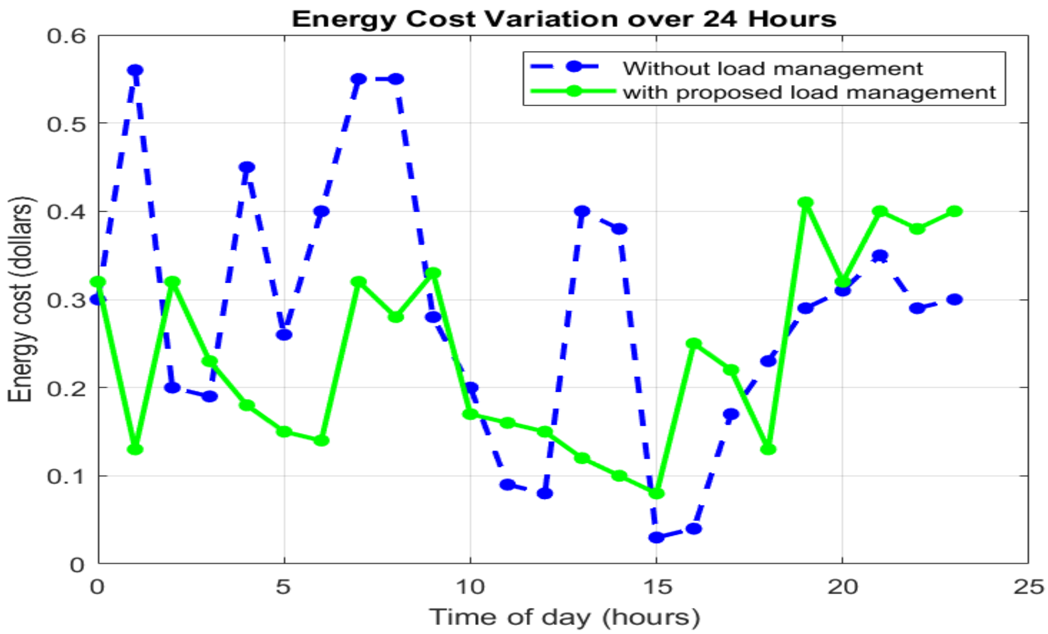

Figure 3. Energy cost ($) variation over 24 hours of the day

Table 1. Energy cost ($) variation over 24 hours of the day

Time (h)	Without load management	With proposed load management
0	0.30	0.32
1	0.56	0.13
2	0.20	0.32
3	0.19	0.23
4	0.45	0.18
5	0.26	0.15
6	0.40	0.14
7	0.55	0.32
8	0.55	0.28
9	0.28	0.33
10	0.20	0.17
11	0.09	0.16
12	0.08	0.15
13	0.40	0.12
14	0.38	0.10
15	0.03	0.08
16	0.04	0.25
17	0.17	0.22
18	0.23	0.13
19	0.29	0.41
20	0.31	0.32
21	0.35	0.40
22	0.29	0.38
23	0.30	0.40

Table 2. Equivalent greenhouse emission energy cost ($) variation over 24 hours of the day

Time (h)	Without load management	With proposed load management
0	1.25	1.05
1	1.28	1.08
2	1.36	1.16
3	1.28	1.18
4	1.22	1.02
5	1.26	1.06
6	0.82	0.62
7	0.50	0.35
8	0.49	0.34
9	0.52	0.37
10	0.70	0.55
11	0.72	0.52
12	0.75	0.55
13	0.76	0.56
14	0.82	0.67
15	1.30	1.15
16	1.42	1.22
17	1.39	1.19
18	1.29	1.09
19	1.43	1.23
20	1.42	1.22
21	1.40	1.20
22	1.35	1.15
23	1.30	1.10

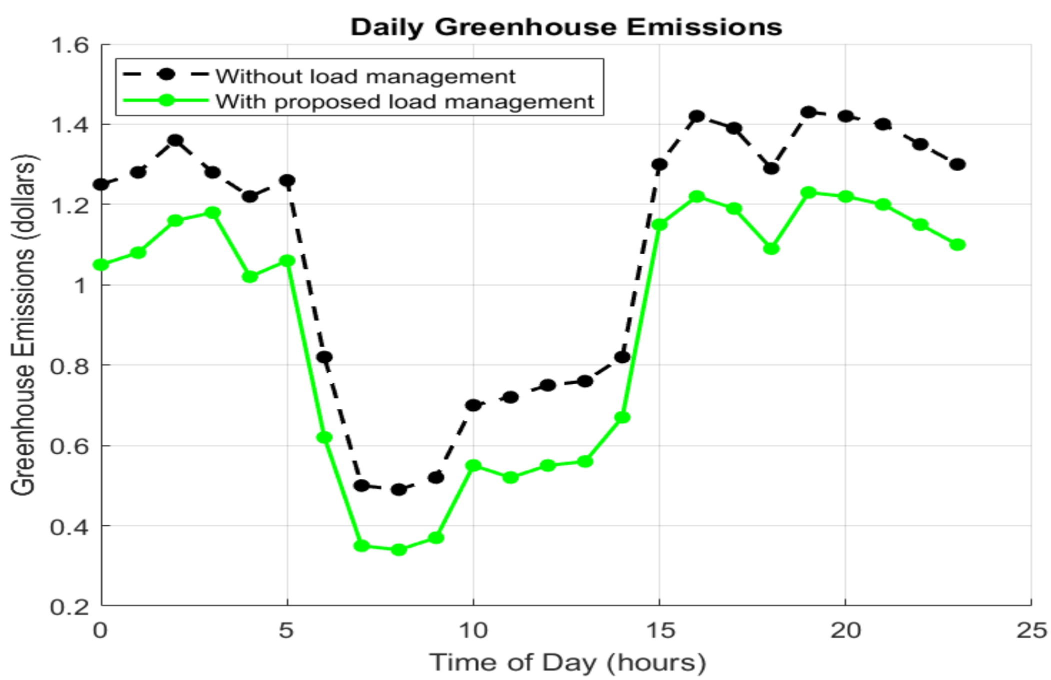

Figure 4. Equivalent greenhouse emission energy cost ($) variation over 24 hours of the day

Thus, the application of the proposed hybrid GA-PSO optimization technique for the intelligent load management system not only reduces various kinds of energy costs but also makes the overall system very efficient. At the same time, the whole smart grid becomes interactive with the possibilities of various demand response programs, giving the consumers a choice to be a part of the system. The reliability of the grid also increases, and energy security is ensured.

5. Conclusion

This paper proposes a novel intelligent optimisation-based demand-side management paradigm for smart grids with renewable energy integration. The proposed system uses fuzzy logic to estimate consumer energy usage patterns and incorporates real-time demand response programmes from electric utility companies. A smart energy management controller modifies consumer energy usage projections using demand response programmes to create an operation schedule. It has been demonstrated that the suggested hybrid GA-PSO optimisation technique for intelligent load management in the smart grid greatly lowers energy costs and increases system efficiency. The suggested approach ensures the smart grid is interactive and dependable while also giving customers a choice to participate in the system through various demand response programmes by integrating renewable resources and energy storage systems. The quantitative findings reported in this research show how the suggested strategy is effective at lowering energy expenses associated with greenhouse gas emissions as well as electricity bills.

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