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Heuristic-based optimization for smart home energy management with renewable integration and energy storage systems

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ABSTRACT

The rapid growth of energy demand in urban areas emphasizes the necessity of efficient demand-side management (DSM) strategies in smart homes. This study presents a heuristic-based optimization framework for appliance scheduling in smart home environments that incorporates renewable and sustainable energy resources (RSERs) and energy storage systems (ESSs). The objective is to minimize the electricity cost and the peak-to-average ratio (PAR) while satisfying the user comfort constraints. Three optimization techniques, genetic algorithm (GA), binary particle swarm optimization (BPSO), and wind-driven optimization (WDO), are implemented and evaluated in three scenarios: without renewable integration, with RSERs, and with both RSERs and ESSs. Simulation results show that BPSO has the lowest electricity cost and carbon emissions, while WDO has a faster convergence speed and competitive performance in PAR reduction. RSER and ESS integration has a major positive impact on energy efficiency, grid dependence, and sustainability. The results give useful insights to choose appropriate optimization methods and contribute to the development of effective, sustainable, and user-centric smart home energy management systems.

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1. INTRODUCTION

Rapid urbanization in some areas has caused an increase in the demand for energy management systems in residential buildings. Smart homes (SHs) with smart metering infrastructure, smart controllers, and automated appliances are key elements of modern demand side management (DSM) programs. These systems are able to perform dynamic load control using real-time electricity pricing, demand response (DR) signals, and local energy availability [1]-[5]. In addition, the incorporation of renewable and sustainable energy resources (RSERs) such as solar photovoltaic (PV) systems with energy storage systems (ESSs) enhances the capability of households to decrease grid dependency, operational costs, and carbon emissions [6]-[8].

However, efficient appliance scheduling in smart homes is still a challenging task due to the stochastic nature of renewable generation, time-varying electricity tariffs, and user comfort constraints. The scheduling problem is inherently nonlinear, combinatorial, and multi-objective, so traditional optimization techniques are not sufficient to find optimal solutions in a reasonable computational time [9]-[12]. Moreover, DSM strategies are limited in effectiveness by poor scheduling, which can lead to high peak demand, increased electricity cost, and user discomfort [13]-[14].

Heuristic and meta-heuristic optimization techniques have been widely adopted to overcome these challenges, due to their flexibility and ability to solve complex optimization problems. Genetic algorithm (GA) and particle swarm optimization (PSO) based methods have been proved effective in reducing the electricity cost and peak-to-average ratio (PAR) in residential energy systems [15]-[18]. For example, Junior *et al.* [10] and Bharathi *et al*. [9] reported remarkable improvements in load scheduling using GA based approaches. Likewise, the effectiveness of PSO and binary particle swarm optimization (BPSO) for discrete appliance scheduling problems was demonstrated by Menos-Aikateriniadis *et al.* [3]. Recently, wind-driven optimization (WDO) and some other advanced heuristic techniques have been studied for their enhanced convergence characteristics and robustness under dynamic conditions [19]-[23].

However, a lot of the research that has already been done focuses mostly on simplified system models or single-algorithm implementations. Renewable integration, storage systems, and user comfort criteria are frequently overlooked or oversimplified. The requirement for updated and thorough comparative assessments is further highlighted by the fact that previous methods [24]-[28] are not adaptable to contemporary smart grid setups.

Despite substantial advancements, there are still a number of research gaps. First, there aren't many unified frameworks that assess various heuristic optimization methods in a methodical manner under the same operating conditions. Second, not enough research has been done on how RSERs and ESSs together affect DSM performance in various progressive integration settings [29]-[31]. Third, the actual applicability of many studies is limited by their inadequate modeling of user comfort, delay tolerance, and environmental impact. Lastly, the capacity to determine the best optimization method for practical smart home applications is limited by the lack of thorough comparison analysis.

This study creates a thorough heuristic-based DSM framework for smart home energy management in order to fill in these gaps. The following are this work's main contributions:

- The creation of a multi-objective optimization approach to reduce PAR and electricity costs while preserving user comfort.
- Three heuristic approaches are implemented and evaluated in comparison: WDO, BPSO, and GA.
- Three realistic scenarios are analyzed for system performance: i) without RSER/ESS, ii) with RSERs, and iii) with both RSERs and ESSs.
- The incorporation of many performance measures, including user discomfort, carbon emissions, PAR, and power cost.
- Examining each algorithm's convergence behavior and optimization effectiveness under the same constraints.

