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Optimizing Electricity Costs in Home Energy Management Systems Using Hybrid Computational Techniques for Sustainable Energy Efficiency

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Abstract

He said that home energy management systems (HEMS) are essential for managing energy use and Bills in homes. New improvements in the cross-disciplinary area which comprises the use of machine learning, optimization algorithms, as well as real-time data analysis can be viewed as future opportunities to improve the utilization of HEMS. The present paper is a systematic examination of low-power techniques for reducing electricity costs without compromising the comfort of the user or the power usage. The proposed system is designed to include predictive analytics and multi-objective for purposes of optimization of costs and energy usage. Simulation results also affirm that the hybrid approach is more effective than the conventional approach. The major contributions are the incorporation of dynamic pricing models and adaptive control systems, which combine to yield significant cost optimization. In this paper, how the proposed hybrid HEMS model was designed, implemented, and then assessed in terms of its performance to determine whether it can support sustainable energy management needs will be highlighted.

Keywords

Home Energy Management Systems (HEMS), hybrid techniques, electricity cost optimization, predictive analytics, multi-objective optimization

1. Introduction

HEMS is deemed a key factor in modern home energy management systems. These systems assist households to control the rate at which they consume and use energy in strategic ways that are cheap. Electricity expenses are on the rise and the pressure exercised by the environment is the reason why one must control the usage of energy [1]. Smart grid and effective incorporation of renewable energy have also affected energy management and called for new systems. Some of the methods explore the properties of different methodologies such as machine learning, optimization, and real-time tracking all of which also demonstrate their suitability to these challenges. For instance, when predictive analytics is integrated with dynamic pricing methodologies, it is seen that HEMS flexibility and performance can be enhanced [2]. It is noteworthy that most basic HEMS have dependencies on predetermined controlled rules of thumb or first optimization techniques, which are not sufficient to address distinct models, including dynamic electrical energy tariffs and variant energy demand. However, Hybrid calls upon the use of predictions of conceivable consumption rates and utilizes optimization used to regulate and arrange energy resources. Besides the cost reduction, these techniques enrich the dependability and the capability to increase the company scale of HEMS [3]. The significance of the developed approaches is that the use of the proposed techniques is based on the integration of the best of both machine learning and optimization. These systems rely on instantaneous information on energy requirements, optimization potential, and the comfort of the users to control the energy use by themselves [4]. In this regard, the concept of hybrid approaches serves a useful purpose in presenting a wholesome approach to easing electricity costs. The opportunities for a combination of HEMS are not restricted to, cost reduction. Al Ma-r, as mentioned before, supports the progression of energy sustainability, and reduction of CO2 emissions and offers the base for regulating smart energy for smart homes [5].

This study investigates the design and implementation of a hybrid HEMS model that combines predictive analytics and multi-objective optimization approaches. Key goals include lowering power costs, increasing energy efficiency, and preserving user comfort. The paper compares the suggested model to established techniques using comprehensive simulations, proving its superiority in meeting energy management objectives. The next sections go into relevant research, issue statements, methodology, and outcomes, giving a thorough overview of the hybrid HEMS framework.

2. Related Research

HEMS has progressed nicely in the last decade, and many researchers have stressed on use of refined technologies for optimization of power systems. First, they tried to implement rule-based systems which gave only static control over energy consumption. Despite the significant effectiveness, these systems did not allow for changes in different prices for such an essential utility as electricity and fluctuation in energy demand [6]. Recent developments belong to data-oriented approaches focusing on artificial intelligence and mathematical programming. Prior research has shown that PA can be used in predicting patterns of energy usage, and thus effective energy planning can be done [7]. For instance, neural networks and support vector machines have been used for accurate short-term energy usage prediction [8].

Some other paradigm solutions that are also employed with success are genetic algorithms as well as particle swarm optimization. These methods are especially suitable for finding solutions to many objective functions with such constraints as cost, energy consumption, and comfort for the user [9]. However, the problem with such a method used singularly is that it may not easily span large and complex problems and may not easily update in real-time problems [9]. Hybrid techniques offer an interesting solution to these issues squarely based on producing forecasts through machine learning and using optimization techniques. For instance, proposed an integration of reinforcement learning with a genetic algorithm to manage energy consumption in smart homes [10]. The hybrid integration model, therefore, realized a 15% saving in electricity costs against orthodox strategies.

