Efficient Deep Reinforcement Learning for Smart Buildings: Integrating Energy Storage Systems Through Advanced Energy Management Strategies

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Abstract*—This study presents a novel and workable approach to solving the critical issue of improving energy management in smart buildings. Using a large dataset from a seven-story office building in Bangkok, Thailand, our work introduces a novel approach that combines Deep Q-network (DQN) algorithms with energy storage models and cost optimization strategies. The suggested approach is intended to reduce operational expenses, improve the energy economic performance, and efficiently control peak demand. The energy storage model used in this research incorporates the use of the capabilities of advanced storage models in smart buildings, particularly lithium-ion batteries and supercapacitors. When the cost optimization approach is applied using linear programming, energy consumption costs are significantly reduced. Notably, our method outperforms current algorithms, specifically outperforming them, to show its effectiveness in smart building energy management by outperforming current algorithms, especially Genetic and Fuzzy Algorithms. In comparison to traditional methods, the DQN algorithm exhibits an impressive 8.6% reduction in Mean Square Error (MSE) and a 6.4% drop in Mean Absolute Error (MAE), making it a standout performer in the research through Python software. The results highlight the significance of optimizing DQN algorithm parameters for best outcomes, with a focus on adaptability to various properties of smart buildings. This investigation is novel because it integrates cost optimization, reinforcement learning, and energy storage. This results in a flexible and all-inclusive framework that can be used for effective and sustainable energy management in smart buildings.

***Keywords*—Deep q-network; cost optimization; smart building; energy management; peak demand**

I. Introduction

Reinforcement learning integration with smart energy management is an attainable approach to improving energy system efficiency and optimizing consumption of energy. A subfield of machine learning called reinforcement learning (RL) trains agents to make decisions through interaction with their surroundings and feedback in the form of rewards or punishments. Applying reinforcement learning (RL) to smart energy management can help with complicated and dynamic decision-making problems [1]. RL algorithms perform well in settings where making decisions is dynamic and necessitates flexibility in response to shifting circumstances. With smart energy management, control techniques could be dynamically adjusted by RL for optimal energy utilization, taking into account variable elements such as weather patterns, user behaviors, and energy costs [2]. The algorithms have the potential to be utilized for precise load forecasting, energy demand pattern prediction, and energy-consuming device scheduling [3]. This lowers peak demand and maximizes the usage of energy resources. It may be used to enhance techniques for demand response. To take part in demand-side management programmes and gain incentives, agents can be trained to react to signals from utilities or energy suppliers and modify their patterns of energy usage [4]. The energy system can more easily incorporate renewable energy sources like wind and solar electricity thanks to these learning algorithms [5]. RL agents are able to optimize the use of renewable resources, balance supply and demand, and manage energy storage systems. It can maximize the control of distributed energy resources (DERs), such as solar panels, batteries, and electric cars, in microgrid settings [6]. Within the microgrid, agents can learn to balance the production and consumption of energy, increasing overall efficiency. RL is ideal for managing energy storage systems in an optimal way. Agents are able to acquire the best battery charging and discharging techniques, accounting for user preferences, grid circumstances, and power pricing [7]. Additionally, algorithms can assist energy management systems in adhering to legal and policy requirements [8]. Agents can be trained to make choices that adhere to regulatory requirements, energy efficiency standards, and other environmental considerations. Because these models can learn and adapt continuously, intelligent energy management systems can get better over time as they interact with their surroundings and gather input [9].

The implementation of machine learning techniques has led to significant improvements in energy management in smart buildings. Machine learning algorithms, especially those that employ supervised and unsupervised learning, provide insightful information and prediction powers that improve energy efficiency. To optimize lighting, other energy-consuming devices, HVAC systems, and occupancy trends, predictive models may be trained to examine historical data, weather patterns, and other pertinent variables [10]. Furthermore, anomaly detection algorithms can spot anomalous patterns in energy use, which allows for early intervention in the event of possible inefficiencies. Real-time adaptability is provided via reinforcement learning approaches, which dynamically modify control strategies in response to changing situations. The necessity for sizable labeled datasets, the interpretability of intricate ML models, and the possibility of biases in training data remain obstacles in spite of recent developments [11]. In order to protect against possible vulnerabilities, the deployment of ML models necessitates comprehensive consideration of cyber security measures [12]. Despite the encouraging outcomes of ML integration in smart buildings, these issues must be resolved to guarantee the stability and dependability of these systems in practical settings. Ongoing research and development initiatives are crucial to overcoming these obstacles and realizing the full potential of machine learning in smart building energy management as the field develops [13]. The capability of managing the intricate, nonlinear interactions present in energy systems is one of DRL's main advantages in smart buildings. Through constant environmental interaction and feedback in the form of incentives or penalties, DRL algorithms can acquire the best control rules for energy-intensive equipment such as lighting, HVAC systems, and other gadgets. Because of their adaptable nature, smart buildings can react quickly to changes in the weather, occupancy patterns, and energy prices, resulting in effective energy management. Deep learning integration makes it easier to uncover complex patterns from data, which leads to more precise forecasts and well-informed decision-making. Achieving a feasible deployment requires balancing the interpretability of the model with computing performance. The promise for significant gains in energy efficiency, cost savings, and sustainability continues to be a driving factor behind the development of intelligent building management systems as research into efficient DRL for smart buildings advances.

In the modern energy landscape, integrating energy storage technologies with sophisticated energy management methods is a critical first step towards improving efficiency, dependability, and sustainability. Because it may be used to store extra energy during times of surplus and release it during times of low generation or high demand, energy storage is essential for mitigating the intermittent nature of renewable energy sources. Advanced energy management strategies use complex algorithms, which frequently include machine learning and optimization approaches, to automatically regulate the cycles of energy storage systems' charging and discharging. These solutions optimize energy storage use by analyzing weather forecasts, historical data, and real-time demand patterns. This ensures that stored energy is strategically deployed to balance peak demand, minimize grid stress, and improve overall system resilience. Moreover, grid stability is enhanced and the integration of decentralized renewable energy resources is supported by the incorporation of energy storage into the energy management system. Despite these benefits, broad use will need to address issues including high upfront costs, the current generation of storage technologies' low energy density, and regulatory barriers. The secret to opening the door to a more robust and sustainable energy future lies in the smooth integration of energy storage systems through sophisticated energy management tactics, which will be made possible by ongoing technological and scientific developments. The following are the research study's main contributions,

