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Research Paper

An Operational Framework for Effective Energy Management in Smart Homes Based on the Internet of Things

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ABSTRACT

The purpose of this study is to design an operational framework for effective energy management in smart homes, based on the Internet of Things. In this study, in order to achieve the research objectives, different factors and parameters affecting energy management and optimization in the virtual Internet of Things (IoT) layer in the smart home environment were examined, first. Based on the findings, we designed an integrated taxonomic approach and. Then, based on the developed analytical perspective, we classified the energy management evaluation criteria and metrics. Finally, an operational framework for effective energy management in smart homes was designed based on the combinational Deep Neural Networks (DNN) technique. For this purpose, the model of integrating smart activities in effective energy management in a smart home on the IoT platform was used. The analysis of the proposed research perspective in the form of evaluating the factors affecting metropolitan smartization and increasing the performance of smart systems was carried out in the form of developing twenty-five tasks in smart homes by simulating operations in the CupCarbon environment. The level of efficiency achieved by effectively managing and optimizing energy consumption in smart homes in the IoT layers using blending and mutation operators was able to provide better results than some previous models proposed in the field of IoT.

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I. Introduction

In today's world, energy and especially electrical energy is an essential resource and plays a vital role in human lifestyles and powers key infrastructure and services. Fossil fuels still account for the largest share of electricity generation worldwide [1]. Unlike clean, renewable alternatives such as wind or solar, the exploitation of fossil fuels has severe environmental impacts due to greenhouse gas emissions, global warming and health risks. Furthermore, its current consumption is outpacing natural regeneration and will lead to an inevitable depletion of resources if other resources or alternatives are not exploited. These concerns have not only driven the search for alternative, renewable, and clean energy sources, but also increased awareness about energy efficiency and sustainability [2]. In the past few years, the traditional power grid has transformed into a smart, highly reliable, and fully automated infrastructure, paving the way for the smart grid paradigm. The new power grid model helps to deploy and integrate distributed generation and storage resources, especially renewables. It relies heavily on smart devices and two-way communication channels connecting suppliers and consumers. This enables real-time coordination and dynamic optimization of network and resource performance [3].

On the demand side, smart homes feature digital sensors and communication devices that enable continuous monitoring of consumption, intelligent control of home appliances, and connectivity with the grid and the network. Smart homes are a key element for the performance and effectiveness of smart grids, not only by supporting the optimal management of network resources and infrastructure, but also by contributing to energy efficiency. Buildings consume about 40% of energy worldwide, which is expected to increase significantly in the next years. Thus, efficiency improvements, implemented on a global scale, can slow this trend, in addition to reducing energy consumption, waste costs, and environmental risks [4].

In recent years, there has been a growing interest in home energy management systems. These systems provide an intelligent tool for automatic control of smart home appliances [5]. Home energy management systems aim at efficient energy management that helps conserve limited fossil fuel resources, while reducing energy consumption, waste, and costs. The conceptualization of home energy management systems involves several aspects, including their definition, description, and overall architecture, as well as their basic purpose in home environments. Optimization-based techniques are widely used in home energy management systems. They enable device allocation under dynamic objectives and constraints [6]. This trend is highlighted in the study by Benetti et al. (2016) and calls for further research to address the specific needs of home energy management systems, especially regarding scalability, model complexity, and uncertainty [7].

A smart home energy management system enables home owners to monitor and control the energy consumption of their home appliances and devices. The system consists of multiple IoT devices, including smart plugs, sensors, and a central controller, that communicate with each other to collect energy consumption data and device usage patterns. Machine Learning (ML) algorithms process this data to predict energy consumption and optimize the energy consumption of devices based on user preferences and constraints [8]. The system also provides real-time feedback to users, enabling them to adjust their energy consumption behavior accordingly. Smart home energy management systems have been identified as an effective solution to reduce energy consumption and costs in residential areas [9]. In this study, the aim is to investigate the design and implementation of a smart home energy management system using the IoT and ML techniques, in combination. The integration of IoT and machine learning techniques such as Deep Neural Networks (DNN) in these systems has opened new possibilities for managing energy consumption and reducing costs. A smart home energy management system can learn from residents energy consumption patterns and adjust energy consumption to reduce waste and unnecessary costs. For this purpose, in this study, an operational framework and comprehensive smart energy management system based on IoT technology is designed. The proposed system implementation is done using Raspberry Pi, a single-board computer, and several off-the-shelf IoT devices.