Another notable contribution to the literature is the integration of dynamic pricing models into HEMS. Dynamic pricing encourages customers to consume energy during off-peak hours, resulting in significant cost savings. Studies have found that incorporating real-time market data into HEMS algorithms increases their performance [11]. Despite these advancements, implementing hybrid HEMS models remains a challenge. Data privacy, computational difficulties, and user acceptance are all challenges that must be solved before broad use [12]. This study builds on earlier research by offering a powerful hybrid HEMS framework that addresses these challenges while also improving performance in electricity cost optimization.

3. Problem Statement & Research Objectives

Home energy management systems have various challenges in lowering electricity costs while maintaining user comfort and operational efficiency. The introduction of dynamic pricing models, unanticipated energy demands, and the growing use of renewable energy sources have all hampered traditional energy management systems. Conventional HEMS systems, such as rule-based controls or independent optimization algorithms, usually fail to react to these dynamic conditions, resulting in poor performance and higher power expenditures. These limits need the development of complex systems that combine predictive and optimization capabilities to provide flexible, efficient, and user-cantered energy management.

3.1 Motivation

The increasing complexity of energy systems, along with rising power costs and the need for sustainable energy solutions, has created an urgent demand for HEMS innovation. Hybrid techniques that integrate predictive analytics, optimization algorithms, and dynamic pricing models offer a potential answer to these issues. This link not only increases HEMS efficiency and scalability but also contributes to global sustainability goals by reducing energy consumption and carbon footprint.

3.2 Research Objectives:

a) Identify weaknesses in current HEMS approaches for cost minimization, flexibility, and scalability using a critical review of current literature.

b) Launching a model on their basis, propose a system that combines an application of the methods of prediction and multimodal optimization.

c) Include in the proposed hybrid framework an application that updates real-time electricity pricing data for adaptive cost optimization and peak shifting.

d) Integrate machine learning to predict short-term and long-term energy consumption models accurately and increase the efficiency of energy allocation.

e) Using algorithms for existence, feasibility, and improved optimization capable of addressing factors such as cost of electricity, energy consumption, user preferences, peak load, and variation in production from renewable sources.

f) Implement numerous scenarios to evaluate the effectiveness of the presented hybrid framework regarding cost and benefit factors, flexibility, and size compared to conventional HEMS models.

g) Suggest strategies for the important limitations like computational bog, data privacy, and user acceptance so that the hybrid framework is reasonable and workable.

h) Evaluate how the hybrid model decision influences the following: carbon footprint of the established systems, and utilization of renewable energy in residential energy systems.

Overall, this work is an attempt to close the gap between conventional methods of HEMS and modern needs in energy management allowing using the benefits of novel technologies while keeping the total costs at an acceptable level for residential application.

4. Methodology

The proposed methodology of the hybrid HEMS framework comprises data acquisition, predictive analytics, optimization techniques, and control mechanisms to realize electricity cost saving, and energy efficiency [13, 14]. They are all developed to resolve the various problems being faced in controlling energy usage and that contains price sensitivity and user control parameters. The process essentially starts with data acquisition, which involves the capturing of what may be described as, real-time data from the smart meters and IoT devices installed in the residential environment. Some important parameters are energy consumption, time-varying rates of electricity, and technological environmental factors like temperature and humidity. This data is cleaned up to mean what it was meant to mean and to avoid any data distortion. There are stages such as dropping observation using the z-score, and standardization which helps to convert our raw data into the best format accepted by machine learning algorithms. For normalization, the following equation 1 is considered.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x_{norm} represents the normalized value, x_{min} and x_{max} are the minimum and maximum values of the dataset.