- For the purpose of improving energy management in smart buildings, the study presents and uses Deep Reinforcement Learning algorithms. The study improves the system's capacity to make wise choices in a dynamic environment by utilizing DRL and taking into account variables like cost savings, peak demand reduction, and occupant comfort.
- The research provides a contribution by integrating a sophisticated energy storage model into the infrastructure of smart buildings. Modern technologies like lithium-ion batteries and supercapacitors are integrated into this concept and are arranged to store and harvest extra energy from renewable sources, improving sustainability and the economy.
- With the objective of minimizing overall energy consumption costs, the study presents a linear programming-based cost optimization model. This model offers a comprehensive approach to effective energy management by taking into account factors including electricity tariffs, operational costs, and potential fines for exceeding energy thresholds.
- A number of quantitative parameters are used in the study to evaluate the degree to which the suggested technique performs. These measures include the accuracy of the reinforcement learning model, cost savings, and percentage reductions in peak demand.
- The study emphasizes that the suggested tactics affect the lowering of peak demand. The results show that demand charges are significantly lower during peak hours, proving that the DRL strategy is effective in optimizing and modifying energy usage patterns.
- A comparative examination of the suggested DRL technique and a Genetic Algorithm (GA) approach is included in the paper. This comparison analysis shows that the DRL technique performs better in terms of peak load control and cost savings.

The paper's summary is given in Section I. Reviewing previous research, Section II highlights the gaps in the field's understanding of energy storage and management. The primary research question about the intricacies of smart building management is defined in Section III. Section IV presents the suggested technique. By comparing classifier performance, presenting empirical data in Section V, and examining conclusions and future research goals, Section VI demonstrates the importance of this research for smart building energy management.

II. Related Works

Elsisi et al. [14] presents a fresh and creative solution to the major problems associated with reducing energy usage and utilization in smart buildings, especially in the residential and commercial sectors. An impressive endeavor that places deep learning and the Internet of Things at the center of Industry 4.0 is the combination of these two technologies. A forward-thinking approach to effective energy management is demonstrated by the use of artificial intelligence tools in conjunction with the Internet of Things to share signals across machines and equipment. The paper's main contribution is the introduction of a people identification method based on deep learning that uses the YOLOv3 algorithm to maximize air conditioner performance and thereby cut energy usage. This method, which is based on precisely counting the people in a given space, allows for creative choices to be made for real-time air conditioner operational management in the context of smart buildings. The incorporation of the suggested system with an Internet of Things platform is also highlighted in the research. A dashboard receives internet-based updates on the number of people spotted and the condition of the air conditioners. This integration improves energy-related decision-making by offering insightful data on utilization trends and air conditioning usage. The simulation results that are reported in the research offer strong proof of the suggested approach's usefulness and effectiveness. The capacity of the deep learning-based identification algorithm to model extremely non-linear connections in data is demonstrated by its effective and accurate detection of the number of people in the designated region. The smooth broadcast of identification status on the dashboard of the IoT platform validates the system's usefulness. In conclusion, by utilizing deep learning and Internet of Things technology, the article significantly advances the subject of smart building power management. In addition to addressing the issues associated with energy consumption, the suggested method has potential uses in the remote control of a variety of controllable equipment. This study is positioned as a useful and innovative addition to the convergence of artificial intelligence, IoT, and energy conservation in smart buildings due to its integration of state-of-the-art technology and its encouraging simulation findings.

Shivam, Tzou, and Wu [15] presents a thorough machine learning-based multi-objective forecasting energy management plan for home grid-connected PV-battery hybrid systems. The hybrid approach under discussion combines an electric load in the form of a residential building, a bank of batteries for storing electricity, and a solar array. The suggested approach makes use of a three-tiered control framework: a dual forecasting framework based on residual causal dilation convolutional networks for generating electricity and electric load; a logical level for managing computational load and accuracy; and a multi-objective optimization for effective energy trade with the utility grid by means of battery charge scheduling. The prediction model exhibits precise one-step forward estimates for solar energy output and load, having been developed via a sliding window approach. The suggested energy management strategy is to minimize energy acquired through the utility grid, maximize the state of charge of the battery bank, and lower carbon dioxide emissions. Limits are placed on the highest amount of carbon dioxide that can be produced and the state of charge of battery banks. Using hourly power and load data, the approach is assessed under static as well as dynamic electricity pricing scenarios. The suggested dual prediction model has a high coefficient of predictability (93.08% for energy output and 97.25% for electrical load) according to simulation findings. The suggested prediction model shows substantial advances in accuracy when compared to naïve estimation, support vector machine, and artificial neural network (ANN) models. When combined with the sophisticated prediction model, the all-encompassing approach effectively controls more than half of the annual load demand, leading to notable decreases in carbon dioxide emissions and electricity costs when compared to residential structures with no hybrid energy systems or hybrid energy systems without an energy management plan. The research presents an organized and meticulous methodology, supported by comprehensive simulations, demonstrating its usefulness in incorporating machine learning into the predictive management of energy for home grid-connected PV-battery hybrid power systems.

Lan et al. [16] outlines a novel machine learning-based strategy for renewable microgrid energy management, with a special emphasis on a changeable structure made possible by remote tie and sectionalizing switches. The study notably uses sophisticated support vector machines (SVM) to model and estimate the hybrid electric vehicle (HEV) charging needs within the micro grid. To tackle the possible effects of HEV charge on the network, the study presents two discrete scenarios: intelligent and coordinated charging. A revolutionary modified optimization approach based on dragonflies addresses the complex nature of the issue formulation and provides a customized solution to the complicated problem. Also, a self-adaptive modification is suggested, which enables solutions to choose the modification strategy that best fits their particular situation. The effectiveness and suitability of the suggested strategy are shown by simulation findings on an IEEE microgrid evaluation system in both synchronized and autonomous charging scenarios. A high degree of precision is indicated by the mean absolute % inaccuracy of 0.978 for the anticipated total charge demand of HEVs. Moreover, the outcomes demonstrate a significant 2.5% decrease in the micro grid's overall operating expenses when using the intelligent charging strategy in contrast to the coordinated method. The study advances the area by providing a thorough solution to the complex problems associated with controlling energy in renewable microgrids taking into account the needs of HEV charging. The relevance of the research is highlighted by the revolutionary reconfigurable structure, the personalized optimization strategy, and the use of modern machine learning techniques. The simulation findings validate the suggested approach's realistic deployment in renewable microgrid networks and offer compelling proof of its efficacy.