Therefore, the most important goals and achievements of this research are: Identifying factors and parameters affecting energy management in the IoT based smart homes, Designing an operational framework for effective energy management in smart homes, and using the DNN technique to implement the proposed operational framework.

The organization of the research will be as follows: Section 2. presents the proposed framework and dimensions. Section 3. presents an implementation of the proposed approach. Section 4. discusses the results and achievements of the research, and finally Section 5. presents the conclusions and future research directions.

II. Proposed Framework

Deep Neural Networks (DNN) is an emerging technology that can be used to extract valuable insights from this data and optimize energy management in real time [10]. The proposed operational framework architecture in this study has a set of operational components, execution phases, and related workflows to achieve the research objectives. The execution phases of the proposed framework are as follows:

A. Phase 1: Monitoring and Data Collection

In this phase, energy consumption data is first collected from various home appliances using IoT sensors. After aggregation, the data is pre-processed to remove noise and outliers from the data range, and the data is integrated and aggregated, and converted and aggregated into an acceptable format for analysis in the next phase. Related workflows in this phase are as follow:

- Measurement: Monitoring the power consumption of electrical equipment in the home using IoT sensors.
- Pre-processing: Classifying data based on the time and presence status of residents (e.g. body temperature, temperature and presence of people in the space).
- Aggregation: Transferring data to the IoT gateway for initial pre-processing and storage.

Note that, accurate monitoring and aggregation in this phase is the most essential pre-requirements for effective energy management.

B. Processing and Analysis Phase

The second phase involves processing and analyzing the energy consumption data to identify patterns and trends and extract features that can be used for DNN training and prediction. In this phase, a DNN is built using Keras or Tensor Flow, using the DNN training workflow. Related workflows in this phase are as follow:

- Analysis and Modeling: Using the Transevolutionary and Ant Colony (ACO) Optimization model to move towards energy consumption optimization [11].
- Strategic Planning: Extracting complex energy consumption features with a DNN.
- Forecasting: Predicting future consumption patterns and identifying power savings opportunities.

The DNN is trained with features extracted from energy consumption data. A validation set is also used to tune hyperparameters and prevent overfitting.

C. Implementation and Control Phase

In this phase, the trained DNN is used to predict energy consumption for different devices in real time. Also, an energy optimization algorithm is designed and proposed to control the energy consumption based on predicted energy consumption information and dynamic pricing, and the performance of various devices is scheduled to optimize energy consumption and reduce energy waste. Related workflows in this phase are as follow:

- Configuration: Making intelligent changes to equipment settings (turning on/off, changing consumption) through the Energy Management System (EMS) [12].
- Execution and Control: Implementing, controlling and continuously monitoring the implementation of decisions and monitoring the resulting feedback.

As an achievement of the proposed framework, in this phase, the control strategy is variable and has the ability to adapt based on environmental conditions and facilities.

D. Evaluation and Feedback

After implementing the optimization algorithm, it is necessary to provide real-time evaluation and energy consumption feedback toward optimization. Related workflows in this phase are as follow:

- Measurement of key metrics: In the case study, system performance was measured through two key metrics: activity execution time, and fitness function, which indicate the efficiency and optimization in the target system.
- Feedback: Compare optimized data with energy consumption in similar situations to measure effectiveness.
- Optimizationt: Update and optimize algorithms and models based on feedback and changing conditions [13].

