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A Carbon-Aware IoT Scheduling Framework for Sustainable Smart Homes Using Predictive Energy Models

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Abstract: With the widespread popularization of software engineering-based Internet of Things technology, the smart home field has obtained the basic conditions to realize fine-grained monitoring and intelligent control of household energy consumption. Presently, there are two big issues with our home energy management. First, in this paper, our emphasis is only on conserving energy rather than considering whether the energy we consume from the grid is clean or dirty. Second, we are not making sure that the software we use to schedule our energy use is reliable. To address these issues, this study proposes a carbon-aware home energy management framework that integrates predictive modeling, environmentally conscious scheduling, and software reliability validation. The three major entities of the proposed scheme are predicting the closeness, predicting energy usage, and scheduling to utilize energy to reduce our carbon footprint. In this context, utilizing a special formula that considers both energy consumption and carbon emissions, we can find ways to make our homes better and more efficient for the planet. For this newly proposed system, all simulation experiments were completed on the OMNeT++ platform. After the simulation tests were finished, several types of reliability verification tests were also conducted. The results of these tests are clear: all core performance indicators of this new framework outperform those of the benchmark method used as a reference. This system can provide an accurate, long-term usable solution for next-generation smart home energy management systems.

Keywords: smart homes, software engineering, Internet of Things, predictive energy modeling, software testing and validation

1. Introduction

The rapid development of Internet of Things (IoT) technology has transformed traditional homes into intelligent smart home environments [1, 2]. Smart meters, air quality sensors, and "connected" household devices can closely monitor domestic energy use in the home, offering new ways to encourage more efficient and sustainable energy consumption [3–5]. As energy consumption in homes rises, smart homes are increasingly seen as an important factor in the global effort to limit energy waste and lower environmental damage [6, 7].

Most current smart home energy management systems are mainly concerned with the minimization of the total electricity

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used through rule-based control or energy-sensitive scheduling [8, 9]. Although such measures can lead to significant energy saving, it implicitly suggests a constant (static) relationship between using energy and environmental impact [10]. However, modern power grids demonstrate large temporal variation in carbon intensity because of the time-varying contribution from renewable and fossil-based energy. As a result, reducing energy consumption alone doesn't imply that CO_2 emissions would also be minimized, especially for areas with time-varying and heterogeneous generation profiles.

Home energy management and home appliance scheduling, using smart home technology and the IoT, have been broadly recognized over the previous years as a means to improve sustainability. Scholars such as Shewale et al. [11] introduced the concept of Multi-knapsack Scheduling (MKSI) and Multi-knapsack Price (MKPI) algorithms for the multi-knapsack model to minimize the electricity bill and minimize the peak-to-average ratio (PAR) using demand response and dynamic pricing. Previous studies have shown that energy load shifting can optimize energy use in residential systems; however, existing analytical frameworks primarily emphasize minimizing only electricity bills and reducing the PAR and do not include the five modules of the main research. Therefore, the current contributions show the potential of smart home technologies, with the design of the solutions mainly based on static and/or rule-based mechanisms and not considering predictive control or aiming to optimize (explicitly) in terms of carbon [12]. Besides, there is no explicit model of carbon emissions as an optimization objective [13].

Yet another drawback of the present smart home energy management systems is the absence of a predictive nature [14, 15]. If there is no anticipation of what future demand may be, or the state of the grid soon, control decisions remain reactive, which prevents using low-carbon periods or predicting peak loads. Predictive energy modeling remains a promising area to investigate in other domains; however, it is typically analyzed by itself and not yet well integrated with real-time scheduling and control [16]. Furthermore, most of the previous work focuses on functional aspects such as saving energy and fails to consider software engineering issues (e.g., testing, validation, robustness), which are important for a reliable deployment in residential environments [17, 18].

Inspired by the above, this paper presents a practical, software-tested carbon-aware IoT scheduling model for predictive energy models with sustainable smart homes. The current framework is based on the forecasting of energy demand in the short term, the estimation of energy intensities, and the carbon-aware scheduling in a closed-loop control loop. The methodology takes a different approach from other methodologies, with direct CO_2 emission minimization, while respecting user comfort and real-time feasibility. Moreover, this work provides system software testing and validation to guarantee robustness, correctness, and scalability of the proposed system.

This research introduces a novel way of managing energy in environmentally sustainable smart homes. This way, it does not rely on separate models to predict energy use or to optimize the utilization of energy, but rather, it develops one system that incorporates all these functions. In this work, there are four major components of this system: forecasting energy demand, real-time scheduling of energy usage, forecasting energy grid carbon emissions to reduce carbon emissions, and reliability of the system. Thus, the system can proactively manage energy consumption, which can be used to reduce carbon emissions, by predicting energy consumption and making decisions using AI. Consequently, a solution where various components of the system are linked together to address real-world issues. The main goals of this study can be summarized as follows:

1) This research presents a complete system for managing carbon use in smart homes. It's based on a special internet system that can talk to lots of devices in the home. The system has three main parts: one that predicts how much energy the home will use, one that forecasts how much carbon will be released, and one that schedules when appliances should be used.
2) This study came up with a special equation to predict costs related to carbon. It considers how much energy we will need and how much carbon we will release. The idea is to use electricity when it's not making as much carbon but still keep things running smoothly and comfortably for users.
3) We design a lightweight and computationally efficient scheduling methodology with a complexity of $O(NH + N\log N)$, making the framework suitable for real-time deployment on resource-constrained smart home gateways and edge controllers.
4) We present a flexible software framework based on software engineering fields, which is able to manage technical tasks, thereby making it easier to set up and run a smart home energy management system that can predict and manage energy use in order to enhance the efficiency and reliability of these systems.
5) This research uses computer simulations to test a new approach on a large scale. It is developed by comparing the new method to some popular existing methods with a tool known as OMNeT++. Our results indicate that the new approach is superior in four key aspects: low energy consumption, user comfort, and real-time operation. In general, it works much better than the other methods.

The remainder of this paper is organized as follows. Section 2 reviews related work on smart home energy management, carbon-aware IoT systems, and software testing. Section 3 presents the system model and architecture. Predictive energy and carbon modeling are described in Section 4, followed by the carbon-aware scheduling framework in Section 5. Software testing and validation are detailed in Section 6, and the experimental setup and results are presented in Sections 7 and 8, respectively. In the end, Section 9 concludes the paper and outlines future research directions.

2. Related Work

The existing studies related to energy management in smart homes, making IoT systems more aware of carbon usage, energy consumption prediction, and application software engineering in control of the IoT-based framework, were also explored. In addition, it highlights current methods' weaknesses and the need for developing a new method for creating carbon-aware scheduling based on software testing. Hence, our work shows the disadvantages of the existing methods in recent research, demonstrating the need for a novel software testing techniques-based approach to developing carbon-aware scheduling.

2.1. Energy-efficient smart home systems

Some research works of interest have been carried out to be more energy efficient using IoT technologies for enhancing smart homes.

Simon et al. [19] presented a fuzzy control strategy and renewable energy-based smart home heating system for energy savings. Adaptive heating by sensing the environment and occupancy enables a maximum of 40% energy saving while keeping the room comfortable, which supports living green. Furthermore, Lakhan et al. [20] introduced a smart grid for smart homes and Electric Vehicles (EVs) with the utilization of energy-saving mechanisms and the blockchain paradigm. Their proposed system aims to reduce the processing speed and consumption of this system by using fiber optic IoE sensors and a blockchain data scheduling protocol, while the proposed blockchain data scheduling protocol is expected to be more efficient than a conventional blockchain in scheduling the data. On the other hand, Alowaidi et al. in [21] proposed the use of a fuzzy logic controller for energy management in smart home and microgrid networks using IoT. Smart microgrids offer opportunities for optimizing load control, storage, and the renewable energy portion of their work, which can enhance their efficiency in the use of energy, their operation, and their economic and sustainable performance. Besides this, Bhowmik et al. [22] presented an energy-efficient smart home–health monitoring system during the pandemic. Their work combines different multi-sensor measurements using the Dempster–Shafer theory and provides online monitoring of the populace for environmental and physiological data, warns the user if the situation is dangerous, and allows for remote monitoring of health at a lower cost. As well, Doughman et al. [23] discussed how smart-based decision-making can make more efficient, comfortable, and sustainable homes as they explore how smart homes can be transformed with intelligent and adaptive technologies.

Recently, there have been a number of external works trying to address energy-aware scheduling and resource optimization issues in various IoT applications, including mobile crowd sensing in the study by [24]. Other work, like [25], includes wireless rechargeable sensor networks, and these works have led to the identification of the central question of how to develop efficient scheduling strategies.

There are common sensor-based automation, rule-based control, and threshold-based methods that have been used to prevent unnecessary power consumption. While learning-based systems are very positive in reducing energy use, they act reactively and are not "intelligent" enough to deal with the dynamic nature of energy profile minutes and peak hours. The research by Dwivedi et al. [26] conducted an in-depth analysis of an extensive survey of smart homes' sustainability and energy efficiency issues with the help of IoT tools. Although they show the potential of reducing home energy consumption through IoT-based automation, they are mostly static or rule-based systems with no predictive scheduling and optimization. Further, there is qualitative treatment of carbon emissions lacking any model or minimization.