The suggested framework offers a methodical and useful way to maximize energy use in smart homes. This work enhances environmental sustainability, lowers peak demand, and improves energy efficiency by combining advanced heuristic optimization approaches with renewable energy sources and storage systems [26]-[30]. Researchers and practitioners can choose appropriate optimization algorithms for DSM applications with the help of the comparative insights gained from this work. The results also encourage the creation of intelligent, scalable, and user-focused energy management solutions for smart grid scenarios in the future.

2. METHODOLOGY FOR HEURISTIC-BASED APPLIANCE SCHEDULING IN SMART HOMES

In order to control smart home energy under DSM, this study uses a simulation-based multi-objective optimization approach. Subject to user comfort limits, the goal is to schedule household appliances as efficiently as possible while minimizing electricity costs and PAR. Under the same operating conditions, three heuristic optimization methods are implemented and assessed: BPSO, WDO, and GA. The ESSs, renewable and RSERs on system performance are evaluated using a scenario-based methodology.

Three heuristic optimization techniques (HOTs) are used to successfully address this optimization problem: BPSO, WDO, and GA. To find near-optimal schedules, each method encodes the appliance scheduling matrix, iteratively assesses the fitness function, and performs selection, mutation, or velocity updates. WDO uses pressure and velocity dynamics to replicate atmospheric particle movement, BPSO mimics social movement patterns, and GA mimics biological evolution. These algorithms were selected because they can solve multi-objective, nonlinear, and constrained optimization problems that are common in smart home energy scheduling. To guarantee a fair comparison, all procedures are carried out under the same appliance restrictions and energy supply conditions.

Lastly, the effect of RSER and ESS integration is evaluated by testing the performance of GA, BPSO, and WDO in three different situations. Renewable energy and storage are not used in scenario 1; renewable energy is used in scenario 2; and both renewable energy and ESS are used in scenario 3. For every scenario, metrics including electricity cost, PAR, user pain, and carbon emissions are calculated. Plotting the results shows how well the algorithm performs, how it converges, and how it gets better with time from scenario 1 to scenario 3. As illustrated in Figure 1, this methodological approach shows how integrating renewable energy sources with heuristic optimization improves the sustainability and energy efficiency of smart homes.

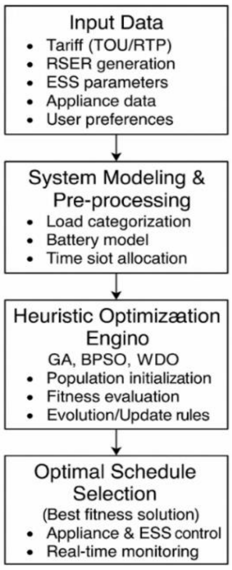

Figure 1. Heuristic-based appliance scheduling in smart homes

2.1. Genetic algorithm (GA)

The genetic algorithm begins by randomly generating an initial population of appliance schedules. Each chromosome represents one feasible schedule. The objective function evaluates each chromosome according to electricity cost, PAR, user comfort, and emissions. Tournament selection is used to identify the fittest individuals. Multi-point crossover and adaptive mutation generate new offspring. The evolutionary process continues until the maximum number of generations is reached or convergence is achieved.

2.2. Binary particle swarm optimization (BPSO)

The traditional PSO algorithm is extended to binary search spaces by BPSO. Each particle represents a potential schedule and uses a sigmoid transfer function in conjunction with a velocity update rule to update its position. The velocity update can be written as (1):

$$\mathrm{v}_i^{t+1} = wv_i^t + c_1 r_1 + (pbest_i + x_i^t) + c_2 r_2 (gbest - x_i^t) \quad (1)$$

and the sigmoid function as shown in (2).