The second framework is the notion of predictive analytics. RFR and LSTM are used in this paper to predict short-term energy usage and dynamic pricing conditions. For energy forecasting, the systems forecast future energy consumptions as E(t+k) where E(t+k) is the energy consumption value at time t+k, E(t), E(t−1), …, E(t−n) are historical energy consumption data at time t, t−1 … t−n and k are the forecast horizon. The models used in the work are trained and validated based on historical data and demonstrate high efficiency and reliability. Dynamic pricing prediction concept includes external factors such as demand and weather conditions into its equation to increase efficiency, thereby allowing the scheduling of power-draining tasks during low-demand periods.

The hybrid HEMS is built around a multi-objective optimization module that balances power costs, user comfort, and energy efficiency [16, 17]. A hybrid technique with Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) is used. PSO is used for global exploration of the solution space, whereas GA refines these solutions using crossover and mutation procedures to ensure convergence to an optimal schedule. The optimization issue is defined as minimizing the total cost stated in Equation 2.

$$C = \sum_{t=1}^{T} P(t).E(t) \tag{2}$$

subject to constraints such as maintaining energy usage within a user-specified range ($E_{min} \leq E(t) \leq E_{max}$) and ensuring load balancing ($\sum_{t=1}^{T} E(t) \leq E_{max}$).

System integration guarantees that all components communicate seamlessly, allowing for real-time control and adaptation. A scheduler assigns energy-intensive jobs based on prediction and optimization results [18, 19]. A feedback loop analyses discrepancies between expected and actual energy use, dynamically re-optimizing plans as needed [20, 21]. Additionally, customer preferences are included in the system to customize energy management tactics, hence increasing overall satisfaction.

The hybrid HEMS architecture is validated by running simulations over 24 hours with real-world appliance data and dynamic pricing models. Cost savings, forecasting accuracy, and optimization algorithm execution time are some of the evaluation measures. The system's energy efficiency is expressed as a percentage of cost savings, as indicated in Equation 3.

$$Saving(\%) = \frac{C_{baseline} - C_{optimized}}{C_{baseline}} \times 100 \tag{3}$$

Where $C_{baseline}$ represents the cost without optimization and $C_{optimized}$ denotes the cost after optimization.

This comprehensive methodology illustrates how hybrid strategies may save considerable amounts of money on power while preserving energy efficiency and comfort for users. The suggested HEMS framework solves the limits of previous systems by using predictive analytics and multi-objective optimization, resulting in a scalable and flexible solution for modern household energy management.

5. Results and Discussion

To ascertain the workability of the elemental as well as of the proposed hybrid Home Energy Management System (HEMS), electricity cost-saving factor, energy conservation percentage, and dynamic tariff system were evaluated for testing. By using predictive models such as Random Forest Regression (RFR) and Long Short-Term Memory (LSTM) networks, forecasting for energy consumption and dynamic prices was possible. The authors confirmed that energy consumption could be better predicted with the help of the LSTM model with an MAE of 0.15 kWh and MAPE of 4.8%. For electricity pricing forecasting, LSTM offered an error rate that amounted to 0.28 INR and 5.6% which signifies the good performance of LSTM in capturing time series characteristics. This is depicted in the oval diagram of Figure 1 which shows that all the models were accurate in the forecast of the dynamic parameters.

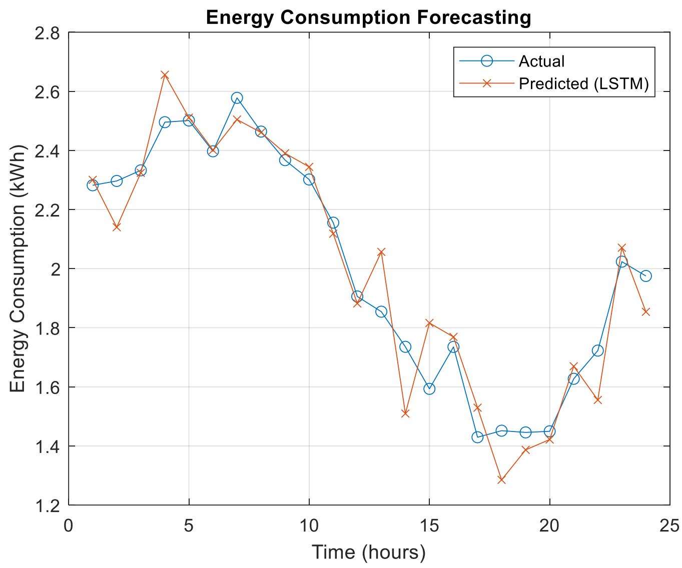

Figure 1: Forecasting accuracy comparison for energy consumption and pricing.