2.2. Carbon-aware and sustainable IoT systems

More recent works have extended energy systems' optimization to carbon awareness by taking grid carbon intensity and renewable availability into account. Song et al. [27] present LSCEA-AIoT, a low-carbon sustainable computing framework for Artificial Intelligence of Things (AIoT) systems by considering energy-efficient data acquisition and carbon-aware task offloading. Pournazari et al. [28] propose a carbon-aware multi-objective optimization framework for fog computing that jointly minimizes energy consumption, makespan, and CO_2 emissions. Ghosh et al. [29] introduce a modular framework to quantify and investigate the carbon footprint of blockchain-based IoMT systems. Alevizos et al. [30] introduced a runtime carbon-aware system for swarm-based optimization in High-Performance Computing (HPC) that links algorithmic behavior to measured emissions. This research demonstrated that aligning energy consumption with periods of low grid carbon intensity can significantly reduce carbon emissions. While most carbon-aware strategies target large-scale power systems, data centers, and industrial applications, very few studies address residential smart homes.

For the smart home domain, carbon awareness is usually addressed implicitly through energy consumption reduction, supposing that CO_2 emissions are directly proportional to energy usage. Hence, this assumption might not remain valid in today's power networks, where the mix of generation units is subject to frequent temporal changes. Therefore, current smart home IoT models, such as those of Dwivedi et al. [26], cannot completely exploit the opportunities offered by temporal variations in carbon emission factors.

2.3. Predictive energy modeling in smart homes

Predictive energy modeling approaches commonly employ time-series analysis and machine learning methods, including recurrent neural networks, autoregressive models, and deep learning algorithms. For example, Priyadarshini et al. [31] presented energy consumption of intelligent homes based on ensemble methodology and machine learning models. Khan et al. [32] have introduced a dynamic model of energy optimization based on the edge with the support of deep learning, fuzzy control, and whale optimization to satisfy a balance between people's energy pricing requirements and comfort degree in real time. Otherwise, Gellert et al. [33] have studied Photovoltaic (PV) production forecasting and home energy consumption using statistical models and neural networks. As such, these models can be used for short-term forecasting of household energy demands and for developing proactive control strategies.

Moreover, predictive models are typically verified for prediction accuracy only and not tested for system-level sustainability metrics or downstream decision-making. In the real world, approaches such as these are not readily applicable in real operational smart home environments due to the lack of integration between prediction, scheduling, and validation.

2.4. Software engineering and testing in IoT frameworks

As IoT smart home systems or applications become more mature, less attention is given to software engineering-related issues, such as testing, validation, and robustness analysis. As mentioned by the research of Taylor et al. [34], the key challenges in cybersecurity testing of IoT environments include life-cycle-aware risk assessment on software engineering practices, propagation of threats among distributed devices connected in IoT, and limitations of low-power distributed devices. To make security testing reproducible, scalable, verifiable, and unbiased, Cristea et al. [35] have released open-source software, mock IoT applications, and a behavior-driven framework for functional testing. Existing research focuses primarily on functional attributes (e.g., energy), and there has been little or no systematic study of software correctness, execution performance, and dependability.

Shewale et al. [11] developed two scheduling algorithms, MKSI and MKPI, which used Demand Response (DR) and Dynamic Pricing (DP) strategies to reduce electricity cost and

PAR and to balance and manage energy to obtain good results. However, this research does not cover carbon-intensity estimation, carbon-based scheduling, software verification, etc., which are part of the research that is needed to address this. However, the existing studies do not fully consider carbon-intensity estimation, carbon-aware scheduling, or software verification and validation, and this is the very gap that the current study fills from an integrated software engineering approach.

2.5. Research gap and novelty analysis

In this regard, current solutions tend to focus on minimizing electricity usage by developing fixed rules or schedules generated by traditional optimization methods. Many solutions, nevertheless, did not take into account the time-varying carbon intensity of the grid, depending on modern techniques of software engineering. Thus, electricity savings may not necessarily mean energy usage during the least polluting times. The usage of carbon-aware techniques in the context of smart homes, with strategies of software engineering, is less systematic and has been investigated less extensively than in other contexts, like data centers, industrial energy, and cloud computing systems.

Another challenge has to do with the correlation between energy usage and carbon emissions in big computing systems and how much carbon is being released by the grid at different times. Therefore, many of the existing studies, which are implicit, take it for granted that more electricity usage is directly associated with more carbon emissions. The carbon intensity of electricity, however, can vary significantly over time in practice and can even change as the electricity generation mix of the grid shifts. Many of the current smart home energy management studies do not acknowledge this temporal and future variability. In addition, there is a frequent approach of energy demand forecasting and energy scheduling as separate tasks. Without forecasting consumption and using that forecasted consumption to inform energy-scheduling decisions, the environmental impact of energy consumption can be evaluated and managed only after it has occurred.

The proposed framework does not offer to bring a new optimization theory or a fundamentally new forecasting innovation. Instead, it is in the ways that it combines well-known methods and system needs that are typically studied separately in the current literature. The distinction of this paper is significant because the primary research gap identified in this study is the lack of an integrated approach that takes into account energy demand, grid carbon intensity, scheduling, and software engineering under one roof to provide a comprehensive solution.

This paper introduces a framework that combines four complementary functionalities: short-term energy demand forecasting, carbon-intensity forecasting, carbon-aware energy scheduling, and software engineering assurance to overcome these limitations. The framework intends to make these functions part of a single process of smart home energy management. Here, the carbon-intensity information is used to inform decisions based on a predicted energy demand. The software engineering component, in turn, tackles the needs essential for the reliable implementation and operation of the system that results.

As described in Table 1, current research focuses only on some or a limited number of these capabilities. Some of them are primarily concerned with energy forecasting, others are concerned with optimization or scheduling, and a smaller group is concerned with carbon-related considerations. Requirements in software engineering are also not typically considered as part of the energy management system. The proposed method, in contrast, integrates all four aspects to offer a more comprehensive base for sustainable and reliable smart home energy management.

The resulting framework focuses not just on the electricity use but also on the time, the way, and the reliability of supporting software in a real-world environment. This integration can enable smart homes to make better energy use decisions and decrease the carbon footprint of their use. The proposed framework is thus structured to address the research gaps identified while not trying to develop new optimization theories or algorithms but rather to focus the study on system integration.

3. System Model and Architecture

This section provides the system model and architecture of our proposed software-tested carbon-aware IoT scheduling framework.

Table 1
Comparison of existing studies and the proposed framework

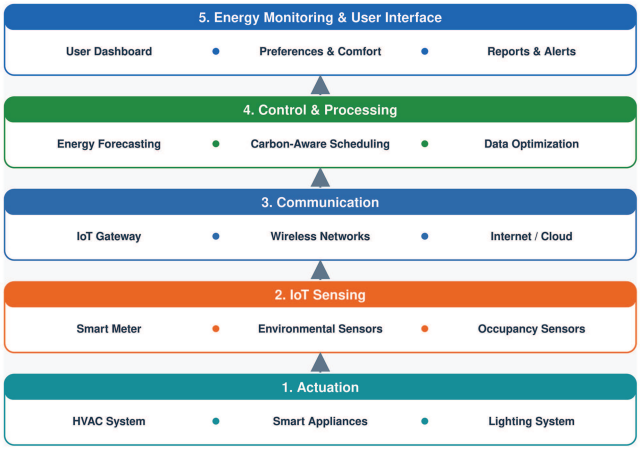
Reference	Key characteristics and research gaps
Dwivedi et al. [26]	Reviewed IoT technologies for sustainable smart homes and highlighted the importance of energy management. However, existing solutions are primarily static and lack predictive scheduling, explicit carbon modeling, and software validation.
Song et al. [27]	Introduced a low-carbon AIoT framework considering carbon-aware task offloading. The framework targets large-scale computing environments rather than residential smart homes.
Pournazari et al. [28]	Proposed a carbon-aware optimization framework for fog computing. Does not address predictive energy management or software testing in smart homes.
Khan et al. [32]	Developed an edge-based dynamic energy optimization model using deep learning and fuzzy control. Carbon-intensity forecasting and software engineering aspects are not considered.
Gellert et al. [33]	Investigated household energy forecasting utilizing neural network and statistical models. Prediction studied in isolation without integration into sustainability and scheduling objectives.
Proposed Framework	Integrates short-term energy demand forecasting, carbon-intensity prediction, carbon-aware scheduling, and comprehensive software testing within a unified smart home IoT framework. Provides an end-to-end deployable architecture for reliable and sustainable residential energy management.

The architecture is created to support predictive, emission-aware, and stable control of smart home devices by formulating the IoT sensor data acquisition, processing, predictive modeling, and deterministic scheduling in a closed loop with control.

3.1. Smart home IoT architecture

The proposed modular and layered smart home IoT architecture supports predictive control, carbon-aware scheduling, and systematic software testing, as illustrated in Figure 1. Every architectural component is designed with a singular role in mind, which in turn lends itself to robustness, scalability, and logical separation of concerns. The main elements of the design are as follows.

Figure 1
Architecture of the proposed software-tested carbon-aware smart home scheduling framework



1) IoT Sensing Layer: This layer contains smart meters, occupancy sensors, and environmental sensors that monitor household electricity consumption as well as contextual information such as temperature, humidity, and lighting. The accumulated field data are the raw input for short-term energy demand and carbon emission estimates.
2) Communication Layer: The sensor signals can be sent to the control unit by utilizing lightweight and trustworthy IoT communication protocols. Data transmission is guaranteed timely and securely with low overhead acceptable in a residential setting based on the environment to enhance continuous monitoring.
3) Control and Processing Layer: It runs the predictive energy and carbon-modeling modules by combining sensor information. It contains a carbon-aware scheduler that utilizes predicted demand, carbon intensity, and operational restrictions to compute the optimal dispatching decisions.
4) Actuation Layer: This layer contains controllable home appliances, such as Heating, Ventilation, and Air Conditioning (HVAC) systems, light bulbs, and smart plugs. Actuators are commanded by scheduler units and modify the operation of the devices so that carbon emissions are minimized without sacrificing comfort to the user.
5) User Interface and Management Layer: The user interface and management layer support three types of user operations including energy consumption visualization and are equipped with an additional two types of system support capabilities, thereby enhancing decision-making transparency, user participation, and trust.