$$s(v) = \frac{1}{1+e^{-v}} \quad (2)$$

2.3. Wind-driven optimization (WDO)

WDO simulates atmospheric motion, in which solution particles are subject to Coriolis influences, pressure, and gravity. Strong global search capabilities are made possible by this physics-based behavior, which enhances energy optimization by effectively reducing cost, PAR, and carbon emissions.

$$v_{new} = (1-\alpha)v_{current} - g \cdot x_{current} + RT \cdot \left|1 - \frac{1}{i}\right| \cdot (x_{best} - x_{current}) + \frac{c \cdot v_{other}^{dim}}{i} \quad (3)$$

3. PERFORMANCE METRICS

3.1. Cost saving

The household's overall cost for grid energy usage throughout the scheduling horizon is assessed by the electricity cost metric. This measure accurately captures the optimization algorithm's financial performance as well as its capacity to take advantage of low-cost times and renewable energy sources.

$$C = \sum_{t=1}^{T}\left(P_{grid}(t) \cdot \Delta t \cdot \rho(t)\right) \quad (4)$$

$$\text{cost Saving} = \frac{C_{base}-C_{algo}}{C_{base}} \times 100\% \quad (5)$$

3.2. PAR reduction

The algorithm's ability to reduce peak electricity demand in relation to average usage is measured by PAR reduction. Smoother load distribution is indicated by lower PAR values, which lessen grid stress and improve overall system stability and efficiency. The PAR is defined as (6) and (7).

$$PAR = \frac{\max_{t\in T}(P_{total}(t))}{\frac{1}{T}\sum_{t=1}^{T} P_{total}(t)} \quad (6)$$

$$\text{PAR Reduction}=\frac{Par_{base}-Par_{algo}}{Par_{base}}*100 \quad (7)$$

3.3. Emission reduction

The amount by which carbon emissions are reduced following optimization is measured by this statistic. Greater reduction percentages demonstrate the smart home energy management system's efficient utilization of renewable energy, decreased reliance on the grid, and enhanced environmental sustainability. The total carbon emissions are calculated as:

$$E = \sum_{t=1}^{T}\left(P_{grid}(t) \cdot \Delta t \cdot \epsilon\right) \quad (8)$$

$$\text{Emission Reduction}=\frac{E_{base}-E_{algo}}{E_{base}}*100 \quad (9)$$

4. PERFORMANCE COMPARISON OF GA, BPSO, AND WDO FOR SMART HOME ENERGY OPTIMIZATION

Three optimization strategies are contrasted in the table according to cost, PAR, emissions, and execution time. WDO operates at the fastest rate, whereas BPSO achieves the lowest cost and emissions. As Table 1 illustrates, GA and WDO exhibit the same cost and PAR, suggesting similar optimization behavior under these circumstances.

Table 1. Performance comparison of GA, BPSO, and WDO

Sl.no	Algorithm (algo)	Cost	PAR	Emissions	Time (s)
1	GA	2.22	4.378	15.34	7.20
2	BPSO	2.20	4.451	15.09	7.65
3	WDO	2.22	4.378	15.34	6.21

5. RESULTS AND DISCUSSION

5.1. Convergence curve comparison

During appliance scheduling, the convergence curve assesses how well the optimization algorithms (GA, BPSO, and WDO) approach ideal solutions. The fitness function's variation over iterations is shown in Figure 2. The fitness value of all three algorithms shows a steady declining trend, indicating that they are capable of successfully resolving the multi-objective DSM issue. Because of its physics-based approach, which guarantees a better balance between exploration and exploitation, WDO exhibits the fastest convergence among them, attaining stability in fewer iterations. GA, on the other hand, converges more slowly because its stochastic crossover and mutation procedures may postpone convergence while increasing search diversity. BPSO performs moderately and benefits from swarm intelligence, although, as Figure 2 illustrates, it occasionally has premature convergence.

5.2. Metric comparison of GA, BPSO and WDO

Four important performance parameters for the three optimization algorithms are compared in this bar graph: power cost, peak-to-average ratio (PAR), emissions, and user discomfort. Plotting these numbers side by side makes it easy to see which approach offers better scheduling and more energy savings. The display makes it easy to compare algorithm capabilities and illustrates trade-offs across metrics. As seen in Figure 3, this study is crucial for choosing the best heuristic optimization technique for demand-side control and smart home energy management.