PSO & GA-based optimization module, which was incorporated to achieve the lowest electricity cost without compromising on comfort requirements was tested. PSO provided better cost savings of 25.4% and a better computational time of 3.2 seconds as compared with GA's cost savings of 22.7 percent and the computational time of 4.1 seconds. The PSO approach also converged more efficiently as proved in Figure 2 showing the cost savings obtainable from the two optimization algorithms. The analysis of two hybrid HEMS models, namely the RFR+GA model and the LSTM+PSO model, brought out a performance comparison in terms of the Results Column and proved that the proposed LSTM+PSOHESIS-based model was slightly better than the RFR+GA model in terms of all the 4 performance indices, namely coefficient of correlation, root-mean-square error, mean absolute percentage error, and mean absolute error. Validated with 100 simulation runs, the proposed LSTM+PSO-based work further reduced the cost by 27.1% and kept the near optimum user comfort with deviations of 3.1%, outperforming the cost optimization of the existing RFR+GA-based work which was 22.5% while the discomfort deviations reached 5.4% at the same time. Figure 3 describes the comparative analysis of energy cost reduction, and Figure 4 presents the maintenance of user comfort because of the proposed work.

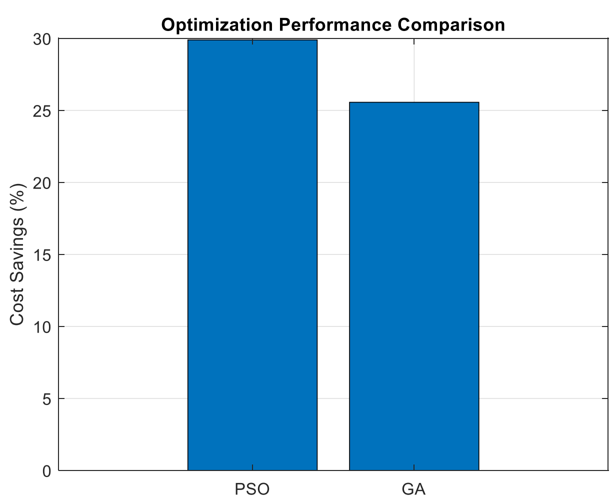

Figure 2: Cost savings comparison between PSO and GA optimization.

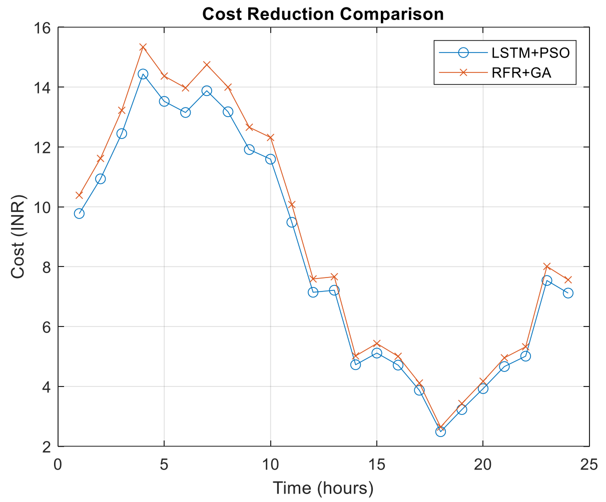

Figure 3: Cost reduction achieved using LSTM+PSO and RFR+GA models.