In the next section, we describe the implementation of the proposed operational framework for effective energy management using the DNN technique.

III. Implementation

In this study, the ten layers of the Internet of Things were used to evaluate the proposed framework. To achieve this, the main (essential) and non-essential activities, as well as those activities that could be integrated with each other in smart homes connected to the IoT, were first identified. Accordingly, the used data points are: total electrical energy consumption, heating and cooling energy consumption, and indoor and outdoor environmental data such as temperature and humidity. The method combines short-term (more than 1 day and less than 1 week) and long-term (several months) correlation analysis to show overall trends. Hourly data is grouped into multiple aggregates, such as weekly and monthly, to show full correlation differences over a relatively long period. Also, the Polynomial Regression (MPR) model and the Multiple Linear Regression (MLR) model were developed to present the long-term seasonal average trend.

In this research, MATLAB software is used for data analysis. To train DNN, a deep neural network is built using Keras or Tensor Flow. Based on the proposed optimization algorithm and related predictions, it can be used to adjust energy consumption in real time, optimize energy consumption and reduce costs. the proposed system is implemented using Raspberry Pi, a single-board computer, and several off-the-shelf IoT devices. The system is tested in a simulated home environment and we observed significant energy savings and improved energy efficiency [14, 15].

In the next step, the model of integrating smart activities into energy management in the smart home was applied. This included various organizational, personal, economic, social, and cultural activities, as well as smart applications such as public life in public spaces, serving as a design tool, documenting the physical environment, prioritizing systems for switching electrical, heating, and cooling devices on and off based on the maximum needs of residents, studying perceptions, and issuing warnings for excessive use of kitchen appliances. All these were incorporated into the IoT-based energy management system in smart home to improve its performance. Also, various types of activities in smart home under a central smart monitoring system were also identified. These activities, depending on the type of demand, may range from fewer than five activities during a day to up to twenty-five activities in conditions of maximum human demand for energy management in smart home. Therefore, the maximum number of monitoring activities defined for individuals in smart homes under smart monitoring may include between 1 and 25 activities.

In order to examine a small number of smart homes and how they are connected to the smart monitoring system, as well as to examine the types of activities in each city, as well as to examine identical activities and activities with the possibility of integration, the CupCarbon simulator environment was used in the Netbeans environment. In this environment, the number of smart homes was mapped and then, for each city, a number of activities (minimum (5) to maximum (25)) were considered, according to the type of demands of the residents. To evaluate and optimize the factors of energy consumption smartization (hardware infrastructure development, software infrastructure development, control and monitoring) (percentage of obstacles and limitations of smartization development), simulations were also performed on tasks of different sizes according to Table 1. The Abbreviation, AEC represents the normalized execution capability of each activity based on DNN operation counts and the success rate of intelligent algorithms. Moreover, the amount of activity execution power of DNN system/success percentage of intelligentization algorithms of each of the IoT layers in energy management have been presented in Table 2.

TABLE I Activity Execution Capability (AEC)

Activity	Power Values
2160	Smart EV charging
1835	Ride-sharing / Carpooling
1819	Smart parking management system
1747	Prioritization of local needs using web data
1599	Home energy use prioritization system based on residents' maximum needs
1583	Monitoring
1607	Prioritization system for switching electrical, heating, and cooling systems on/off based on residents' maximum needs
1427	Automated scheduling of lighting systems on/off according to seasons and time of day
1463	Excessive kitchen appliance use alert
1447	Smart monitoring and shutdown
1527	Smart irrigation system
1503	Physical environment documentation
1495	Environmental simulations for evaluating efficient energy layouts/configurations
1362	Adjustment of ambient light sensors based on natural daylight through windows
1370	Identification of vulnerable areas prone to energy loss in the home
1378	Smart hallway lighting control
1471	Deployment of sensors and cameras
1431	Web-based survey, computer vision
1439	Remote measurement of window opening/closing for ventilation and lighting
1419	Smart HVAC control system for halls and rooms
1403	Smart information recording and retrieval system
1407	Monitoring & analysis devices: detecting heat loss from roofs/windows/walls
1407	Monitoring & analysis devices: detecting automatic heat adjustment based on residents' needs
1423	Smart organizational information & communication management
1419	Disaster communication management