3.2. Data flow and control loop

The proposed method adopts a closed-loop data model that enables real-time monitoring, prediction, and carbon-conscious control of smart home appliances. The control loop consists of the following key phases.

1) Data Collection: The data acquisition module of this study adopts IoT sensors to collect four categories of core research data.
2) Data Transmission and Aggregation: After collection of data by sensors, they are transferred to the controller through communication layer, and after synchronization, filtering, and aggregation, the coherent treatment status output is achieved.
3) Predictive Modeling: In the process of predictive modeling, the whole combined dataset is put into two kinds of models, which, respectively, give out the forecasted energy consumption and power grid carbon emissions within a definite time range.
4) Carbon-Aware Scheduling: In the process of carbon-aware scheduling, predicted cost signals are taken as inputs, subject to the limitations from equipment inherent restrictions and user comfort level requirements, and the optimum control policies that minimize the expectation of carbon emissions are outputted.
5) Actuation and Execution: The actuation drive execution function module of this study-designed smart home scheduling system can automatically adjust the operating parameters and on-off status of different kinds of thermostats and smart lighting.
6) Feedback and Adaptation: In the sensing layer of the system, outcome data are collected in the time period after the execution of actions, and feedback signals are generated.

3.3. Assumptions and design considerations

The smart home system model and self-developed framework proposed by the authors of this paper are built upon the practical conditions and design trade-offs of real-world deployment scenarios and possess the core characteristics of tractability, scalability, and reliability.

1) Time Synchronization: The foundational concept postulated in this paper is that all IoT devices use the same time benchmark and provide their data periodically, which forms the basis of unified data alignment needed for predictive modeling and scheduling.
2) Reliable Communication: In this paper, it is stated that the communication level of the proposed architecture should provide reliable and low-latency communication for three types of core nodes: sensors, control heads, and actuators. The communication layer could employ only coaching and timed retransmissions as a means to deal with occasional packet losses and latency issues within a limited margin.
3) Device Heterogeneity: This paper offers some preliminary concepts in order to conduct load scheduling research. Smart home devices are heterogeneous; in this paper, the author distinguishes between rigid loads and flexible loads that could be shifted in time by the scheduler and provides the logic of classification unambiguously.

4) User Comfort Preserving: Based on the paper's context of low-carbon regulation policies, it identifies that the thermal and lighting user comfort preferences could be categorized as hard and soft constraints, whereas preserving comfort and reducing carbon emissions are two primary objectives of the proposed approach of this research.
5) Modular and Testable Framework: In this paper, the technical framework uses a modular approach that has four modules, including sensing, prediction, scheduling, and execution. Hence, these modules could be verified with unit testing and integration testing.
6) Scalability and Deployability: In this paper, the proposed control logic is designed to be adapted to IoT device scaling and might be applied to edge controllers and/or cloud environments, which depend on computational requirements and latency constraints.

4. Predictive Energy and Carbon Modeling

In this study, the second layer of the carbon-aware smart home framework is the predictive modeling module, which covers two core tasks: (i) short-term household energy demand forecasting based on IoT observations and (ii) estimation of carbon intensity to calculate emission-aware future operating costs. The prediction outputs are sent to the carbon-aware scheduler, which actively shifts flexible loads to low-emission time periods. A detailed introduction of this modeling framework is shown in Figure 2.

4.1. Notation and data representation

The operation of the smart home system in this study is decomposed into discrete periods of time, and the key operational data, such as energy consumption, environmental status, and device status, are collected by IoT sensors. To confirm clarity and consistency throughout the study, all of the main key symbols, variables, and parameters of the energy and carbon emission forecasting modeling system for this study are presented in Table 2. As such, these multiple entities of the proposed components are recognized by the unified system, which establishes a consistent foundation for our later analysis.

4.2. Short-term energy demand forecasting

Short-term household energy demand forecasting refers to the practice of predicting future household electricity consumption based on historical energy consumption data and real-time contextual information from the IoT. Let E_t denote the aggregated household energy consumption at time slot t. Using a sliding observation window of length w, the forecasted demand for the next time slot is expressed as:

$$\hat{E}_{t+1} = f_{\phi}(E_t, E_{t-1}, \ldots, E_{t-w+1}, \mathbf{x}_t, \mathbf{x}_{t-1}, \ldots, \mathbf{x}_{t-w+1}) \quad (1)$$

where $f_{\varphi}(\cdot)$ represents the forecasting model parameterized by φ and x_t is the IoT context feature vector containing occupancy information, environmental conditions, appliance states, and user preferences.

This study is based on the household energy demand forecasting module that utilizes long short-term memory (LSTM) networks to capture the temporal dependence and nonlinear characteristics of household energy consumption data. The model receives energy consumption measurements from the past and context features from software engineering-based IoT and returns the energy demand for the next time slot. The network consists of 64 memory units, with the optimization algorithm and a learning rate set to 0.001; all of the listed parameters are used for full reproduction of the model. The loss function used for training the model is the mean squared error (MSE) function.

$$L_E = \frac{1}{N}\sum_{t=1}^{N}\left(E_t - \hat{E}_t\right)^2 \quad (2)$$

where N denotes the number of training samples. The prediction performance is evaluated using mean absolute error (MAE) and root mean square error (RMSE), which quantify the deviation between actual and predicted energy consumption values. Table 3 shows the LSTM forecasting model parameters.

The smart home controller in this study uses short-term energy demand forecasting to optimize load scheduling while also simultaneously addressing the two key scheduling objectives, which include carbon emissions reduction and energy efficiency.

In order to test and verify the rationality of using LSTM networks, this study used four benchmark models: the persistent

Figure 2
Predictive energy and carbon-modeling framework

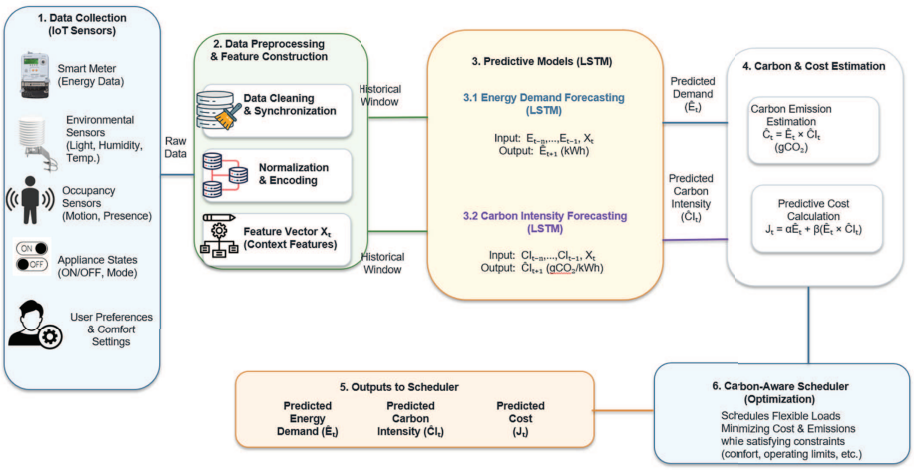


Table 2
Notation and data representation are used in predictive energy and carbon modeling

Symbol	description
T	Discrete time slot index
$\triangle t$	Duration of each time slot
T	Total number of time slots in the observation horizon
E_t	Actual household energy consumption at time slot t (kWh)
$E\hat{}t$	Predicted household energy consumption at time slot t (kWh)
CI_t	Grid carbon intensity at time slot t (gCO_2/kWh)
$CI_c t$	Predicted grid carbon intensity at time slot t (gCO_2/kWh)
C_t	Carbon emissions at time slot t (gCO_2)
$C_b t$	Predicted carbon emissions at time slot t (gCO_2)
x_t	IoT context feature vector at time slot t
O_t	Occupancy level at time slot t
θ_t^{in}	Indoor temperature at time slot t
θ_t^{out}	Outdoor temperature at time slot t
H_t	Humidity level at time slot t
L_t	Illumination level at time slot t
s_t	Appliance operational states vector
u_t	User preference and comfort profile
w	Historical window size for energy prediction
w_c	Historical window size for carbon-intensity prediction
$f_\varphi(\cdot)$	Energy demand prediction model
$g_\psi(\cdot)$	Carbon-intensity prediction model
α, β	Weighting factors for energy and carbon objectives

Table 3
LSTM forecasting model parameters

Parameter	Value
Forecasting model	LSTM
Hidden units	64
Optimizer	Adam
Learning rate	0.001
Loss function	MSE
Input window size	w
Output horizon	One-step ahead
Evaluation metrics	MAE, RMSE

prediction method, linear regression, Autoregressive Integrated Moving Average (ARIMA), and Gated Recurrent Unit (GRU) as the test models. The earlier-mentioned models are selected to represent traditional statistical approaches and modern deep learning approaches in smart energy management; all the comparison results are summarized in Table 4.

Table 4
Forecasting performance comparison

Model	MAE	RMSE
Persistence forecasting	0.86	1.11
Linear regression	0.74	0.96
ARIMA	0.62	0.81
GRU	0.49	0.67
Proposed LSTM	0.41	0.58

We verified through comparative model experiments that the LSTM proposed in this paper achieves outstanding performance across two core metrics: MAE and RMSE. This model can capture the long-term temporal dependencies and nonlinear consumption patterns inherent in household energy data, so it is designated as the dedicated prediction engine for our self-developed carbon-aware scheduling framework.