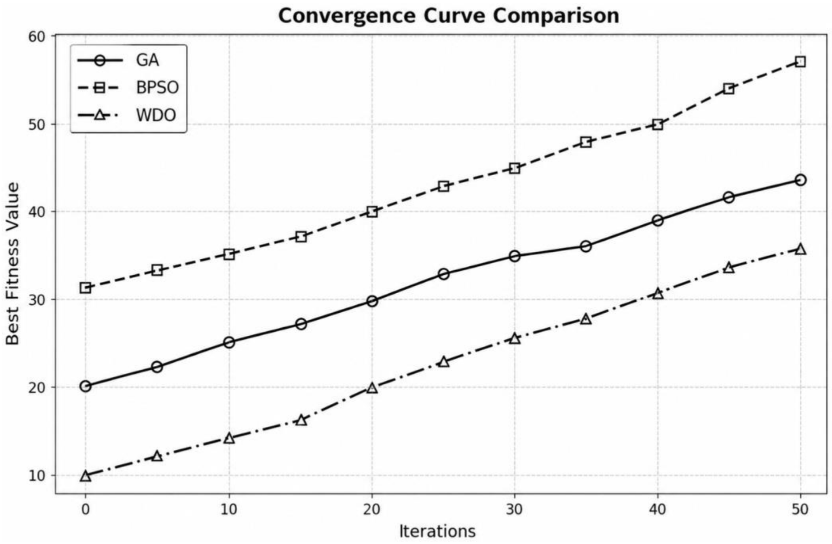

Figure 2. Convergence curve comparison

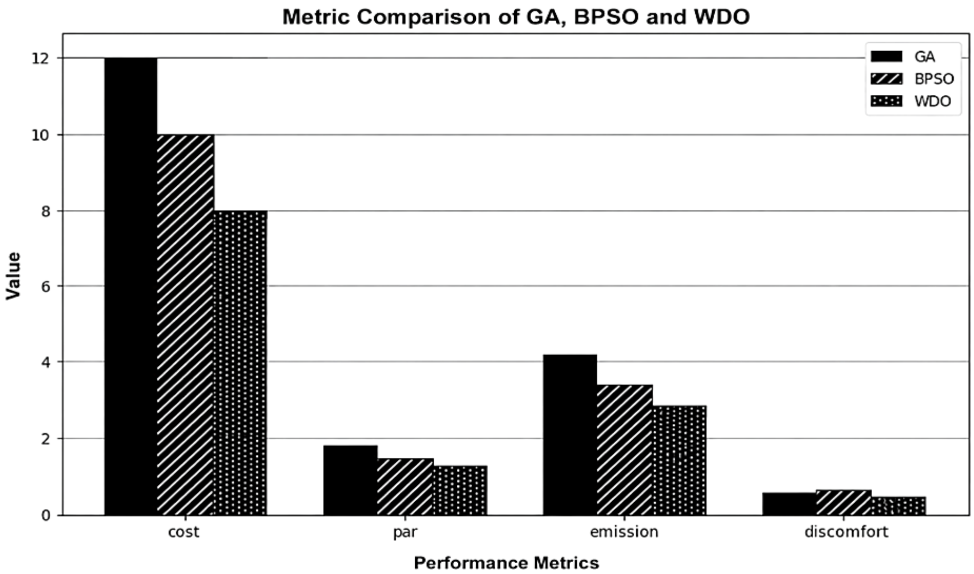

Figure 3. Metric comparison of GA, BPSO, and WDO

5.3. Grid vs solar energy

The fluctuation of solar PV generation and grid energy usage over a 24-hour period is shown in Figure 4. The findings demonstrate that solar energy makes a substantial contribution during the day, lowering dependency on the grid. A significant amount of the load is provided by renewable energy during peak sunlight hours, which lowers power prices and emissions. However, the system relies on grid power at night or at times when solar generation is minimal, highlighting the necessity of energy storage systems (ESSs) to increase energy availability and autonomy. Optimized appliance scheduling and solar integration work together to reduce peak demand and smooth the load profile.