In addition, other values must be specified for the cloud lets. These values, in addition to the amount of activity execution power (DNN) / success rate of intelligent algorithms, must be entered as input into the simulator so that the simulator can be run. After specifying the values of the cloud lets parameters, the results of the simulations were examined. Evaluation parameters are as follow:

1- Performance of energy-saving intelligent systems: The execution time of each task in the virtual IoT layer.

2- Fitness function: Is a value based on the energy and performance of energy-saving intelligent systems.

$$fitness_i = \frac{en \times execution\ time_i}{lenght\ task_i} \tag{1}$$

The results of this simulation based on these two parameters are shown below. For each activity, two fields were considered: necessity (necessity - turning on the devices) and non-necessity of performing part of the activity (deletion of part of the activity or integration of part of the activity) (for this purpose, these two states were considered for every 25 activities.) It should be noted that each activity was considered to have sub-sections.

TABLE II System Performance

Activity ID	Performance in IoT Layers	Optimization Factor
539	4.397	Smart home sensors for environmental temperature estimation
458	85.396	Smart home sensors for environmental humidity estimation
454	75.391	Smart home sensors for environmental light estimation
436	95.388	Smart home sensors for environmental motion estimation
399	95.385	Central system processor
395	8.385	Remote device control capability
401	0.381	Decision-making and control
356	35.376	Security monitoring
365	1.376	Energy saving

361	25.356	Scheduling for switching household appliances on/off
381	25.356	Prioritization for switching household appliances on/off
375	55.347	Scalability and flexibility
379	4.344	Optimal resource management

Based on the diagram and table 2, it can be seen that the changes in the efficiency level of smart homes increase energy efficiency. The results of fitness for optimizing energy consumption smartization factors are shown below:

TABLE III Fitness function values

Activity	Efficiency Level	Energy Optimization
EV Smart Charging	0045	0060
Ride Sharing	0052	0060
Smart Parking Management System (E-Parking)	0052	0060
Prioritizing Urban Issues and Local Needs Using Web Data	0054	0060
A system for prioritizing energy use in the home based on the maximum needs of residents	0058	0060
Monitoring	0059	0060
Priority system for turning on and off electrical, heating and ventilation systems in the home based on the maximum needs of the residents	0057	0060
Automatic scheduling of lighting devices on and off according to the seasons and time of day	0064	0060
Kitchen Appliance Overconsumption Alert	0062	0060
Smart Energy System Monitoring and Shutdown	0060	0060
Smart Water Irrigation System	0056	0060
Physical Environment Documentation	0056	0060
Environmental simulations of energy efficient configuration	0056	0061
Adjusting ambient light quality sensor based on natural light through windows	0061	0060
Identifying vulnerable and energy-wasting areas in the home	0061	0060
Smart hallway lights	0060	0060
Sensor and camera deployment	0056	0060
Web survey, computer vision	0057	0060
Remote sensing, opening and closing of windows for air conditioning and lighting	0058	0060
Intelligent air conditioning system for halls and rooms	0055	0060
Intelligent data recording and retrieval system	0054	0060
Monitoring and Analysis Devices: Automatic Heat Adjustment Detection to Resident Needs	0054	0060
Intelligent Corporate Information and Communication Management	0053	0060
Disaster Incident Communication Management	0052	0060