4.3. Carbon emission estimation

Carbon emission estimation is used to account for the environmental footprint of household electricity by measuring the carbon intensity of the electric grid. Carbon intensity is defined as the amount of CO_2 emitted to produce 1kWh of electricity and is expressed in gCO_2/kWh. Consequently, carbon intensity will have a lot of variation over time of day as electricity grids are made up of different mixes of renewable and fossil fuel generation. So, if carbon intensity is treated as a dynamic parameter, more environmentally friendly and sustainable scheduling decisions can be made.

Let CI_t denote the grid carbon intensity at time slot t. Similar to energy demand forecasting, future carbon-intensity values are estimated using historical carbon intensity observations collected over a sliding window of length w_c. The carbon-intensity prediction is expressed as:

$$\widehat{CI}_{t+1} = g_\psi\left(CI_t, CI_{t-1}, \ldots, CI_{t-w_c+1}\right) \tag{3}$$

where $g_\psi(\cdot)$ denotes the carbon-intensity forecasting model parameterized by ψ. Let $\hat{E}_t$ denote the predicted household energy consumption at time slot t and CI_{ct} the corresponding predicted grid carbon intensity. The expected carbon emissions for a single time slot are computed as:

$$\widehat{C}_t = \hat{E}_t \times \widehat{CI}_t \tag{4}$$

where C_{bt} is measured in grams of CO_2. This formulation explicitly captures the relationship between electricity consumption and the carbon characteristics of the power grid at a given time. For a prediction horizon of length H, the cumulative carbon emissions are estimated as:

$$\widehat{C}_{t:t+H} = \sum_{\tau=t}^{t+H} \hat{E}_\tau \times \widehat{CI}_\tau \tag{5}$$

which provides an assessment of future emission trends across multiple time slots rather than isolated intervals. Table 5 presents parameters of carbon-intensity prediction.

This paper proposes a carbon-aware power grid dispatch framework, whose core design decouples the two major

Table 5
Carbon-intensity prediction parameters

Parameter	Description
Carbon-intensity unit	gCO∗2/kWh
Input variable	Historical carbon-intensity values
Prediction model	$g*\psi(\cdot)$
Observation window	w_c
Prediction horizon	H
Output variable	$CI_c t$
Application	Carbon-aware scheduling

prediction modules of energy demand and carbon intensity. Under the premise that total energy consumption remains unchanged, this framework can shift residential flexible loads to low-carbon time periods and outperforms traditional energy-centric optimization methods. The core content of this framework is elaborated in detail in the following sections.

4.4. Carbon-aware predictive cost signal

In order to enable proactive and sustainable decision-making, this subsection introduces a carbon-aware predictive cost signal that is based on energy consumption and the carbon emissions associated with this consumption. Next, in contrast to classical energy-only cost functions, the abovementioned signal combines economic and environmental aspects and is used as the objective function for our software engineering-based IoT scheduler. Let $\hat{E}_t$ be the energy demand predicted at time slot t and $CIct$ be the carbon intensity of the grid predicted at time slot t. The carbon-aware cost of a single slot is defined as:

$$J_t = \alpha \hat{E}_t + \beta \left(\hat{E}_t \times \widehat{CI}_t \right) \tag{6}$$

where α and β are non-negative weighting coefficients that balance energy efficiency and carbon emission reduction objectives, respectively. The first term reflects the anticipated energy usage, while the second term quantifies the environmental impact of that usage.

Over a prediction horizon of length H, the cumulative predictive cost is expressed as:

$$J_{t:t+H} = \sum_{\tau=t}^{t+H} \left[\alpha \hat{E}_\tau + \beta \left(\hat{E}_\tau \times \widehat{CI}_\tau \right) \right] \tag{7}$$

Measurement based on costs rather than instantaneous performance measurements enables the controller to evaluate alternative scheduling decisions in a way that is independent of their immediate lifetime performance. The smart home controller implicitly biases operation to times with lower carbon intensity regardless of equal instantaneous energy consumption by minimizing the predictive cost $J_{t:t+H}$. This anticipatory cost signal is the crux of the relationship between predictive modeling and carbon-aware actuation, thus allowing a mechanism to generalize how system behavior could be updated given user-specified sustainability preferences and policy objectives.

4.5. Prediction error propagation analysis

The proposed scheduling framework relies on predicted energy demand and future carbon intensity to construct the carbon-aware cost signal. Consequently, forecasting errors may propagate into the scheduling decisions and influence the overall system performance. Let ΔE_t denote the energy demand prediction error and ΔCI_t denote the carbon-intensity prediction error.

From the predictive cost formulation in (6), the perturbation in the cost function caused by forecasting errors can be approximated as $\Delta J_t = \alpha \Delta E_t + \beta (CI_t \Delta E_t + E_t \Delta CI_t)$, where ΔJ_t denotes the variation in the predictive cost signal.

The above expression indicates that inaccuracies in both forecasting modules directly affect scheduling decisions. However, because the proposed framework continuously updates predictions in a receding-horizon manner and preserves feasibility constraints, the impact of moderate forecasting errors remains bounded. Therefore, the scheduling mechanism exhibits graceful performance degradation rather than catastrophic failure when prediction uncertainty increases.

5. Carbon-Aware IoT Scheduling Framework

The carbon-aware IoT scheduling structure is a main decision-making unit of the system. The structure utilizes energy consumption and carbon emission forecasts to schedule the smart home devices in a way that minimizes their environmental footprint while ensuring the user's comfort. As shown in Figure 3, the structure receives the energy demand and carbon-intensity information from the prediction module, generates the carbon-aware cost signals, creates plans for the appliances within four predefined constraints, and achieves three core objectives.

5.1. Problem formulation

We assume time is divided into a finite number of time slots, $t \in \{1,2,...,T\}$. Assume $D = \{d1, ..., dn\}$ is a set of controllable smart home devices, with each device $d \in D$ having a power rating, time of operation, and flexibility. The goal of the scheduler is to find an activation schedule that achieves minimum activation carbon-aware cost over the prediction horizon. The optimization objective is written as:

$$\min \sum_{t=1}^{T} J_t \tag{8}$$

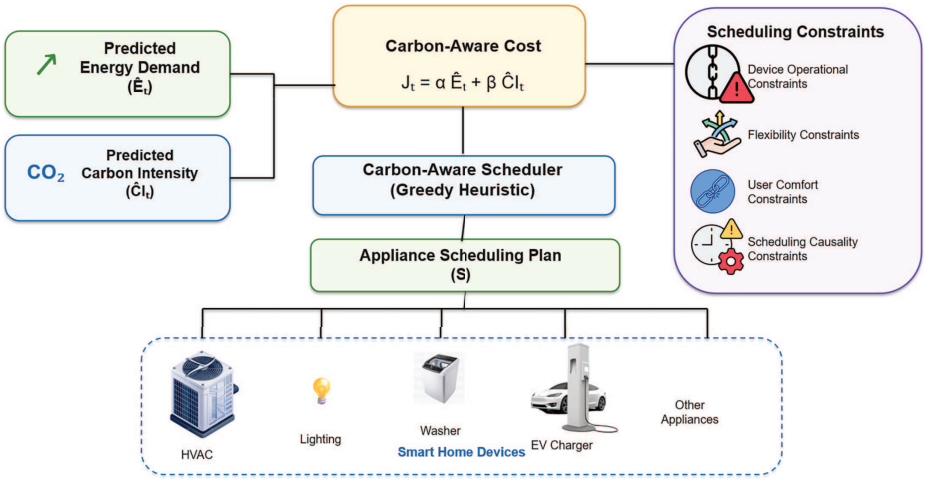
where J_t combines predicted energy consumption and associated carbon emissions. This formulation enables forward-looking decisions that account for temporal variations in grid carbon intensity.

5.2. Scheduling constraints

The scheduling process faces a series of realistic conditions that guarantee the feasibility and satisfaction of the users, as identified below:

1) Each device can be operated within its preset power limits and time limits.
2) Flexibility Constraints: For flexibilities, we are interested in the inflexible loads, which are continuous operations or only operate at certain fixed periods, and flexible operations, which can be operated in a shifted manner within certain time intervals without altering the functional use of the operation.
3) User Comfort Constraints: Indoor temperature and lighting level (or comfort heat index) must be kept within user-defined comfort bounds.

Figure 3
Carbon-aware IoT scheduling framework



4) Scheduling Causality: Control decisions in time slot t depend on information available until time t and predictions for future slots.

5.3. Carbon-aware scheduling algorithm

The proposed carbon-aware scheduling procedure is given in Algorithm 1. The scheduling model uses forecast energy demand and carbon intensity to decide the most economical time to turn on and off flexible appliances while maintaining the user's satisfied requirements.

Algorithm 1: Carbon-Aware Scheduling Algorithm

Require: Predicted energy demand $\hat{E}_t$, predicted carbon intensity CI_{ct}, flexible appliance set A, comfort constraints C
Ensure: Appliance scheduling plan S
1: for each scheduling interval t do
2: Compute carbon-aware cost:

$$J_t = \alpha \hat{E}_t + \beta \left(\hat{E}_t \times \widehat{CI}_t \right)$$

3: Sort flexible appliances according to scheduling priority
4: for each appliance $a \in A$ do
5: if comfort constraints are satisfied then
6: Assign appliance to the lowest-cost feasible time slot
7: else
8: Preserve current operating state
9: end if
10: end for
11: end for
12: Return scheduling plan S

5.4. Computational complexity analysis

Let N refer to the numbers of flexible appliances and H refer to the scheduling horizon. During each scheduling interval, the proposed framework evaluates the carbon-aware cost and searches for feasible operating slots for each appliance. The operation of dominant corresponds to appliance-slot evaluation, resulting in a computational complexity of

$$O(NH). \tag{9}$$

If appliance priorities are sorted before scheduling, an additional sorting cost of $O(N\log N)$ is incurred. Therefore, the overall complexity becomes

$$O(NH + N\log N) \tag{10}$$

Since both the number of household appliances and scheduling horizons are relatively small in typical smart home environments, the proposed scheduler remains computationally efficient and suitable for real-time deployment.