Syed et al. [17] focuses on the crucial component of dynamism estimating at the home level in smart constructions inside the larger framework of smart grid management of energy. Precise forecasts of energy usage in smart constructions are required for effective power generation and administration. The two primary phases of the suggested hybrid deep learning approach are model construction and data cleansing. Pre-processing techniques, such as adding lag values as extra features, are applied to raw data during the data-cleaning step. A hybrid deep learning architecture, comprising fully linked layers, unidirectional long-term short-term memory, and bidirectional LSTMs, is employed throughout the model-building stage. The objective of the model is to efficiently capture temporal relationships while maintaining high forecasting accuracy, low training time, and computing economy. The suggested model performs better than popular hybrid models like Convolutional Neural Networks, ConvLSTM, LSTM encoder-decoder frameworks, and stacking models, according to the evaluation of two benchmark energy consumption datasets. The suggested model achieves a mean percentage error in absolute terms of 2.00% for Case Study 1 and 3.71% for Case Study 2, indicating significant improvements. On the other hand, for the corresponding datasets, LSTM-based models produced greater MAPE readings of 7.80% and 5.099%. Furthermore, for the used energy consumption datasets, the suggested model shows promise in multi-step week-ahead everyday projections, exhibiting improvements in MAPE of 8.368% and 20.99% when compared to LSTM-based models. By presenting a unique hybrid deep learning model designed for household-level energy forecasts in Smart Buildings, the research makes a substantial contribution to the area. The thorough testing of the suggested method against well-known models and the documented increases in predicting accuracy highlight its possible applicability. This study offers useful insights for researchers and practitioners working in the fields of Smart Grid management of energy and Smart Buildings, especially about improving accuracy in forecasting household-level energy usage.

Han et al. [18] focuses on the potential of edge intelligence in the Internet of Things for green energy management, filling a major gap in the literature. The main goal is to provide a system based on deep learning for intelligent management of energy that can meet the needs of modern homes, businesses, and smart grids. The system attempts to forecast future short-term energy convention and enable effective statement among customers and energy providers. The paper's main contributions are the following: an innovative sequences learning-based energy forecasting mechanism, optimum normalization technique selection, and real-time energy management via devices at the edge interacting with a shared cloud-based data supervisory server. The lowest mistake rates and less temporal complexity are features of this forecasting system. According to the suggested architecture, edge devices connect in real time to a shared cloud server inside an IoT network, enabling efficient interactions across related smart grids and energy demand and response. To address the heterogeneous nature of electrical data, the study employs a number of preprocessing approaches. Next, an effective algorithm for decision-making is implemented for forecasting the immediate future on devices with limited resources. The efficiency of the suggested framework is demonstrated by extensive tests, which indicate a considerable decrease of 3.77 units for root MSE (RMSE) and 0.15 units for mean-square error (MSE) for commercial and residential datasets, respectively. The paper provides a significant addition to green energy conservation in the Internet of Things networks, especially when discussing edge intelligence. The suggested framework is a notable development in the field because of its useful applications in forecasting energy usage, improving communication, and lowering forecasting mistakes.

The reviewed studies collectively advance the field of energy management across diverse domains. According to one study, a novel solution to smart building energy management combines deep learning and IoT to maximize air conditioner efficiency by identifying individuals. A multi-objective forecasting strategy for residential grid-connected PV-battery hybrid systems is presented in another research. It uses a three-tiered control framework and achieves significant savings in power prices and carbon emissions. Within the field of renewable microgrid energy management, a study employing a modified optimization technique with support vector machines demonstrates efficacy in lowering total operating costs. Another study presents a hybrid deep learning approach with improved accuracy over conventional models, focusing on home-level energy forecasting in smart buildings. Finally, a study highlights the potential of edge intelligence in green energy management by putting forth a deep learning-based system that significantly lowers predicting errors and intelligently manages energy in Internet of Things networks. When taken as a whole, these research help to bridge the gap between cutting edge technologies such as IoT, machine learning, and deep learning by providing more effective and sustainable energy management techniques for a variety of applications.

III. PROBLEM STATEMENT

The effective management of energy in smart buildings is the issue that the literature addresses, with a special emphasis on the integration of energy storage systems using sophisticated energy management techniques. One of the current issues is making decisions effectively in a changing environment in order to maximize the utilization of energy, cut expenses, and improve overall operational efficiency. The research highlights the importance of using the Deep Q-Networks algorithm—a type of deep reinforcement learning (DRL)—as a solution to these problems. Emphasis is placed on the DQN algorithm's capacity to estimate and optimize the action-value function in a network of deep neural networks, demonstrating its efficacy in teaching appropriate energy management tactics. The suggested approach is to use DQN to help smart building managers make defensible choices about lighting, HVAC, and energy storage. Reducing peak demand, occupant discomfort, and costs significantly depends on the DQN algorithm's ability to manage intricate and dynamic interactions in the smart building environment. According to the literature, combining DQN with cost optimization methods and complex energy storage models results in a more effective and sophisticated method of managing energy in smart buildings [19].

IV. PROPOSED EMDQN FRAMEWORK FOR ENERGY MANAGEMENT IN SMART BUILDING

The proposed energy management methodology for smart buildings follows a systematic sequence, beginning with the collection of a diverse dataset. Through Min-Max normalization, the dataset is pre-processed to ensure consistent scaling. The application of reinforcement learning evaluates the effects of centralized and decentralized model predictive controllers on peak demand and operational expenses. Simultaneously, an advanced energy storage model is introduced, utilizing lithium-ion batteries and supercapacitors to strategically capture and use excess energy. A cost optimization model, employing linear programming, aims to minimize overall energy consumption costs. The results and discussion section then analyzes the methodology's performance, focusing on metrics like peak demand reduction and cost-effectiveness. Deep Q-Networks (DQN) play a pivotal role in optimizing energy management, aligning decisions with objectives such as cost reduction, peak demand reduction, and occupant comfort. The entire process is illustrated through a flowchart, providing a comprehensive overview of the methodology's implementation from preprocessing to performance assessment. The entire methodology process is represented in Fig. 1.