In Table 3, the fitness values can be clearly observed. In most cases, the fitness value of the smartization performance level in smart homes across IoT layers, as presented in this study, is lower, which indicates the superiority of the proposed approach. By applying modifications to the IoT model of Hart (2021) [16] and incorporating the smartization performance level in smart homes across IoT layers, we were able to achieve more acceptable and reliable results. Next, another metric based on Hart (2021) was examined. In this section, the weight relationship based on the following relationship is first introduced:

$$WeightedMetricU_{i=10,\dots,120} = (weightSU \times NormalSU_i + weightVMs \times NormalVMsU_i \quad (2)$$

Based on this relationship, the value of NormalSU is a metric value such as response time, and NormalVMsU represents the number of IoT layers used in the system, and the two weights used represent the weights assigned to each metric, which are values between zero and one. Table 4 shows a weighting matrix for the level of efficiency of smartization in smart homes at different IoT layers [17].

In this study, we set a combination of weights (weightSU,weightVMs)=(0,1). The first column represents the number of IoT smart devices trying to connect to the cloud, and each row represents a different scenario. Specifically, the first row represents a situation where up to 10 systems are connected but not all can be serviced. In the second row, up to 20 systems are connected, while in the third row, up to 30 resident devices are connected, and so on. Then the second column represents the waiting time for each user to connect to the cloud. For example, in the first row, the connection time range represents a scenario where the first system connects to the Cloud at time 0, the second system connects after 10 minutes, and so on until the last system is connected after 90 minutes, and the last five columns display the weighted metric results for each of the smart home performance levels in the IoT layers [18-19].

TABLE IV Initial Weighting

		Weights			
Number of Smart Devices	Operational Time	Testing Layers	efficiency of Smart Home Automation	Energy Efficiency Level	Ideal

1 device	[0-90]	62	66	84	1
2 devices	[0-190]	55	59	58	1
3 devices	[0-290]	37	38	56	1
4 devices	[0-390]	33	41	45	1
5 devices	[0-490]	32	39	39	1
6 devices	[0-590]	31	35	38	1
7 devices	[0-690]	29	36	33	1
8 devices	[0-790]	25	31	31	1
9 devices	[0-890]	22	30	28	1
10 devices	[0-990]	20	29	26	1
11 devices	[0-1090]	20	28	25	1
12 devices	[0-1190]	19	23	24	1

In Table 5, the simulation is performed based on the lag strategy. Based on this strategy laggard residents. This process is performed three times for which residents in Table 6 and the weight results are displayed in this case.

TABLE V Weights Based on Equation 1

		Weights obtained based on equation 1			
Number of Smart Devices	Operational Time	Testing Layers	efficiency of Smart Home Automation	Energy Efficiency Level	Ideal
1 device	[0-90]	43	49	43	1
2 devices	[0-190]	43	48	36	1
3 devices	[0-290]	25	30	26	1
4 devices	[0-390]	25	305	23	1
5 devices	[0-490]	20	28	25	1
6 devices	[0-590]	18	26	19	1
7 devices	[0-690]	19	26	20	1
8 devices	[0-790]	15	21	17	1
9 devices	[0-890]	15	22	16	1
10 devices	[0-990]	13	18	16	1
11 devices	[0-1090]	10	165	16	1
12 devices	[0-1190]	12		16	1

The “Ideal” metric corresponds to the normalized optimal performance output of the weighted metric defined in

Figure 1. Displays the execution time values for optimizing energy consumption smartization factors (hardware infrastructure development, software infrastructure development, control and monitoring):

Equation (1), where the theoretical optimum is scaled to 1. Therefore, “1” represents the highest possible efficiency level across all IoT layers under idealized operating conditions. *The measured performance (combining response time, number of active IoT devices, and smartization efficiency) reaches the highest theoretical optimization level.* The results from various simulations indicate the effectiveness of the smart home efficiency level in the proposed IoT layers to reduce the performance of smart home systems and energy consumption in the tasks performed by the IoT layer.