5.5. Theoretical properties of the scheduling algorithm

The heuristic scheduling algorithm proposed in this paper, while unable to guarantee a global optimum, meets the theoretical conditions required for adaptation to real-time smart home systems.

Proposition 1 (Termination): For a finite number of flexible appliances N and a finite scheduling horizon H, Algorithm 1 always terminates after a finite number of operations.

Proof: The flexible home appliance scheduling algorithm studied in this paper traverses each scheduling interval and only evaluates each home appliance once within the corresponding time window. Since both the total number of home appliances N and the time window length H are finite values, the upper limit of the total number of evaluations is NH, so the algorithm is guaranteed to terminate.

Proposition 2 (Feasibility Guarantee): If a feasible schedule exists that satisfies device operational constraints, flexibility constraints, and user comfort requirements, Algorithm 1 returns a feasible scheduling plan.

Proof: The home appliance scheduling algorithm proposed in this study, within each scheduling cycle, only allocates to household appliances time slots that satisfy all preset constraints. If no feasible time slot exists, the algorithm retains the current operating state of the relevant appliances. It never generates infeasible scheduling decisions, and all output scheduling plans always comply with all constraint requirements.

Proposition 3 (Computational Complexity): The worst-case computational complexity of the proposed scheduling algorithm is $O(NH + N\log N)$, where N denotes the number of flexible appliances and H denotes the scheduling horizon.

Proof: The appliance prioritization stage requires O(NlogN) operations due to the sorting process. Subsequently, the scheduler evaluates at most H candidate time slots for each of the N appliances, resulting in a computational complexity of O(NH). Therefore, the overall computational complexity of the proposed algorithm is $O(NH + N\log N)$.

This work introduces a lightweight heuristic scheduling algorithm with the goals of improving operational efficiency and reducing energy consumption. The algorithm is verified as feasible through numerical calculations and can be deployed in real time in scenarios of smart home, though it is not a globally optimal solution.

5.6. Approximation discussion and practical guarantees

This section proposes a lightweight greedy heuristic scheduling algorithm for real-time smart home environments. In subsequent work, there are two types of exact methods based on mixed-integer linear programming and dynamic programming that will be used as testing benchmarks. This algorithm is required to process a highly constrained combinatorial optimization problem that involves four categories of variables; it cannot guarantee a globally optimal solution, nor does it have a formal approximation ratio.

Although the proposed algorithm does not have theoretical optimality guarantees, it has many practical advantages. The first is that it has a good computational complexity of "O" ("NH + N" with "log" and "N") that can be executed in real time on a smart home gateway with limited resources. Hence, the algorithm is quite effective in making a good decision in scheduling so that people will feel comfortable and satisfied. It also helps to reduce energy consumption and carbon emissions significantly, compared to other methods. The results are useful in revealing that the algorithm is effective and can make a difference. This is significant since it may assist us in conserving energy and minimizing our ecological footprint. In general, the algorithm is an excellent resource for making intelligent decisions about scheduling to optimize people and planet. So, this study was not theory-based to create a perfect scheduling algorithm. Rather, it focused on developing a scheduling system that was good for predicting and lowering carbon use and was also practical to use.

In the future, the plan is to develop algorithms that can work well with big residential energy systems and figure out the best possible results.

6. Software Testing and Validation

This part of our work is about ensuring our system is well engineered from a software engineering perspective. We want to show that our software has been well verified, just as we stated at the beginning of this work. The primary aim is to ensure all the various entities are compatible and fit together and that it all works well in the real world, as listed in Table 6. Finally, we're testing all levels to check if the proposed solution is correct. Therefore, we're testing individual components to ensure they're performing correctly by taking them end to end and pushing them to the limit to see how they will react with high loads and loud inputs.

6.1. Software testing results

This study uses the OMNeT++ simulation environment and follows a preset workflow to verify the correctness and reliability of the self-developed technical framework. The framework is found to functionally meet the required standards, be reliable, and be applicable to real-time applications, as all the test items listed in Table 7 satisfy the set requirements.

Table 6
Summary of software testing and validation procedures

Testing procedure	Evaluation metrics/criteria	Validation outcome
Unit testing	MAE, RMSE, validity, stability	Valid outputs; errors within limits.
Integration testing	Compatibility, consistency, constraints	Feasible schedules; no mismatches.
Performance testing	Latency, memory, CPU	Low overhead; real-time operation.
Stress testing	Execution time, workload	Graceful degradation; no failure.
Robustness testing	Comfort, feasibility, emissions	Stable under uncertainty.
Fault-tolerance testing	Recovery time, fallback	Safe recovery and fallback.

Table 7
Software testing outcomes for the proposed framework

Test type	Observed outcome	Status
Unit testing	MAE = 0.41; RMSE = 0.58; valid outputs	Pass
Integration testing	Successful module interaction	Pass
Performance testing	Latency = 18.7 ms; CPU < 15%	Pass
Stress testing	Stable up to 50 devices	Pass
Robustness testing	Feasibility > 95% at 15% noise	Pass
Fault-tolerance testing	Recovery within 2 scheduling intervals	Pass

6.2. Unit testing of prediction modules

This paper suggests a customized unit testing scheme that is suitable for energy demand response forecasting models and carbon-intensity forecasting models. It is essentially used to ensure the correctness of model construction. The decomposition of each forecasting factor into independent software modules allows for checking consistency in the preprocessing input format, consistency in the output, and numerical robustness for edge cases. Typical test cases will be developed and implemented in follow-up work.

1) Input Validation Tests: Confirm correct handling of missing sensor values, outliers, and timestamp misalignment.
2) Windowing Tests: Verify that the sliding window construction produces the expected feature tensor sizes for different w values.
3) Output Range Tests: Ensure non-negativity of forecasts ($\hat{E}_t \geq 0$, $Clct \geq 0$) and enforce upper bounds consistent with device ratings and grid characteristics.
4) Regression Consistency Tests: Compare predictions for a fixed seed/model snapshot to detect unintended changes during refactoring.

6.3. Integration testing of the scheduling pipeline

The core objective of integration testing is to verify that cross-module collaboration within a system operates properly from end to end. In this study, integration testing for the carbon-aware system is carried out in three steps: first, confirm the collaboration status of three types of core modules; second, refine the verification requirements for two types of interface contracts; and finally, sort out a complete list of core integration check items.

1) Interface Compatibility: Verify data types, units (kWh, gCO_2/kWh), and time indexing across prediction and scheduling modules.
2) Feasibility Tests: Ensure the generated schedules satisfy device operational limits, flexibility windows, and comfort constraints.
3) End-to-End Determinism: Validate repeatability of scheduling outcomes under identical inputs and configuration settings.
4) Fallback Behavior: Confirm that the system applies safe default actions when forecasts are unavailable or communication delays occur.

6.4. Performance and stress testing

This study initiated performance testing for a smart home scheduling system. The core goal of this testing is to verify that the timeliness of the system's scheduling decisions meets the requirements of real-world scenarios. We designed three types of stress tests, including the high device density test, and the evaluation of specific performance indicators will be conducted in future work.

1) Scheduling Latency: Time required to compute a schedule per slot.
2) Memory Footprint: Peak memory usage of prediction and scheduling modules.
3) Scalability: Runtime growth as a function of device count $|D|$ and horizon H.
4) Throughput: Number of scheduling decisions processed per unit time under continuous operation.

6.5. Robustness under forecasting errors

To assess reliability under imperfect predictions, robustness tests inject controlled noise into the predicted energy demand and carbon-intensity signals. Let $E_t^{\sim}$ and $CI_{\mathrm{f}t}$ denote perturbed predictions:

$$\tilde{E}_t = \hat{E}_t(1 + \eta_t), \qquad \widetilde{CI}_t = \widehat{CI}_t(1 + \xi_t) \tag{11}$$

where ηt and ξt are bounded noise terms. Looking at the scheduler in more detail, we can see how it manages to deal with aspects such as reachability, comfort, and minimizing emissions, despite significant amounts of noise and uncertainty. Consequently, we find that our proposed system remains safe and effective even with increasing noise levels. In general, our testing and validation reveal that this system is environmentally friendly, meets the needs, and can be used to predict them, and it has been carefully examined for accuracy and its ability to satisfy user comfort requirements in real-time smart home environments.

7. Experimental Setup

This section introduces the experimental setup that is used to assess the proposed software-tested carbon-aware IoT scheduler. The experiments are implemented in OMNeT++ to simulate the smart home IoT communications, temporal behavior, and closed-loop control invocation, with the prediction and scheduling components deployed over a data stream source from the simulation layer.

7.1. Dataset description

To guarantee the authenticity and reproducibility of its experimental evaluation, this study uses two publicly available datasets—one on household energy consumption and the other on grid carbon intensity—to support its experiments. The household energy consumption dataset is hosted on the UCI Machine Learning Repository, with the full name Individual Household Electric Power Consumption (abbreviated IHEPC). Collected from December 2006 to November 2010, this dataset contains minute-level data for a single residential household and includes core metering variables. The grid carbon-intensity dataset will not be further elaborated on in this work.