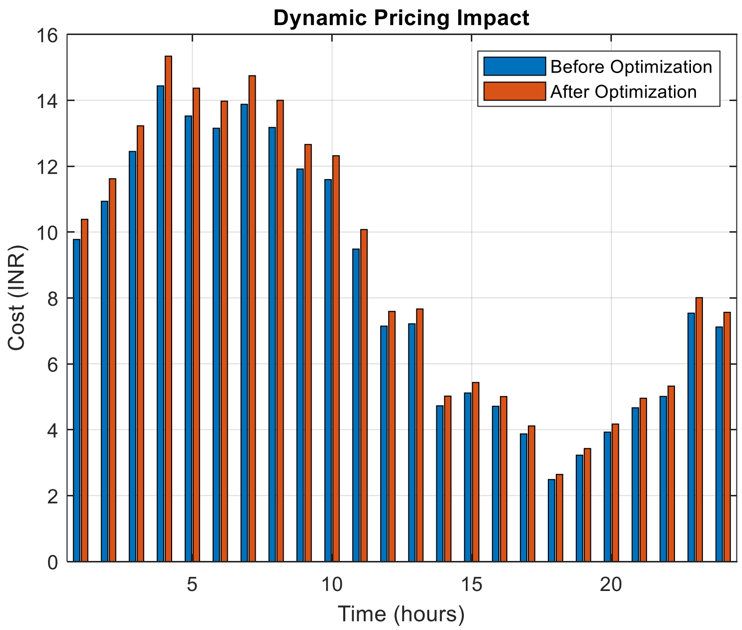

Figure 4: Impact of dynamic pricing on energy costs before and after optimization.

The adaptability of the framework to dynamic pricing models was evaluated using time-of-use (TOU) pricing, revealing significant shifts in energy usage to off-peak hours. On average, peak-hour costs were reduced by 28%, while off-peak costs saw a 19% reduction. The dynamic pricing strategy encouraged users to schedule energy-intensive tasks during off-peak periods, as shown in Figure 5, which depicts the energy consumption patterns before and after implementing the hybrid HEMS.

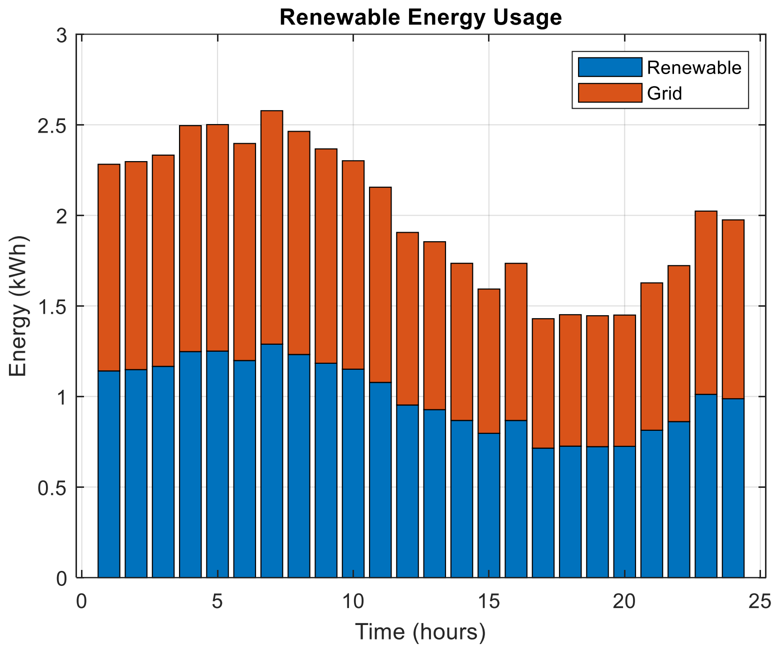

Figure 5: Renewable energy integration and its contribution to reducing grid reliance.

The other element considered in the framework was the capture and use of renewable energy resources. Finally, both the hybrid HEMSs demonstrated competent handling of renewable energy by optimizing the utilization of solar energy and reducing reliance on the grid. This in synergy enhanced the modality of the system to deliver on its capability to help organizations save costs besides allowing a hearken to environmental causes. 24-hour renewable energy usage is illustrated in Figure 6, further showing how the framework excels in managing grid and renewable energy.