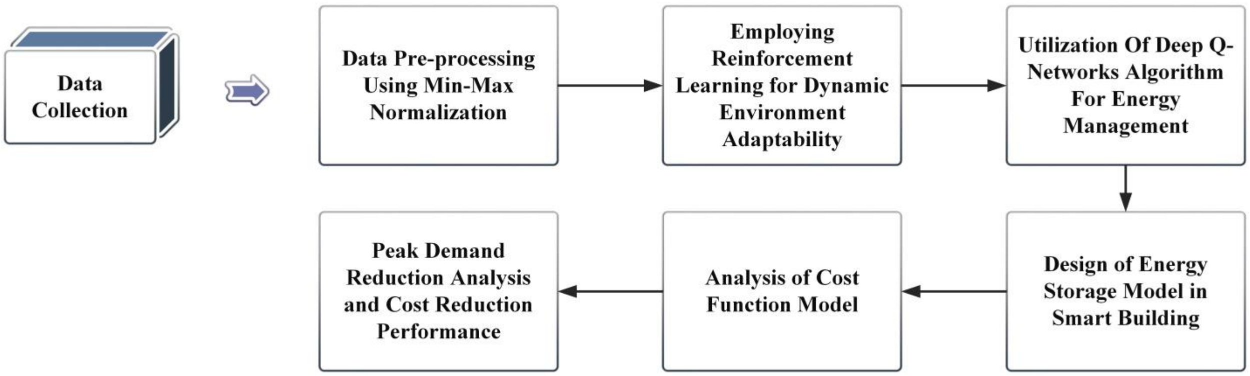

Fig. 1. Proposed framework for energy management in smart building.

A. Data Collection

The valuable tool for study and advancement in the area of smart building energy management is the dataset gathered from Kaggle. This comprehensive dataset, which comes from a seven-story office building in Bangkok, Thailand, includes one-minute interval records of power usage and interior environmental measures. It covers the period from July 1, 2018, to December 31, 2019. The data on power use covers each of the building's 33 zones for plug loads, lights, and air conditioning systems. The collection is further enhanced by complementary interior environmental sensor data, which includes ambient light, relative humidity, and temperature readings for the same zones. The CU-BEMS dataset is distinct because it provides a thorough analysis of the electricity consumption at the building level, broken down by zone and floor, and it captures the functioning of important loads in commercial buildings. Numerous applications benefit greatly from such a dataset, such as multiple-level load forecasting, the development of indoor thermal models, the validation of building simulation models, the creation of demand response algorithms based on load types, and the application of reinforcement learning algorithms for multiple AC unit control. This dataset provides a solid foundation for optimizing energy consumption and storage techniques in smart buildings, which is in line with the goals of our planned study on smart buildings [20].

B. Data Pre-processing using Min-Max Normalization

The distributional properties of the original data are maintained by using Min-Max normalization. It provides a normalized representation that keeps the crucial data for training the model while scaling the values and preserving the connections and trends within the feature. All of the data points inside a feature are guaranteed to be scaled to a common range between 0 and 1 as a consequence of the normalization procedure. Outliers, which are data points significantly deviating from the majority, can distort the effectiveness of the subsequent analysis and modeling. Outliers can distort the uniform scaling intended by Min-Max normalization, leading to suboptimal model performance. By addressing outliers effectively during pre-processing, the dataset's integrity is preserved, ensuring that the subsequent energy management model is robust and reflective of the true underlying patterns in the smart building data. This uniform scaling is essential for preventing certain features from dominating the learning process due to their larger magnitudes is represented in Eq. (1).

$$X_i^m = \frac{X_i^m - X_{Min}^m}{X_{Max}^m - X_{Min}^n} \tag{1}$$

where, x_i^m is any value of a variable m; $X_{Max}^m$and X_{Min}^n are the maximum and the minimum values of that variable; $x_{i,scaled}^m$ is the value after scaling. By utilizing the Min-Max Scaler to normalize the input data, it is possible to prevent the issue where one characteristic overwhelms the others because of its larger range of values. If features are not normalized, the model could overweight the characteristics with higher values, thereby resulting in less than-ideal model performance. By scaling all characteristics to the same range, the Min-Max Scaler ensures that every feature has an equal impact on the model predictions.

C. Utilization of Reinforcement Learning in Dynamic Environment

The objective of Reinforcement Learning (RL), a machine learning technique, is to maximize a numerical reward while solving certain challenges in a predetermined environment. Numerous common and specialized engineering problems may be solved with this technology. Within the reinforcement learning paradigm, an agent engages in iterative interactions with its surroundings, picking up and applying certain behaviors based on the state of the environment. After that, the environment offers a reward in addition to its most recent condition, and so on, until the agent maximizes the total rewards obtained. The policy is often defined as the method by which an agent operates from a specific state. Finding the best course of action for the agent to maximize cumulative rewards in the given environment is the main objective. The reinforcement learning structure in Smart building is represented in Fig. 2.

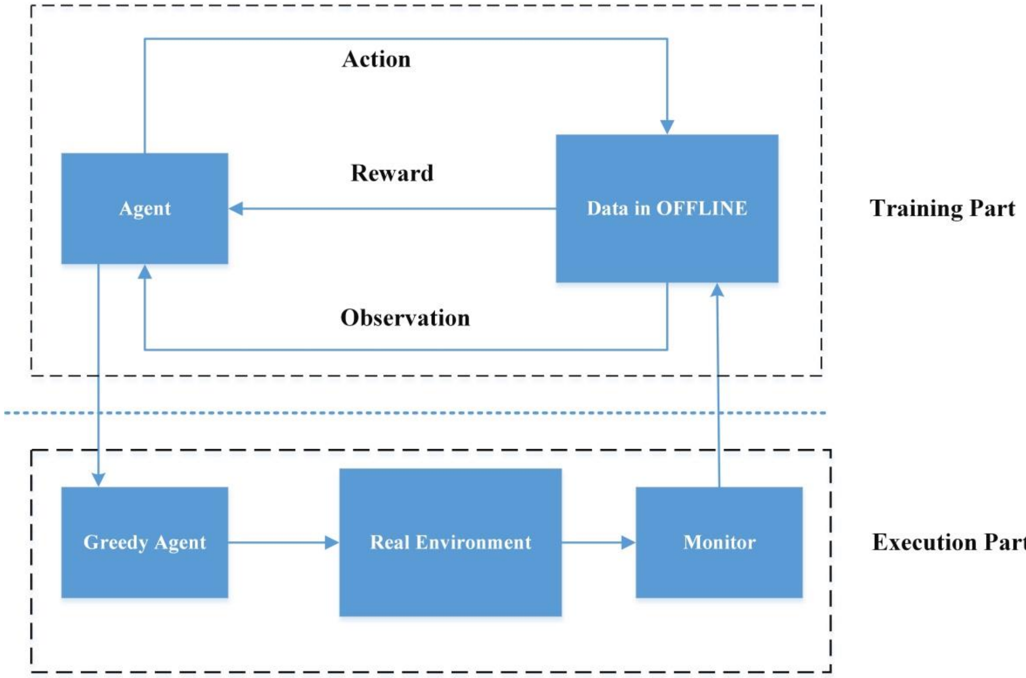

Fig. 2. Decision and control framework for reinforcement learning in smart energy management.