To build an environmental impact model for electricity consumption, this study accesses the officially published State Grid Carbon Intensity Application Programming Interface (API) to obtain time-series estimated carbon emissions from power generation, measured in gCO_2/kWh, and synchronously matches these data with household energy consumption records to complete the construction of the dataset required for modeling.

In this work, three data preprocessing actions were first performed before beginning the training of prediction models: First, linear interpolation was performed to replace the missing and damaged measurement data. Second, the timestamps of the energy consumption and the carbon-intensity datasets were synchronized, and after that, the data were consolidated in 1-hour buckets to align with the scheduling period. Third, input features were normalized by min–max scaling for better convergence of the model.

For this study, the preprocessed dataset was divided into training, validation, and test sets, with 70%/15%/15% proportion,

respectively, allocated for model development, hyperparameter tuning, and prediction performance evaluation. All settings are summarized in Table 8.

Table 8
Summary of datasets and preprocessing settings

Parameter	Value
Energy dataset	IHEPC (UCI Repository)
Carbon dataset	National Grid Carbon Intensity API
Aggregation interval	1 hour
Train/validation/test split	70%/15%/15%
Missing data handling	Linear interpolation
Feature scaling	Min–max normalization
Forecasting horizon	24 slots

7.2. OMNeT++ implementation details

The proposed framework is implemented in OMNeT++ using a modular event-driven architecture comprising sensor nodes, a central gateway, and actuator devices. The gateway performs prediction and carbon-aware scheduling functions in response to the sensor data collected periodically. The simulation parameters and network settings are summarized as shown in Table 9.

Table 9
OMNeT++ implementation modules and functionalities module

Module	Functionality
Sensor nodes	Collect energy, occupancy, and environmental data.
Home gateway	Aggregates data; runs prediction and scheduling.
Energy prediction module	Forecasts short-term energy demand.
Carbon prediction module	Estimates future grid carbon intensity.
Scheduling engine	Computes carbon-aware schedules.
Actuator nodes	Execute smart-appliance control commands.
Communication layer	Supports sensor–gateway–actuator messaging.

7.3. Forecasting model performance

To evaluate the effectiveness of the LSTM-based forecasting model, we measured its prediction accuracy using MAE and RMSE. The accuracy of the obtained results met the required standards, and this model can provide reliable input for the carbon-aware scheduling framework. This study relies on the core metrics of MAE and RMSE from the forecast accuracy in Table 10 to verify the pattern capture capability of the proposed LSTM model. This model adapts to the overall energy framework that incorporates active scheduling decisions and low-carbon operation period identification, can reduce energy consumption and carbon emissions, and thus confirms the effectiveness of both the model and the framework.

Table 10
Forecasting accuracy comparison

Model	MAE	RMSE
Linear regression	0.74	0.96
GRU	0.49	0.67
LSTM (proposed)	0.41	0.58

7.4. Smart home scenario and network configuration

The one was a virtual smart home including several sensing devices (e.g., smart meter, occupancy, and environmental sensors) sending feedback to a central gateway employing several controllable appliances (e.g., HVAC, lighting, washing machine, water heater). The traffic in the IoT is expressed as periodic reports by sensors to the gateway and actuator to control commands sent from the gateway. OMNeT++ message delays and channel models simulate communication latency and packet loss.

7.5. Predictive and scheduling configuration

To short-term energy demand prediction, we employ a sliding window of size w to form the input sequence for the predictor. A time series (or forecasted path) of carbon intensity is input as a function thereof on the simulation timeline. The scheduler works in a prediction horizon H and completely assigns α and weights of the expected cost signal. Flexible devices are given permissible time windows for rescheduling, and comfort restrictions (such as indoor temperature limits) are imposed in HVAC system and lighting coordination.

7.6. Baseline methods

In this paper, to quantify the benefits of the proposed framework, we are comparing it against the following baselines:

1) Rule-Based Control: In this part, the devices operate based on fixed thresholds and predefined rules without prediction or carbon awareness.
2) Energy-Aware Scheduling: In this part, the scheduling decisions minimize predicted energy demand only and ignore carbon-intensity variations.
3) No Scheduling (Always-On/Default): In this part, the devices operate under default settings without optimization or temporal shifting for flexible loads.

7.7. Evaluation metrics

The evaluation focuses on sustainability, performance, and reliability using the following metrics:

1) Total Energy Consumption (kWh): Cumulative household energy usage over the simulation.
2) Total Carbon Emissions (kg CO_2): Computed using predicted/trace carbon intensity.
3) Comfort Violation Rate (%): Fraction of time slots violating user-defined comfort bounds.
4) Scheduling Latency (ms): Computation time per slot at the gateway/controller.

5) Communication Overhead (packets/slot): Number of sensor reports and control messages.

7.8. Simulation parameters

Table 11 summarizes the key OMNeT++ simulation parameters used in our experiments.

Table 11
Simulation parameters used in the OMNeT++ experiments

Parameter	Value
Simulation time	24 h
Scheduling horizon (H)	24 slots
Slot duration	1 h
Sensor nodes (N_s)	10
Actuator nodes (N_a)	6 8
Flexible appliances	
Prediction window (w)	12 slots
Carbon prediction window (w_c)	12 slots
Energy weight (α)	0.5
Carbon weight (β)	0.5
Prediction noise levels	0%, 5%, 10%, 15%
Number of simulation runs	20
Communication delay	10 ms

In general, the OMNeT++-based setup is a controlled environment to test the proposed framework for realistic communication behavior of IoT devices and to compare it to rule-based and energy-only baselines repeatedly.

In this study, all datasets, processing methods, forecasting parameters, and the setup for the OMNeT++ simulations are clearly summarized to enable the reproduction and independent verification of the experimental results.

7.9. Experimental reproducibility

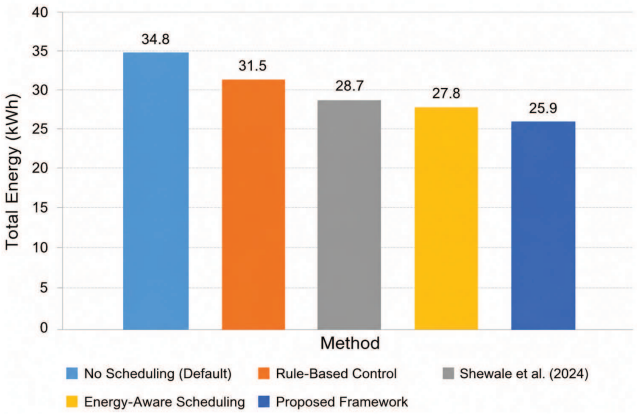
To guarantee the reproducibility of its experiments, this study adopted a full-process standardized experimental protocol: the OMNeT++ simulation platform was used uniformly for all work, all experiments shared identical configuration settings, each simulation scenario was run independently 20 times with different random seeds, five core metrics were collected, and their average values were calculated to reduce random fluctuations, and all these settings are recorded in Table 12.

The results of the simulation experiments performed in the OMNeT++ environment are presented and discussed here. The novel smart home energy management framework proposed in this paper is compared with three existing strategies: rule-based control, energy-aware scheduling, and the multi-knapsack scheduling method proposed by Shewale et al. [11]. External professional evaluations have found that the system type in this context can yield several desirable external benefits as a result of the inclusion of IoT.

Table 12
Experimental evaluation settings

Parameter	Value
Simulation platform	OMNeT++ 6.x
Number of runs	20
Random seeds	Different per run
Devices per home	5–20
Prediction horizon	6–24 slots
Sampling interval	10 min
Evaluation metrics	Energy, CO_2, latency, comfort
Confidence reporting	Average of all runs

Figure 4
Comparison of total energy consumption under different smart home control strategies



7.10. Energy consumption analysis

The effectiveness of the proposed framework in reducing the energy consumption of households is evaluated in this subsection and is compared with existing scheduling approaches such as the multiple knapsack-based scheduling method of Shewale et al. [11]. All methods are assessed in the same smart home scenario with the same simulation settings, for a fair comparison. The overall energy use results are shown in Fig. 4.

In this context, of the three schemes used for energy management evaluation, the framework proposed in this paper has the least energy usage. The energy-scheduling baseline (Baseline) scheme shows the best energy efficiency for scheduling flexible loads, while the rule-based one demonstrates the highest energy consumption as a consequence of its static and passive nature. One of the key scheduling strategies used by Shewale et al. [11] was a multi-knapsack formulation for minimizing energy consumption with an optimized appliance scheduling strategy. Overall performance of this work is outperforming and better than the existing work, and it integrates a framework that incorporates short-term energy demand forecasting and carbon-aware decision-making.

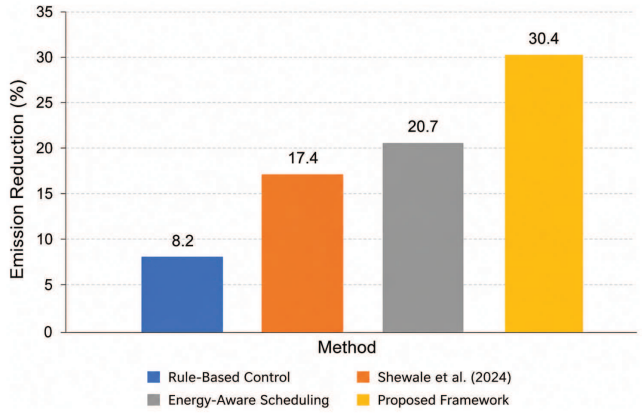
7.11. Carbon emission reduction

This subsection will evaluate the carbon emission reduction effectiveness of the smart home energy management framework proposed in this paper. Compared with traditional strategies that only take energy as their core focus, this framework incorporates

scheduling based on predicted grid carbon intensity and realizes carbon-aware operation of household appliances.