During appliance scheduling, the convergence curve contrasts the speed and efficiency with which GA, BPSO, and WDO arrive at ideal solutions. The graph displays algorithm stability, search efficiency, and improvement trends by charting the optimal fitness value over iterations. A more effective optimization strategy is indicated by faster convergence. The optimization behavior and performance consistency of each heuristic technique are highlighted in this visualization, which aids in determining which algorithm reduces cost, PAR, emissions, and discomfort the best.

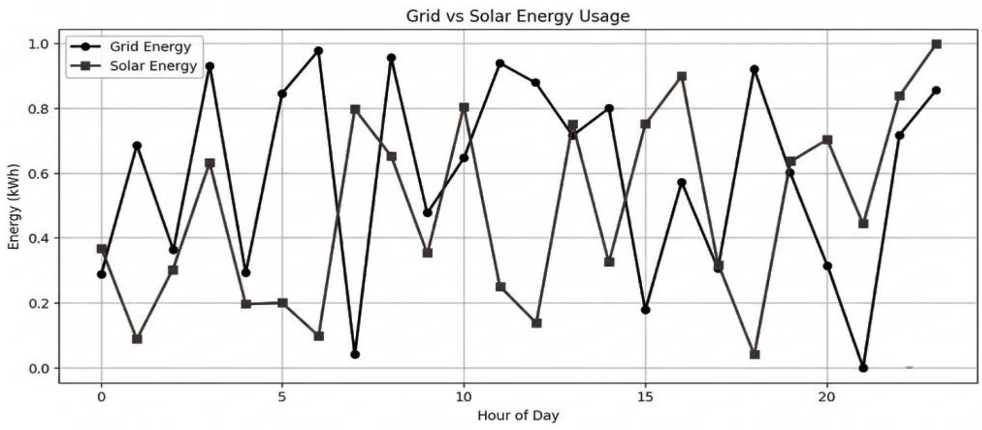

Figure 4. Grid vs solar energy usage

6. CONCLUSION

All three heuristic algorithms (GA, BPSO, and WDO) progressively lower the fitness value over iterations, demonstrating successful optimization, according to the convergence study. WDO has better exploration and exploitation capabilities for appliance scheduling, converging more quickly and reaching a lower fitness value. This pattern is further supported by the metric comparison, which shows that WDO has the lowest electricity cost, PAR, emissions, and user discomfort, followed by BPSO and GA. These results imply that WDO offers a more effective and balanced optimization performance for energy management in smart homes. The load shifting curve, where the optimized load profile shows fewer peaks and a smoother distribution throughout the day, demonstrates the efficacy of DSM. This change reduces energy costs under time-of-use pricing and lessens the strain on the grid. Lastly, the solar versus grid energy graph shows that renewable energy makes a substantial contribution during the day, lowering reliance on the grid and promoting sustainable operation. In general, heuristic optimization combined with renewable energy improves cost effectiveness, lowers peak demand, and improves environmental performance in smart homes.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests, personal relationships, or professional associations that could have influenced the work reported in this paper. No political, religious, ideological, academic, or intellectual conflicts are associated with this manuscript. The authors state that there is no conflict of interest.

DATA AVAILABILITY

Raw data is not publicly available due to privacy or institutional restrictions.

REFERENCES

[1] N. Javaid *et al.*, "A hybrid genetic wind driven heuristic optimization algorithm for demand side management in smart grid," *Energies*, vol. 10, no. 3, p. 319, Mar. 2017, doi: 10.3390/en10030319.

[2] H. Alghamdi, L.-G. Hua, G. Hafeez, S. Murawwat, I. Bouazzi, and B. Alghamdi, "Optimal adaptive heuristic algorithm based energy optimization with flexible loads using demand response in smart grid," *PLOS ONE*, vol. 19, no. 11, p. e0307228, Nov. 2024, doi: 10.1371/journal.pone.0307228.

[3] C. Menos-Aikateriniadis, I. Lamprinos, and P. S. Georgilakis, "Particle swarm optimization in residential demand-side management: A review on scheduling and control algorithms for demand response provision," *Energies*, vol. 15, no. 6, p. 2211, Mar. 2022, doi: 10.3390/en15062211.