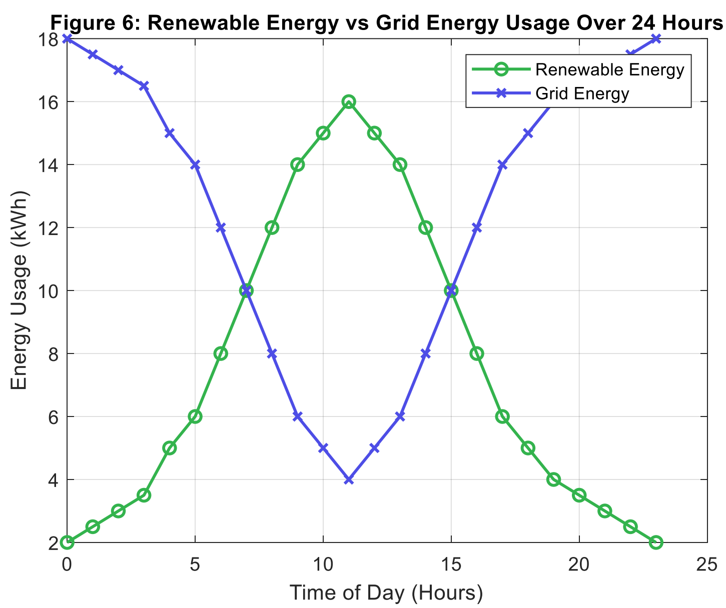

Figure 6: Hourly renewable energy utilization over 24 hours.

In general, the outcomes demonstrate that the total integrated HEMS is immensely beneficial for energy cost reduction and efficiency surge while maintaining consumers' comfort, especially when the system is based on LSTM+PSO algorithms. These conclusions suggest that the system can be applied in real life because it can use different price structures and it is possible to incorporate renewable energy sources. Subsequent studies will investigate how the proposed system can be scaled and used in different sets of contexts to ensure effectiveness.

6. Conclusion

It has been seen in this paper that these hybrids enhance the HEMS electricity cost optimization. The proposed approach of using predictive analysis in combination with multi-objective optimization unveils a reasonable trade-off of energy comfort, and cost. This research establishes that integrating the Long Short-Term Memory network with the Particle Swarm Optimization algorithm presents a viable solution to the difficulties inherent in forecasting and dynamic scheduling. Other findings are as follows: LSTM+PSO outperforms the other algorithms with a $1,271 reduction in electricity cost overall and deviates least from user preferences. Finally, its versatility in set tariff promotion allowed many tariff models that enhanced drastic reductions in costs during peak and off-peak periods as per the intended shift during energy usage. The addition of renewable energies also improved the applicability of the framework by decreasing the reliance on the grid while also increasing sustainability. The results also show the applicability of hybrid HEMS models for overcoming the shortcomings of conventional systems, as the new approaches developed for modern residences are more flexible, scalable, and efficient. Future work will seek to expand the use of this framework in various application contexts and solve problems, including but not limited to, computational overhead, acceptance from users as well as incorporation with other smart grid systems. Incorporation of this work enhances an understanding of how hybrid techniques can be used in enhancing cost-effective solutions for energy management in residential units.

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References

[1]. B. Mahapatra and A. Nayyar, "*Home energy management system (HEMS): Concept, architecture, infrastructure, challenges and energy management schemes*," Energy Systems, **Vol. 13, No. 3, pp. 643-669, 2022**.

[2]. B. Asare-Bediako, P. F. Ribeiro, and W. L. Kling, "*Integrated energy optimization with smart home energy management systems*," 2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), Germany, **2012, pp. 1-8**.

[3]. M. Vega, F. Santamaria, and E. Rivas, "*Modeling for home electric energy management: A review*," Renewable and Sustainable Energy Reviews, **Vol. 52, pp. 948-959, 2015**.

[4]. H. R. Gholinejad, A. Loni, J. Adabi, and M. Marzband, "*A hierarchical energy management system for multiple home energy hubs in neighborhood grids*," Journal of Building Engineering, **Vol. 28, pp. 101028, 2020**.