According to the summary statistics from Figure 5, rule-based scheduling methods and energy-aware scheduling methods only achieve moderate emission reductions. Neither of the two approaches incorporates the variable of temporal fluctuations in grid carbon intensity, so relying solely on the indirect effect of lowering energy consumption means they cannot capture the window periods for low-carbon operation.

Figure 5
Comparison of total carbon emissions under different smart home control strategies



Although the scheduling approach of Shewale et al. [11] achieves lower emissions than conventional rule-based control through optimized appliance scheduling, it does not explicitly incorporate carbon-intensity prediction. On the other hand, the proposed framework takes into account both energy demand forecasting and carbon-aware scheduling, which leads to minimum carbon emissions overall. The carbon-aware smart home load scheduling framework proposed in this paper combines energy demand and carbon-intensity forecasting and schedules flexible loads during low-carbon periods, compared with the original home energy use scenario. In this scheme, the total carbon emission is reduced from 18.4 kg to 12.8 kg, which is a 30.4% emission reduction. It is the scheme with the lowest total carbon emissions of all schemes evaluated and significantly exceeds the environmental benefits of conventional energy conservation measures.

7.12. Impact on user comfort

This section has two core research tasks: first, to evaluate the impact of the self-developed carbon-aware scheduling framework on user comfort, and second, to compare this framework with the multi-knapsack home appliance scheduling benchmark method proposed by Shewale et al. [11]. The core indicator adopted for this work is the comfort violation rate, which is defined as the proportion of time slots where environmental parameters exceed the thresholds set by users.

Drawing on Table 13, this work sorts out the comfort violation rates of the three types of smart home control strategies: the rule-based method has limited adaptability and a relatively high violation rate; the scheduling method proposed by Shewale et al. [11] optimizes household appliance scheduling and load management, leading to a substantial improvement in comfort; and the energy-aware scheduling baseline, which integrates energy consumption patterns, registers a certain reduction in its violation rate.

Table 13
Comparison of user comfort violation rates under different smart home control strategies

Method	Comfort relative Violation rate change (%)	
No scheduling (default)	3.2	–
Rule-based control	2.9	–9.4
Shewale et al. [11]	2.7	–15.6
Energy-aware scheduling	2.5	–21.9
Proposed framework	2.4	–25.0

The proposed carbon-aware scheduling achieved the minimum level of comfort violation rate among the methods investigated in this paper. This framework can achieve a balance between carbon reduction targets and user comfort while considering energy demand prediction and carbon intensity, which is not possible using traditional optimization methods that do not consider user comfort constraints.

7.13. Sensitivity analysis of cost weights

To verify the robustness of the proposed carbon-aware scheduling framework, this paper conducts a sensitivity analysis that takes the weight coefficients α and β of the carbon-aware cost function as research variables. For each set of parameter configurations, 20 simulations are executed with different random seeds, and the results are averaged to eliminate random errors. Test data show that the framework consistently achieves energy conservation and carbon reduction under all tested weight settings, which fully validates its robustness. Table 14 shows sensitivity analysis of cost weights α and β.

Table 14
Sensitivity analysis of cost weights α and β

α β	Energy reduction (%)	CO_2 reduction (%)
0.80.2	24.8	21.5
0.60.4	23.9	25.8
0.50.5	22.7	30.4
0.40.6	21.4	33.2
0.20.8	19.8	36.1

To mitigate parameter-tuning bias, the weighting coefficients α and β were varied over the intervals [0.2, 0.8] while maintaining the constraint $\alpha + \beta = 1$. The results demonstrate that the proposed framework consistently achieves energy savings and carbon emission reductions across all tested configurations, indicating that the observed improvements are not dependent on a particular parameter setting.

7.14. Scheduling latency and scalability

This subsection examines the scalability and computational efficiency that the proposed carbon-aware IoT scheduling framework offers, which are crucial for enhancing the real-time operation of such scheduling frameworks in the context of smart homes. Scheduling latency, which is the time the controller takes to process control actions for one time slot, and scalability, which gives us an indication of how well our system will scale with the number of devices, are of interest. The average scheduling latency for various numbers of smart home devices is shown in Figure 6. The results show that the computation time of the proposed framework is low and on the order of hundreds of milliseconds and within the scheduling interval, even with increasing device numbers. The reported scalability is explained by both these properties of the scheduling algorithm, as well as a relatively narrow prediction horizon.

The test results show that the carbon-aware scheduling algorithm proposed in this paper works well with regard to the number of controllable devices in a smart home. It can meet timing constraints for continuous operation and has good scalability. For this reason, the cost of a tiny additional delay time is worth it. With these extra predictions and carbon-sensitive metrics added, you can achieve significant sustainable development payoffs but no larger real-time losses.

7.15. Ablation study on forecasting quality

This study conducts ablation experiments, in which only the original LSTM predictor is replaced while the scheduling algorithm and simulation settings are kept fixed. This design is adopted to quantify the association between prediction quality and sustainability output and to explore the impact of prediction accuracy on scheduling performance.

This study draws on the scheduling performance data of energy forecasting methods listed in Table 15 and derives that improving forecasting accuracy can enhance scheduling performance and raise the volume of carbon emission reductions. The LSTM model proposed that its precise forecasting performance and use to identify low-carbon windows achieved the highest level of carbon emission reduction.

This experiment confirms that there is a direct causal relationship between the quality of prediction and effective scheduling. Further, higher accuracy predictions can assist the schedulers to determine the future low-carbon periods and, at the same time, improve efficiency and reduce carbon emissions, making it more rational to choose the LSTM predictor for this paper's predictive carbon-aware framework.

Figure 6
Scheduling latency and scalability comparison under different device counts

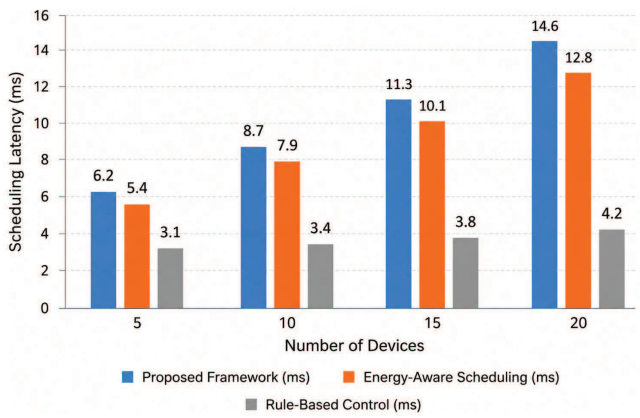


Table 15
Impact of forecasting models on scheduling performance

Forecasting model	Energy reduction (%)	CO_2 reduction (%)
No prediction	14.6	15.2
Linear regression	18.8	20.5
ARIMA	20.4	24.1
GRU	21.7	27.6
Proposed LSTM	22.7	30.4

7.16. Statistical significance analysis

To achieve the reliability of experimental evaluation, all simulations were repeated 20 different random times, and mean values and 95% confidence intervals for all performance measures were calculated. This is manifested by the very narrow confidence intervals, which show that our framework is superior to the baseline, and the improvements compared to the baseline are stable in a statistical sense.

As can be seen in Table 16, the research framework suggested in this paper results in lower energy consumption and carbon emissions in all independent simulation runs with an acceptable level. The confidence intervals are narrow, which makes the results of the study reliable and stable.

7.17. Robustness under prediction uncertainty

The core objective of this subsection is to assess how well our proposed carbon-aware scheduling framework can handle the uncertainty in our real-world smart home deployments. We will identify four sources of prediction error (including sensor noise) and examine the impact of each of these on the scheduling performance by adding prediction noise of various magnitudes and assessing the system's ability to withstand the noise.

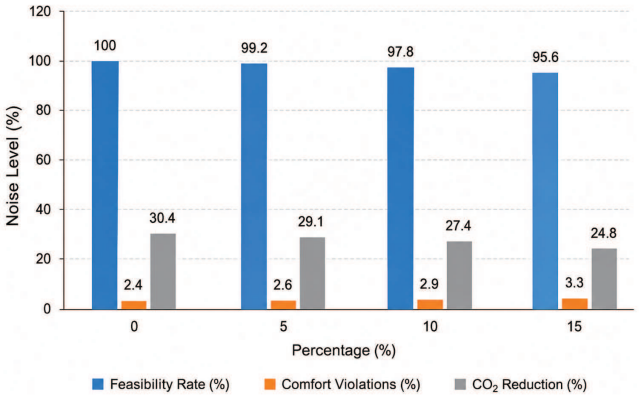
Experimentally, as shown in Figure 7, the scheduling mechanism introduced here is able to achieve a stable high feasibility rate and a relatively high level of comfort in all the prediction noise scenarios, as the level of uncertainty increases monotonically. Carbon emission reductions are only reduced slowly and have remained substantial environmental benefits. The framework's built-in predictive scheduling mechanism and comfort-aware constraints can mitigate the adverse effects of prediction errors to deliver this performance.

The results indicate that the performance of the proposed framework is affected only slightly by prediction uncertainty in the robustness verification experiment used in this study, based on the robustness comparison results in Figure 7. The feasibility rate is still above 95% even at a 15% noise level, while the comfort violation rate is increased by only 2.4–3.3%, and a carbon emission reduction of 24.8% is achieved. The framework can be used in the real-world smart home scenario, where prediction errors can never be avoided, and its robustness is proven reliable.