The environment in our research is assumed to be a Markov decision procedure, in which the agent's next state is determined only by its present state and the action it has selected, ignoring all other states and actions. The chosen value function for the inquiry is the Q-value, which is represented as$Q_p(a_x, b_x)$. The pairing of a state a_x and an action b_x at discrete time x is represented by this Q-value. The main goal of the agent is to maximize the Q-value at each time step. To find the best policy p in scenarios involving decision-making, Q-learning, a basic RL technique, is utilized. The Bellman equation is used in the Q-learning procedure to calculate and update the Q-value(a_x, b_x) is depicted in Eq. (2):

$$Q_p(a_x, b_x) = r(a_x, b_x) + \gamma maxQ(a_x + 1, b_x + 1) \quad (2)$$

In this case, the maximum discount future reward $\gamma maxQ(a_x + 1, b_x + 1)$and the current reward $r(a_x, b_x)$add up to the ideal Q-value$Q_p(a_x, b_x)$. The relative relevance of present and future benefits is usually ascertained using a discounting factor $\gamma \in [0, 1]$. a smaller γ results in a more shortsighted agent that prioritizes immediate gains, whereas a bigger γ supports a more forward-looking strategy. To balance incentives for now and the future, the system operator can change the value of γ.

D. Deep Q-Networks (DQN) Algorithm for Energy Management Strategy

Deep Q-Networks is a reinforcement learning algorithm that combines deep learning with Q-learning to approximate and optimize the action-value function in a deep neural network. To determine the best practices for energy management in smart buildings, DQN is employed. In order to accomplish certain goals like cost reduction, peak demand reduction, and occupant comfort, it assists the system in making decisions about HVAC settings, lighting control, and energy storage measures. The Q-value represents the expected cumulative reward of taking a particular action in a given state is represented in Eq. (3)

$$Q_p(a_x, b_x) \leftarrow (1 - \alpha) \cdot Q_p(a_x, b_x) + \alpha \cdot (r + \gamma \cdot maxa'Q({a_x}', {b_x}')) \quad (3)$$

$Q_p(a_x, b_x)$ is the Q-value for state a_x and actionb_x. α is the learning rate, r is the immediate reward after taking action b_x in state a_x, γ is the discount factor, ${a_x}'$ is the next state, ${b_x}'$ is the next action. With parameters θ, a deep neural network approximates the Q-value. The Mean Squared Error between the goal Q-value and the predicted Q-value is the loss function used to train the network is presented in Eq. (4):

$$Loss(\theta) = E[(Q(a_x, b_x; \theta) - (r + \gamma \cdot maxa'Q({a_x}', {b_x}'; \theta -)))^2] \quad (4)$$

In this case, θ− stands for the parameters of a target network, which are updated with the online network's parameters, θ, on a regular basis. The input of deep neural network architecture is usually the state representation, and the architecture consists of fully linked layers. Each unit in the output layer represents the expected Q-value for a particular action, and there are as many units as there are potential actions. DQN frequently employs an epsilon-greedy strategy, in which the agent chooses an action (exploration) at probability ϵ and an action (exploitation) at probability $1-\epsilon$ based on the maximum projected Q-value.

E. Energy Storage Model in Smart Building

For the purpose of maximizing cost-effectiveness, sustainability, and energy efficiency, an improved energy storage model is essential. In order to effectively store and manage energy and meet the changing demands of the building and its occupants, the model incorporates Super capacitors, lithium-ion batteries, when it comes to smart building energy management, this combination delivers clear benefits. Supercapacitors perform very well in cycles of fast charge and discharge, offering brief bursts of energy at times of peak demand and well balancing the intermittent nature of renewable energy sources. However, over longer periods of time, sustained and effective energy storage is guaranteed by lithium-ion batteries, which are renowned for their high energy density and dependability. Super capacitors, lithium-ion batteries, are the cutting-edge energy storage technologies are cleverly positioned to harvest extra energy produced from solar panels or other renewable energy sources during times of low demand. In order to ensure a steady and dependable power supply, this stored energy may subsequently be effectively used during periods of high demand or when renewable sources are insufficient. Predictive analytics and clever algorithms improve the system's responsiveness, allowing it to adjust to changing grid circumstances and energy needs. Smart building infrastructure is represented in Fig. 3.

The process for generating equations that represent the dynamics of energy storage, including the charging and discharging processes, is necessary to develop an energy storage model for a smart building. There is a single basic equation that determines the charge state (S_c) of the energy storage system over time can be expressed in Eq. (5):

$$S_c(x+1) = S_c(x) + c_x \frac{\gamma^{ch}\Delta x}{Q_{storage}} p_{storage}^{charge}(x) + d_x \frac{\Delta x}{\gamma^{disch} Q_{storage}} p_{storage}^{discharge}(x) \tag{5}$$

where, $p_{storage}^{charge}(x)$ and $p_{storage}^{discharge}(x)$ indicates the charging power and discharging power, $p_{storage}^{charge}(x) + d_x \geq 0$ and $p_{storage}^{discharge}(x) \leq 0$; γ^{ch} and γ^{disch} represents the discharging and charging effectiveness of the energy storage model ; The energy storage capacity and the time step duration are denoted by Δx. This formula is an example of a simplistic model; more intricate models may be developed by adding variables like round-trip efficiency, ageing effects, and temperature's effect on battery performance. These formulas enable the effective use of energy storage supplies while taking the dynamic nature of energy needs and external factors into account. They are crucial parts of a larger smart building energy management system.