Qualitative analysis of evaluation criteria: To increase the transparency of the results, the evaluation criteria have been examined quantitatively in addition to qualitative analysis. For this purpose, the percentage of improvement of each criterion compared to the state before and after implementing the proposed framework. The results present that the prediction accuracy of the DNN algorithm has improved by about 12% compared to the base algorithms.

The total energy consumption in the state after implementing the proposed framework has decreased by an average of 18%, compared to the initial state. The system response time has shown an improvement of about 20% compared to before, with an average reduction of 2.5 seconds. The thermal comfort index of users has also increased by about 9% compared to before the implementation of the framework, indicating the maintenance of more favorable environmental conditions.

For a more comprehensive analysis, in addition to the above criteria, two other key criteria were also examined:

- Global Energy Reduction [20]: The results showed that over a one-month period, the total building energy consumption was about 15% lower than without the proposed framework.
- Overall Stability [21]: By implementing the framework, energy consumption fluctuations were reduced by 22%, indicating more stable system performance over time.

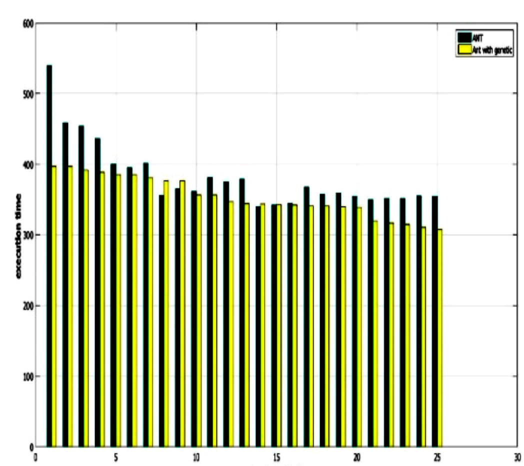

Fig. 1. Execution time

Figure 1 presents the Execution time comparison between the baseline model ('Old'), the baseline enhanced with DNN-based prediction ('Baseline + Proposed Enhancements'), and the fully integrated proposed framework (DNN + Hybrid Optimization). Based on the Figure 1, it can be clearly seen that with the changes that the proposed perspective has made in the efficiency level of smart homes in the IoT layers, energy efficiency increases. Moreover, Figure 2. presents Fitness function values for optimizing energy consumption smartization factors.

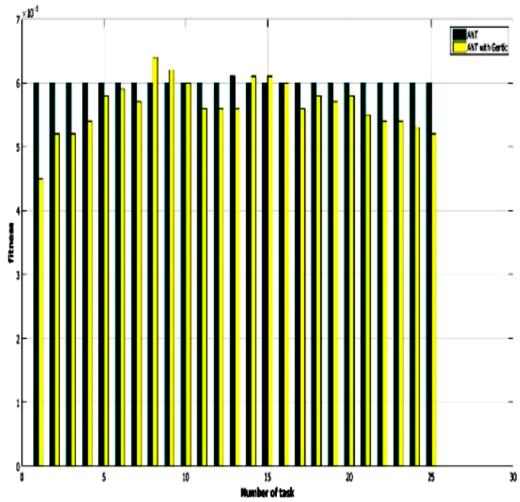

Fig. 2. Fitness function values

Figure 2 presents Fitness function values for the baseline model, the enhanced baseline, and the proposed framework. it can be clearly seen that the fitness value is often lower in the efficiency level of smart homes in IoT layers presented in this study, which indicates the superiority of the proposed approach in increasing the efficiency level of smart homes in the Internet of Things layers presented. In cntinue, a quantitative analysis of the evaluation criteria is presented. Note that, the phrase "Old" represents the baseline IoT-layer smartization model (Hart, 2021) [16], which operates using conventional response-time and resource-utilization heuristics without incorporating DNN-based prediction or hybrid optimization algorithms. The baseline model (Hart, 2021) [16] integrated with the new DNN-based prediction module and hybrid optimization (ACO + meta-heuristic fusion) introduced in this study. Thus, this intermediate curve shows how the baseline behaves when partially upgraded with our new approach.