[4] J. Agneessens, T. Vandoorn, B. Meersman, and L. Vandevelde, "The use of binary particle swarm optimization to obtain a demand side management system," in *IET Conference on Renewable Power Generation (RPG 2011)*, 2011, pp. P32–P32. doi: 10.1049/cp.2011.0228.

[5] N. Tutkun, A. Burgio, M. Jasinski, Z. Leonowicz, and E. Jasinska, "Intelligent scheduling of smart home appliances based on demand response considering the cost and peak-to-average ratio in residential homes," *Energies*, vol. 14, no. 24, p. 8510, Dec. 2021, doi: 10.3390/en14248510.

[6] G. R. Hemanth, S. Charles Raja, J. J. D. Nesamalar, and J. S. Kumar, "Cost effective energy consumption in a residential building by implementing demand side management in the presence of different classes of power loads," *Advances in Building Energy Research*, vol. 16, no. 2, pp. 145–170, Mar. 2022, doi: 10.1080/17512549.2020.1752799.

[7] C. Balasubramanian and R. L. R. Singh, "IoT-based energy management in smart grid under price based demand response based on hybrid FHO-RERNN approach," *Applied Energy*, vol. 361, p. 122851, May 2024, doi: 10.1016/j.apenergy.2024.122851.

[8] L. C. S. Junior *et al.*, "Demand-side management optimization using genetic algorithms: a case study," *Energies*, vol. 17, no. 6, p. 1463, Mar. 2024, doi: 10.3390/en17061463.

[9] C. Bharathi, D. Rekha, and V. Vijayakumar, "Genetic algorithm based demand side management for smart grid," *Wireless Personal Communications*, vol. 93, no. 2, pp. 481–502, Mar. 2017, doi: 10.1007/s11277-017-3959-z.

[10] Q. Zhu, Y. Li, and J. Song, "DSM and optimization of multihop smart grid based on genetic algorithm," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–10, Jun. 2022, doi: 10.1155/2022/5354326.

[11] L. Kong, X. Li, and H. Hayati, "Smart home energy management optimization: An amended sparrow search algorithm for enhanced grid stability and cost efficiency," *Energy*, vol. 330, p. 136944, Sep. 2025, doi: 10.1016/j.energy.2025.136944.

[12] M. Anzar, R. Iqra, A. Kousar, S. Ejaz, M. S. Alvarez-Alvarado, and A. K. Zafar, "Optimization of home energy management system in smart grid for effective demand side management," *Proceedings of 2017 International Renewable and Sustainable Energy Conference, IRSEC 2017*, 2018, doi: 10.1109/IRSEC.2017.8477255.

[13] S. Aznavi, P. Fajri, and A. Asrari, "Smart home energy management considering real-time energy pricing of plug-in electric vehicles," *2018 IEEE Energy Conversion Congress and Exposition, ECCE 2018*, pp. 67–72, 2018, doi: 10.1109/ECCE.2018.8557363.

[14] M. I. El-Afifi, B. E. Sedhom, A. A. Eladl, M. Elgamal, and P. Siano, "Demand side management strategy for smart building using multi-objective hybrid optimization technique," *Results in Engineering*, vol. 22, 2024, doi: 10.1016/j.rineng.2024.102265.

[15] H. Youssef, S. Kamel, and M. H. Hassan, "Meta-heuristic-based home energy management system for optimizing smart appliance scheduling and electricity cost reduction in residential complexes," *Neural Computing and Applications*, vol. 36, no. 36, pp. 23077–23102, Dec. 2024, doi: 10.1007/s00521-024-10275-2.

[16] Z. Mahmood *et al.*, "Efficient scheduling of home energy management controller (HEMC) using heuristic optimization techniques," *Sustainability*, vol. 15, no. 2, p. 1378, Jan. 2023, doi: 10.3390/su15021378.

[17] B. H. Jasim, A. M. J. Al-Aaragee, A. A. A. Alawsi, and A. M. Dakhil, "A heuristic optimization approach for the scheduling home appliances," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 3, pp. 1256–1266, 2023, doi: 10.11591/eei.v12i3.3989.