F. Cost Optimization Model

The utilization of cost optimization models in smart building energy management often entails minimizing the total cost of energy consumption, taking into account variables such as power rates, operating expenses, and possible fines for over-energy thresholds. The following is an example of a popular formulation for this kind of model that uses linear programming is represented in Eq. (6):

$$C_x = \left(\frac{m_x - n_x}{2}|P_x| + \frac{m_x + n_x}{2}P_x\right),\ \forall\, x, \tag{6}$$

where, the energy purchasing and selling prices are represented by m_x and n_x. It is commonly recognised that the ESS's lifespan would be harmed by repeated charging or discharging. The Energy Storage System depreciation cost at time interval x is defined as follows to observe in Eq. (7),

$$C_x = \varphi(|c_x| + |d_x|) \tag{7}$$

where, c_x and d_x are charging and discharging power, and φ indicates the depreciation coefficient.

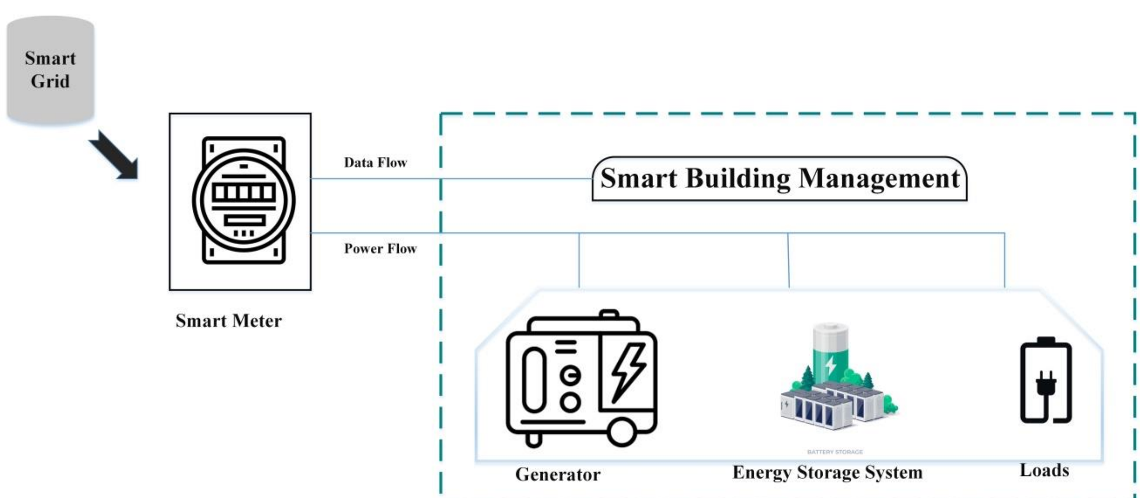

Fig. 3. Energy management system.

G. Reward

The reward function in a reinforcement learning setting typically represents the immediate benefit or cost associated with taking a particular action in a given state. In the context of energy management in smart buildings, the reward function can be designed to reflect the system's objectives. For instance, it might consider factors such as energy cost reduction, peak demand reduction, and occupant comfort. Here is a general form of the reward function, denoted as R in Eq. (8),

$$R(a_x, b_x) = r(a_x, b_x) + \gamma \cdot maxa'Q(a_x + 1, b_x + 1) \quad (8)$$

a_x and b_x represent the state and action at discrete time x. $r(a_x, b_x)$ is the immediate reward after taking action b_x in state ax. γ is the discount factor, determining the relative importance of present and future rewards. It is typically in the range [0, 1], where a smaller γ makes the agent more shortsighted, prioritizing immediate gains, while a larger γ supports a more forward-looking strategy.

Algorithm 1: EMDQN (Energy Management Deep-Q-Learning)

Input:
Raw dataset with power usage and environmental measures
Energy storage parameters: γ^{ch}, γ^{disch}, $Q_{storage}$, Δx, φ
Linear programming parameters: m_x, n_x
Output:
Trained DQN model
Optimized energy storage model
Cost-optimized smart building energy management system

```
def min max normalization(data):                          # Data Pre-processing:
    X^m_Min = min(data)
    X^m_Max = max(data)
    Normalize data using (1)
    Return normalized data
        for t in range (max steps per episode):
            action = epsilon greedy(Q-network, state, ϵ)
            Next state, reward = execute action(action)
            Store experience(state, action, reward, next state)
            Mini batch = sample mini batch()
            Update Q network(Q-network, target Q-network, mini batch)
            if t % τ == 0:
                Update target Q network(Q-network, target Q-network)
def DQN algorithm(Q-network, α, γ):                        # Deep Q-Network (DQN) Algorithm
    for each episode:
        for each step:
            action = epsilon greedy(Q-network, state, ϵ)
            execute action and observe reward and next state
            update Q-value using Eq. (3) and loss function Eq. (4)
def energy storage model(S_c, C_x, d_x):                   # Energy Storage Model
    Evaluate using (5)
def cost optimization model(m_x, n_x, C_x, d_x, φ):        # Cost Optimization Model
     Evaluate using (6)
def reward function(r, γ, Q-value):                        # Reward Computation
    return r + γ * max(Q-value)
Raw data = load dataset()                                  # Main
Normalized data = min max normalization(raw data)
Q-network = initialize Q network()
Target Q-network = initialize Q network()
Reinforcement learning(Q-network, target Q-network)
Optimized energy storage model = energy storage model(parameters)
Optimized cost optimization model = cost optimization model(parameters)
```

V. Results and Discussion

The results section of the study focuses on evaluating the effectiveness and performance of the proposed methodology for efficient deep reinforcement learning in smart buildings, particularly concerning the integration of energy storage systems through advanced energy management strategies. Key metrics are employed to assess various aspects of the system's functionality, including cost optimization, peak demand reduction, occupant comfort, and overall energy efficiency. Quantitative measures, such as cost savings, peak demand reduction percentages, and the accuracy of the reinforcement learning model, will be reported. The results and discussion section receives inputs from the reinforcement learning model, energy storage model, and cost optimization model. The grid peak demand reduction performance and cost reduction performance analyses are part of the Results and Discussion section, providing insights into the effectiveness of the proposed methodology.

A. Cost Reduction Performance Analysis

Fig. 4 illustrates the breakdown of summertime electrical demand charges for the scenarios Without DQN, DQN-Temperature, DQN-Battery, and With DQN. It highlights interesting trends in peak demand management. August demand charges for the typical technique Without DQN are 1897 units; however, when the entire DQN strategy is integrated, these demand charges are significantly reduced to 1234 units, which is an outstanding decrease of almost 35.01%. Reductions are also achieved via the DQN-Battery and DQN-Temperature techniques, which have demand charges of 1698 and 1687 units, respectively. June and July reveal that DQN tactics work as well, with demand charges reduced by around 33.13% and 30.82%, respectively. On the other hand, September offers a special case with an unanticipated rise in demand fees for all DQN methods in contrast to the conventional model.