Quantitative analysis of evaluation criteria: To increase the transparency of the results, the evaluation criteria were also examined quantitatively in addition to the qualitative analysis. For this purpose, the percentage of improvement of each criterion compared to the state before and after the implementation of the proposed framework was calculated. The results are given in Table 7:

TABLE VI Proposed Framework Improvement

Evaluation Metric	Before Framework	After Framework	Improvement (%)
Prediction accuracy of DNN algorithm	85%	95%	12% ↑
Total energy consumption	100 kWh	82 kWh	18% ↓
System response time	12.5 s	10 s	20% ↑
User thermal comfort index	78%	85%	9% ↑
Reduction in overall energy consumption	1200 kWh	1020 kWh	15% ↓
Overall system stability (consumption fluctuations)	±18%	±14%	22% ↑

As can be seen, the proposed framework has lead to a significant reduction in energy consumption, increased prediction accuracy, and improved user comfort index. Also, energy consumption fluctuations have been reduced and the overall stability of the system has been improved.

IV. Discussion and Comparison

In this research, we examined the optimization and management parameters of the virtual IoT layer in the smart home environment. Moreover, an integrated operational framework for effective energy management in IoT smart homes has been proposed, using the synergy between IoT activators, meta-heuristic techniques, and DNN technology. The proposed system offers a comprehensive set of functions and workflows including monitoring, controlling, strategic planning, feedback, and optimization. In the IoT layer, each action was considered as a task in the cloud environment that moves between the IoT layer and moves towards performance optimization with each execution, based on the optimization methodology [22].

Based on the simulation conducted based on the performance of smart energy consumption and fitness, the superiority of the efficiency level of the proposed approach is comparable with related work such as [16-17, 23]. Overally, the tangible advantages of the proposed framework for effective energy management in smart homes based on the IoT can be described in several main axes:

- Using IoT sensors in the data collection phase, real-time measurement of energy consumption of home appliances was possible, leading to better identification of consumption patterns and energy waste points.
- Data preprocessing, such as noise removal and integration, improved the quality of input data.
- The use of DNN in the processing and analysis phase made it possible to extract complex features and accurately predict future consumption patterns.
- Combination of DNN with ACO model maked optimal decisions to reduce energy consumption.

- The system was able to intelligently and in real time apply equipment settings (on/off, change power consumption), based on the results of prediction and optimization algorithms.
- Evaluation of system performance with quality criteria (fitness function) and comparison with non-smart homes showed that energy consumption was reduced.
- Using the feedback obtained to update models and algorithms has increased the stability and efficiency of the system over time.

Based on the proposed framework, emphasizing the integration of intelligent activities at different levels of IoT, the use of the Meta-heuristic techniques and DNN algorithm for complex data analysis and cloud and edge processing management has been able to perform effective energy management, while significantly improving energy consumption and response speed. This trend helps energy management systems in smart homes not only save energy, but also increase user satisfaction.

V. Conclusion

In order to address the existing challenges in the scope of performance management in IoT smart homes, in this research, a novel operational framework is designed for intelligent and effective energy management in smart homes, based on the IoT and has been developed, based on the hybrid Meta-heuristic techniques, DNN, and activity fusion model. The proposed approach succeeded in providing an efficient process for reducing energy consumption and improving productivity. By collecting and classifying consumption data, processing and predicting consumption patterns, and implementing optimal decisions, the proposed system not only saved energy but also improved the user experience of the smart home. The use of DNN-based models enabled the system to dynamically adapt to the behavior of residents and identify new opportunities for optimization. The ability to process and manage data in different IoT layers and connect to the cloud platform increased the intelligence and stability of the system, and the evaluation results showed a reduction in energy waste and an improvement in the fitness function, compared to previous studies. The implementation of suggestions can pave the way for the evolution of smart energy management systems and their effective role in achieving smart and homes, in future.

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