[18] S. M. Daragmeh, A. T. Karlsen, and I. A. Hameed, "Heuristic techniques for reducing energy consumption of household," *Proceedings - European Council for Modelling and Simulation, ECMS*, vol. 2022-May, pp. 254–261, 2022, doi: 10.7148/2022-0254.

[19] M. S. Bakare, A. Abdulkarim, M. Zeeshan, and A. N. Shuaibu, "A comprehensive overview on demand side energy management towards smart grids: challenges, solutions, and future direction," *Energy Informatics*, vol. 6, no. 1, p. 4, Mar. 2023, doi: 10.1186/s42162-023-00262-7.

[20] S. Balasubramaniyan, P. Duraipandy, N. Kalyani, P. Shanmugaraja, D. Shobana, and M. Vimala, "Comparison of recurrent neural network model for future electric power prediction," in *2022 Sixth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*, Nov. 2022, pp. 728–733. doi: 10.1109/I-SMAC55078.2022.9986504.

[21] E. Shirazi and S. Jadid, "Optimal residential appliance scheduling under dynamic pricing scheme via HEMDAS," *Energy and Buildings*, vol. 93, pp. 40–49, Apr. 2015, doi: 10.1016/j.enbuild.2015.01.061.

[22] T. Tagesse, S. Arulkumar, A. Saravanan, C. Vibhakar, D. Shobana, and A. Chokkalingam, "AI-enhanced intelligent control systems for electric vehicles," in *2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM)*, Apr. 2024, pp. 1–6, doi: 10.1109/ICONSTEM60960.2024.10568584.

[23] L. Yu *et al.*, "Deep reinforcement learning for smart home energy management," *IEEE Internet of Things Journal*, vol. 7, no. 4, pp. 2751–2762, Apr. 2020, doi: 10.1109/JIOT.2019.2957289.

[24] Y. Wang, L. Han, X. Deng, and H. Gao, "Optimization scheduling of household integrated energy systems for improving thermal comfort with low cost," *Energy and Buildings*, vol. 329, p. 115229, Feb. 2025, doi: 10.1016/j.enbuild.2024.115229.

[25] J. Han, Y. Fang, Y. Li, E. Du, and N. Zhang, "Optimal planning of multi-microgrid system with shared energy storage based on capacity leasing and energy sharing," *IEEE Transactions on Smart Grid*, vol. 16, no. 1, pp. 16–31, Jan. 2025, doi: 10.1109/TSG.2024.3452064.

[26] N. Alasker, A. Khasawneh, and E. Radwan, "Energy optimization in smart homes through AI-driven systems," in *2025 International Conference on Business Intelligence for Technology Innovation (ICBITI)*, 2025, pp. 1–7. doi: 10.1109/ICBITI65527.2025.11501066.

[27] A. A. Adebiyi and M. Habyarimana, "Systematic review of optimization methodologies for smart home energy management systems," *Energies*, vol. 18, no. 19, p. 5262, Oct. 2025, doi: 10.3390/en18195262.

[28] A. Ibrahim *et al.*, "Hybrid intelligence for predictive analytics of residential energy consumption," *International Journal of Sustainable Energy*, vol. 45, no. 1, Dec. 2026, doi: 10.1080/14786451.2026.2653329.

[29] M. Ebeed, S. Hassan, S. Kamel, L. Nasrat, A. W. Mohamed, and A.-R. Youssef, "Smart building energy management with renewables and storage systems using a modified weighted mean of vectors algorithm," *Scientific Reports*, vol. 15, no. 1, p. 4733, Feb. 2025, doi: 10.1038/s41598-024-79782-5.

[30] S. S. Reka *et al.*, "Decentralized energy trading in smart grid using secured post quantum encryption," *Results in Engineering*, vol. 27, p. 105767, Sep. 2025, doi: 10.1016/j.rineng.2025.105767.

[31] J. C. Vinitha, J. Sumithra, M. J. Suganya, P. A. S. Dhas, B. Ramalingam, and S. Pushparaj, "Predictive machine learning for smart grid demand response and efficiency optimization," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 16, no. 3, p. 1628, Sep. 2025, doi: 10.11591/ijpeds.v16.i3.pp1628-1636.

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