In Fig. 5, the DQN method produces the largest energy charge decrease in the winter, totaling 3897 units as opposed to 6785 units in the conventional Without DQN scenario, or a significant reduction of almost 42.61%. With a decrease in demand charges from 4587 units to 3298 units, or around 28.16% less, the reduction in demand charges is likewise noteworthy. The drop in cost is similarly notable in the summer. Compared to the conventional method, the With DQN technique helps to save around 16.99% in demand charges and 6.07% in energy charges.

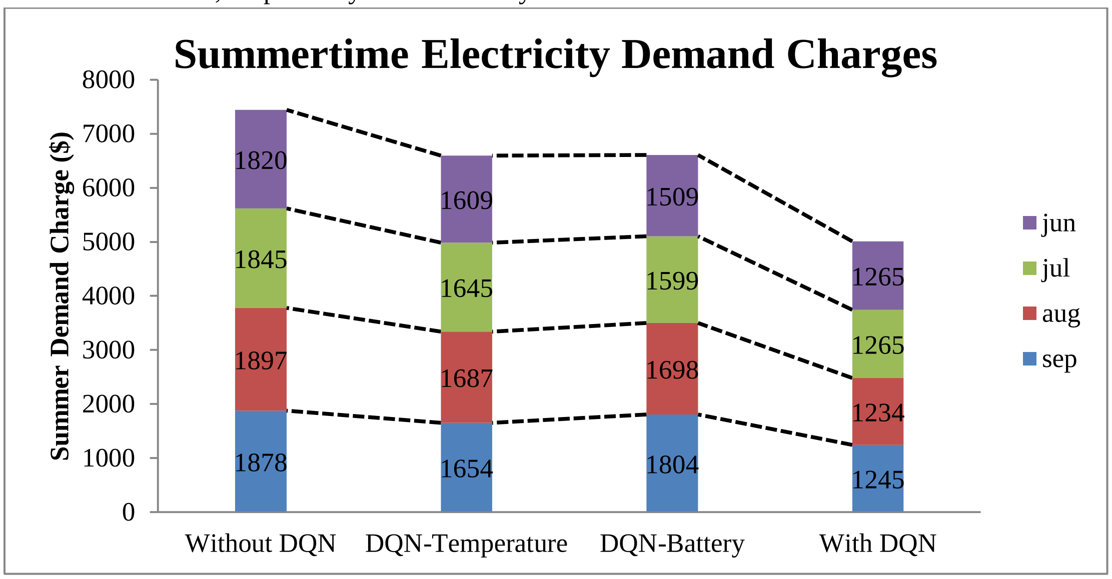

Fig. 4. Analysis of summertime electricity demand charges.

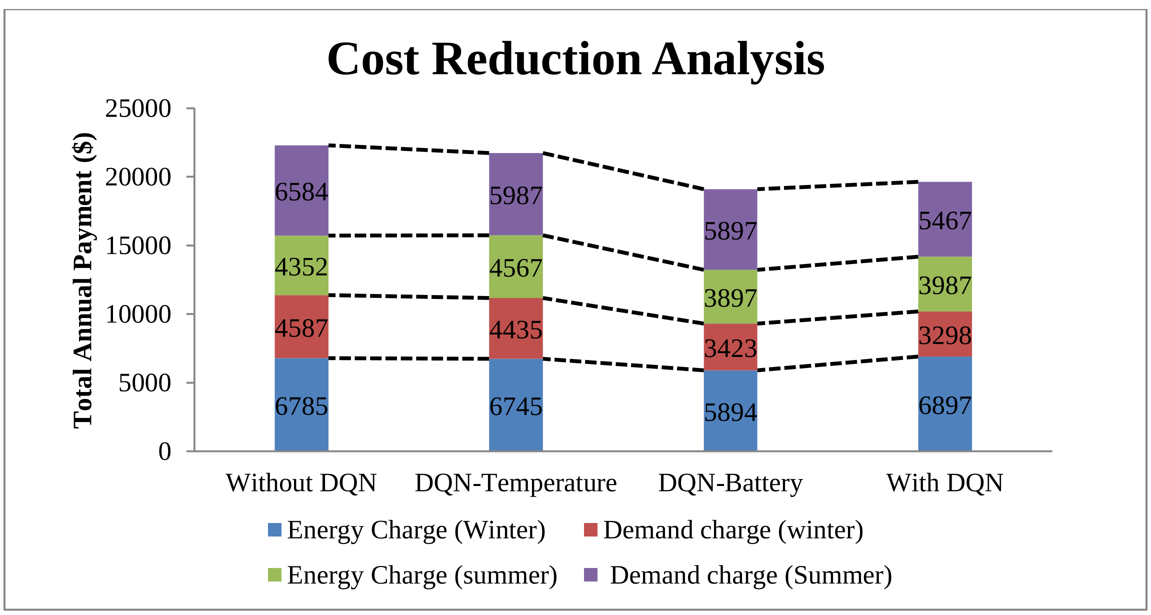

Fig. 5. Total annual cost reduction analysis.

The DQN techniques, especially the all-inclusive With DQN model, demonstrate how well they work to maximize energy use, tactically control peak demand, and eventually lower total operating expenses. This report highlights the potential financial benefits of using advanced energy management strategies and highlights DQN's contribution to the facility's large summer and winter cost savings.

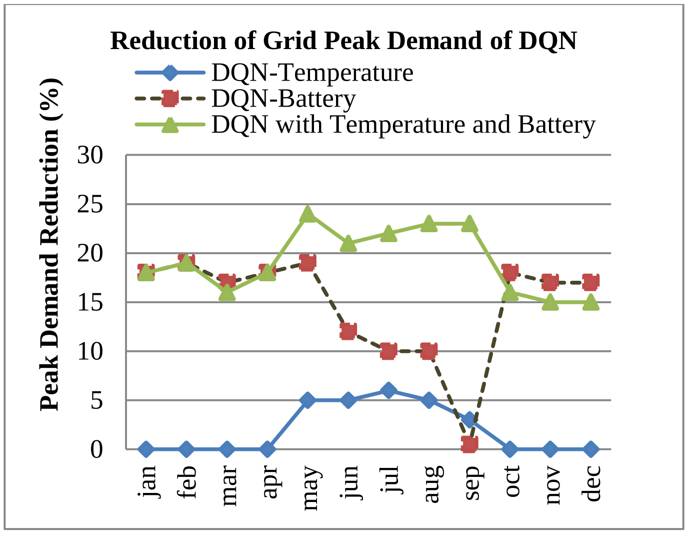

Fig. 6. Peak demand reduction evaluation.