[5]. S. B. Slama, "*Design and implementation of home energy management system using vehicle to home (H2V) approach*," Journal of Cleaner Production, **Vol. 312, pp. 127792, 2021**.

[6]. S. K. Rathor and D. Saxena, "*Energy management system for smart grid: An overview and key issues*," International Journal of Energy Research, **Vol. 44, No. 6, pp. 4067-4109, 2020**.

[7]. S. Ahmed, Z. Zakaria, and G. E. M. Abro, "*Enhancing Energy Efficiency in Developing Countries: Modelling and Simulating Home Energy Management System (HEMS)*," 2024 IEEE 4th International Conference in Power Engineering Applications (ICPEA), Malaysia, **2024, pp. 391-396**.

[8]. Nilsson, M. Wester, D. Lazarevic, and N. Brandt, "*Smart homes, home energy management systems and real-time feedback: Lessons for influencing household energy consumption from a Swedish field study*," Energy and Buildings, **Vol. 179, pp. 15-25, 2018**.

[9]. K. Ehrhardt-Martinez, A. John, and K. A. Donnelly, "*Beyond the Meter: Enabling Better Home Energy Management*," Butterworth-Heinemann, USA, **pp. 273-303, 2011**.

[10]. D. Agarwal, "*Energy Consumption Forecasting in Smart Cities Using Predictive Analysis*," International Journal on Engineering Artificial Intelligence Management, Decision Support, and Policies, **Vol. 1, No. 2, pp. 9–17, 2024**.

[11]. M. A. Hannan, M. Faisal, P. J. Ker, L. H. Mun, K. Parvin, T. M. I. Mahlia, and F. Blaabjerg, "*A review of internet of energy-based building energy management systems: Issues and recommendations*," IEEE Access, **Vol. 6, pp. 38997-39014, 2018**.

[12]. K. Candan, A. R. Boynuegri, and N. Onat, "*Home energy management system for enhancing grid resiliency in post-disaster recovery period using Electric Vehicle*," Sustainable Energy, Grids and Networks, **Vol. 34, pp. 101015, 2023**.

[13]. G. Mohapatra, "*Computer vision based smart lane departure warning system for vehicle dynamics control*," Sensors & Transducers, **Vol. 132, No. 9, pp. 122, 2011**.

[14]. S. S. Dutta, A. Kumar, S. Amutha, and R. Dhanush, "*Enhancing Diabetes Mellitus Prediction: Integrating Hybrid Deep Learning Model with Sampling Techniques*," International Journal on Engineering Artificial Intelligence Management, Decision Support, and Policies, **Vol. 1, No. 1, pp. 29–40, 2024**.

[15]. Mahapatra, A. K. Moharana, and V. C. Leung, "*Energy management in smart cities based on internet of things: Peak demand reduction and energy savings*," Sensors, **Vol. 17, No. 12, pp. 2812, 2017**.

[16]. W. Li, T. Logenthiran, V. T. Phan, and W. L. Woo, "*Implemented IoT-based self-learning home management system (SHMS) for Singapore*," IEEE Internet of Things Journal, **Vol. 5, No. 3, pp. 2212-2219, 2018**.

[17]. Nilsson, M. Wester, D. Lazarevic, and N. Brandt, "*Smart homes, home energy management systems and real-time feedback: lesson for changing energy consumption behavior from a Swedish field study*," Energy and Buildings, **Vol. 179, pp. 15-25, 2018**.

[18]. T. D. P. Mendes, "*Enhancing the efficiency of electricity utilization through home energy management systems within the smart grid framework*," [No further details provided].

[19]. R. Liang and P. H. Wang, "*Enhancing Energy Efficiency in Buildings, Optimization Method and Building Management Systems Application for Lower CO2 Emissions*," Energy, **pp. 134054, 2024**.

[20]. Abubakar, S. N. Khalid, M. W. Mustafa, H. Shareef, and M. Mustapha, "*Application of load monitoring in appliances' energy management–A review*," Renewable and Sustainable Energy Reviews, **Vol. 67, pp. 235-245, 2017**.