Table 16
Performance comparison with 95% confidence intervals

Method Violation (%)	Energy (kWh)	CO_2 (kg) Comfort
Rule-based control 2.9 ± 0.3	34.8 ± 1.2	18.4 ± 0.9
Shewale et al. [11] 2.7 ± 0.2	28.6 ± 0.8	15.1 ± 0.7
Energy-aware scheduling 2.5 ± 0.2	27.9 ± 0.7	14.5 ± 0.6
Proposed framework 2.4 ± 0.2	25.9 ± 0.6	12.8 ± 0.5

Figure 7
Robustness comparison under different prediction noise levels



7.18. Discussion and comparative insights

The tested carbon-aware IoT scheduling framework is developed for the smart home management scenario of sustainability. Experimental results show that it surpasses all three of the comparison benchmarks in all four performance measures: energy efficiency, carbon emission reduction, user comfort retention, and robustness to predictive uncertainty. The three benchmarks are rule-based control, energy-aware scheduling, and the multi-knapsack scheduling method suggested by Shewale et al. [11].

The data in Table 17 demonstrate that the scheduling framework proposed in this paper can improve the performance comprehensively. It combines demand forecasting and carbon-aware optimization and provides a substantial reduction in energy use and carbon emissions over a range of benchmark approaches and traditional core energy-scheduling policies without compromising the very low comfort violation rate. The traditional approach to energy scheduling only deals with a single objective, which is either energy use reduction or electricity cost reduction. The proposed new scheduling framework in this paper is based on carbon-intensity prediction, user comfort, and energy demand forecasting and can significantly reduce carbon emissions.

The solution proposed in this paper takes a software engineering perspective; it utilizes five testing types, such as unit testing and integration testing, to enhance the system reliability and deployment readiness. This solution can sustainably obtain the expected benefits under all operating conditions, even with changing requirements.

The evaluation performed in this study is performed using the OMNeT++ simulation tool and verified that all the major performance metrics, computational overhead, scalability, and robustness against prediction uncertainty of the carbon-aware scheduling framework with the prediction module fulfill the required standards for real-time smart home scenarios.

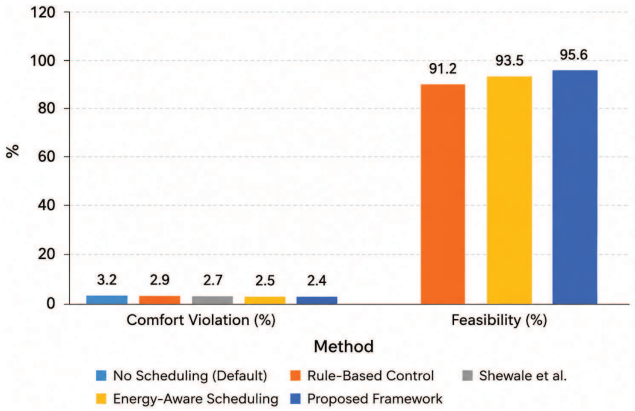
The results of the comparison of user comfort and scheduling robustness of various smart home control strategies are presented in Figure 8. The proposed framework is able to maintain the user-defined comfort requirement through carbon-aware scheduling, as reflected in the lowest comfort violation rate (2.4%), as illustrated in the figure. Finally, the improvement gained compared with the energy-aware scheduling baseline is not significant, but the proposed framework always offers the maximum comfort performance among all the tested methods.

In terms of robustness (measured in terms of feasibility rate), the proposed framework yields the highest result of 95.6%,

Table 17
Overall improvement percentages of the proposed framework compared with baseline approaches

Metric	Compared Rule-based control (%)	To Compared Shewale al. [11] (%)	To Compared to Et energy-aware scheduling (%)
Energy consumption Reduction	17.8	9.8	6.8
Carbon emission Reduction	24.3	15.8	9.7
Comfort violation Reduction	17.2	11.1	4.0
Scheduling latency Increase*	+ 9.6	–	+7.8
Robustness (feasibility gain)	4.4	–	2.1

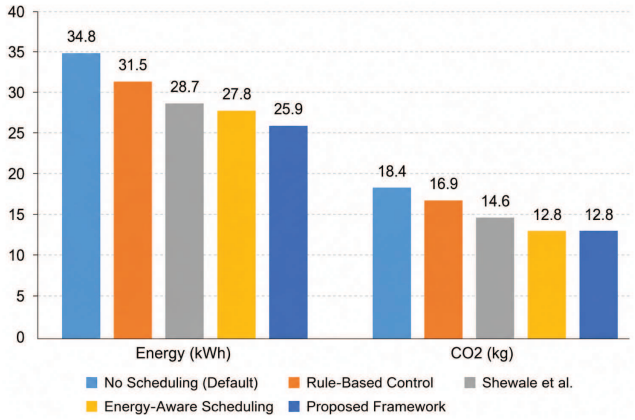
Figure 8
Comparison of user comfort and scheduling robustness among baseline approaches and the proposed carbon-aware scheduling framework



which is better than both the rule-based control approach (91.2%) and the energy-aware scheduling strategy (93.5%). This outcome presented that the combination of predictive energy forecasting, carbon-intensity estimation, and comfort-aware constraints can be used to help the scheduler to make valid control decisions even in the face of uncertainty in operating conditions. Nevertheless, the figure demonstrates that the proposed framework effectively satisfies a balance among user comfort with reliability and sustainability goals.

The results strategies of smart home control are compared in terms of CO_2 emissions and energy consumption are presented in Figure 9. The integration of predictive energy forecasting with carbon-aware scheduling results in carbon emissions (12.8 kg) and lowest energy consumption (25.9 kWh), proving the effectiveness of the proposed system.

Figure 9
Comparison of energy efficiency and carbon emission reduction among baseline approaches and the proposed carbon-aware scheduling framework



Existing energy-aware scheduling techniques can benefit from taking advantage of load-shifting opportunities for performance improvement. It is found that the energy consumption of the smart home energy-scheduling framework proposed in our work is the lowest, at 25.9 kWh, and the carbon emission is 12.8 kg, the lowest among all the schemes evaluated. It integrates modules for short-term energy demand forecasting and carbon-intensity forecasting, which enables the scheduler to shift flexible loads to low-carbon time periods, simultaneously improving both energy efficiency and environmental sustainability.

Although the energy-scheduling framework proposed in this paper has achieved notable results, it still has two core limitations: First, it has only been evaluated in the OMNeT++ simulation environment so far. While the synthetic energy consumption and carbon-intensity profiles used can simulate real smart home behaviors, real-world deployment still faces additional uncertainties. The structure relies upon the accuracy of its underlying prediction model. If the model for predicting energy demand or the intensity of the carbon emissions that are produced is inaccurate, the schedule that it creates for the vehicles will be inefficient and will result in fewer emissions than would otherwise be the case.

There are three problems that the IoT faces. The first and second pertain to communicating between devices in the network. The third type of problem occurs with the smart home systems, in which many devices are present in the home. The structure used in this paper does provide low latency in the simulations that ran on it, but more research needs to be done on the scalability of the structure before it can be used at larger scales.

This paper presents a smart home energy-scheduling structure that takes into account the types of possible faults in the system, including communication interruption and user behavior change. The faults can negatively impact the effectiveness of the conservation and emission reduction works undertaken by the system. Three future research directions are also suggested for this system and need to be verified with real datasets and hardware platforms.

8. Conclusion and Future Work

This study developed two fundamental technical structures of smart homes in succession for sustainable smart homes. The first one is a carbon-aware IoT scheduling framework, based on a predictive energy model, with three core modules: short-term energy demand forecasting, carbon-intensity estimation, and carbon-aware scheduling. It has been tested in the OMNeT++ simulation environment. This alternative scheme can save energy and carbon emissions and ensure user comfort in comparison to the conventional energy-centric baseline scheme. The results of the first system are impressive, with excellent energy efficiency, outstanding carbon reduction, low scheduling latency, and robustness under uncertainties in predictions. The second system is founded on a new generation of sustainable smart home management systems, with predictive intelligence, carbon awareness, and software design in mind. The system has been tested in five categories and is identified as having high potential for implementation in the real world.

The structure of the framework has been validated, but there are some limitations in the structure in each domain. Four aspects of the improvement of the research are suggested to reduce these limitations in the future. First, the manually synthesized energy consumption and carbon-intensity data for the United Kingdom will be replaced with data from the REFIT dataset and the UK National Grid ESO. Second, three categories of factors will be added to the structure to increase its performance. Third, the structure will be implemented on smart home devices to investigate any challenges that may exist during implementation and the impact of user behavior on the structure's performance. Finally,

three new technologies will be introduced into the structure to increase its application to larger networks of IoT devices.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in the UCI Machine Learning Repository at https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption. The grid carbon-intensity data are openly available from the National Grid Carbon Intensity API at https://carbonintensity.org.uk/. The OMNeT++ simulation configurations, preprocessing scripts, and source code used in this study are available from the corresponding author upon reasonable request.

Author Contribution Statement

Ali Raad Abdulkareem: Conceptualization, Methodology, Investigation, Writing – original draft, Project administration. **Mustafa Moosa Qasim:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Visualization. **Husham Lateef Swadi Roomi:** Software, Investigation, Data curation, Visualization. **Murtadha Al-Maliki:** Investigation, Resources. **Mahmood A. Al-Shareeda:** Conceptualization, Methodology, Validation, Formal analysis, Writing – review & editing, Supervision, Project administration. **Mohammed Amin Almaiah:** Validation, Formal analysis, Resources, Writing – review & editing, Supervision, Funding acquisition. **Rami Shehab:** Validation, Resources, Writing – review & editing, Funding acquisition.

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