Fig. 6 describes the observed peak demand reduction of 26.32% in May indicates a noteworthy beneficial impact of the adopted techniques, namely the DQN strategy, in the context of smart buildings. This significant decrease indicates that energy consumption habits were successfully adjusted and optimized during a month when demand is usually higher. The DQN strategy's ability to strategically manage and reallocate energy resources is demonstrated by its efficacy in May, which greatly enhances the building's total energy efficiency.

In Fig. 7, the rewards are received at various times when a reinforcement learning model is being trained or assessed. The rewards corresponding to each episode's progressive numbering show how well the model performed at each level. In this particular case, the incentives exhibit an increasing tendency as the number of episodes rises, going from an initial reward of -7.1 to -5 at episode 12,000 in this particular situation. The objective is to train the model to maximize its cumulative reward over episodes; the negative values indicate that the model is penalized for specific states or behaviors.

Table I compares the performance metrics of a proposed Deep Q-Network strategy with a Genetic Algorithm method for various situations of home energy management strategies. The peak load, power added to the grid, and power taken out of the grid are all represented by the Power figures.

The overall energy consumption and revenue/cost throughout time are tracked by cumulative energy and cumulative revenue/cost. The daily net cost is shown by the Net Cost. Comparing the Proposed DQN method to the GA approach, the percentage changes show that there is a reduction in peak load of 0.8918%, a fall in cumulative income of 3.4972%, a reduction in daily cost of 0.7647%, and an overall decrease in net cost of 6.7887%. These findings demonstrate the potential of the Proposed DQN method as an efficient home energy management strategy by indicating that it performs well in terms of peak load control and cost reduction.

B. Error Rate Evaluation

The mean square error (MSE) is a non-negative quantity, and its units are often the squared units of the original data. In regression analysis and other modeling tasks, it is commonly employed as an unbiased measure to assess how well a model with predictions or estimator is working. It is expressed in Eq. (9).

$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left(X_i - \widehat{X}_i\right)^2 \tag{9}$$

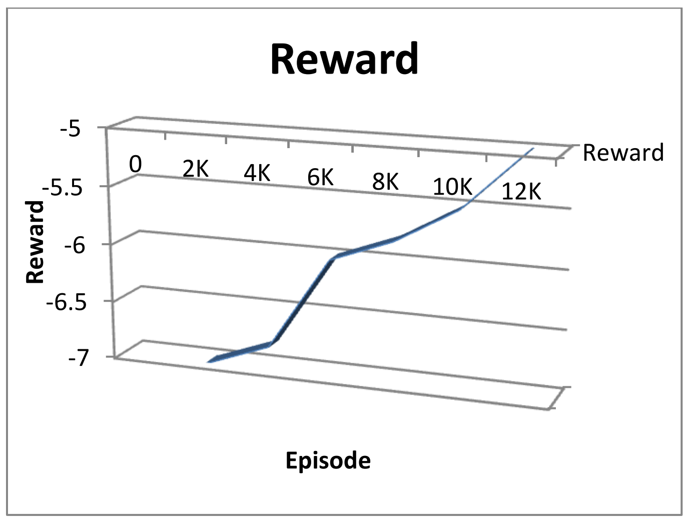

Fig. 7. Reward for proposed DQN algorithm.

TABLE I. COMPARISON OF THE RESULTS BETWEEN USING STRATEGIES GA AND PROPOSED DQN

Algorithm for Home Energy Management Strategy	Power (kW)	Cumulative Energy (kWh)		Cumulative Revenue/Cost (USD)		Net Cost (USD)
	Peak Load	Injected to Grid	Drawn from Grid	Revenue	Cost	Daily Cost
GA [21]	6.7894	53.0567	58.3765	2.7863	3.1243	0.3987
Proposed DQN	5.8976	53.0567	54.8793	2.7863	3.0596	0.3100
Increment (%)	-	-	-	-	-	-
Reduction (%)	0.8918	-	3.4972	-	0.7647	6.7887

where, m is the total amount of data points, X_i is the actual values and $\widehat{X_\iota}$ is the estimated values. MAE is used to indicate the quality of a prediction approach or estimator and is frequently given in the same units as the original data. It is expressed in Eq. (10).

$$MAE = \frac{1}{n}\sum_{i=1}^{m}\left|X_i - \widehat{X_\iota}\right| \quad (10)$$

where, m is the total amount of data points, X_i is the actual values and $\widehat{X_\iota}$ is the estimated values.

TABLE II. COMPARISON OF ERROR RATE

Energy Management Strategic Methods	Mean Square Error (%)	Mean Absolute Error (%)
Fuzzy Algorithm	14.5	15.87
Genetic Algorithm	12.6	14.43
Proposed DQN	8.6	6.4

The performance evaluation of three distinct energy management strategy methods—the Genetic Algorithm, the Proposed Deep Q-Network, and the Fuzzy Algorithm—is shown in Table II. Mean Absolute Error and Mean Square Error, both expressed in percentage terms, are the metrics used for evaluation. With a Mean Square Error of 14.5% and a Mean Absolute Error of 15.87%, the Fuzzy Algorithm exhibits a comparatively elevated degree of prediction mistakes. With a Mean Absolute Error of 14.43% and a Mean Square Error of 12.6%, the Genetic Algorithm performs more effectively. The proposed DQN performs much more effectively than both algorithms, with a Mean Square Error of 8.6% and a significantly lower Mean Absolute Error of 6.4%. Based on these findings, it appears that the Proposed DQN is a more promising method for optimizing energy systems than the Fuzzy and Genetic Algorithms in terms of prediction accuracy in energy management.

C. Discussion

The study's findings center on assessing the effectiveness and performance of the suggested approach for effective deep reinforcement learning in smart buildings, with a special emphasis on how improved energy management techniques integrate energy storage systems. Key performance indicators that are included in the evaluation include overall energy efficiency, peak demand reduction, cost optimization, and occupant comfort. Quantitative metrics are presented, including cost savings, percentages of peak demand decrease, and the accuracy of the reinforcement learning model. The results present the cost reduction study, which shows notable decreases in demand charges, energy charges, and overall operating expenditures in the summer and winter. The peak demand reduction evaluation shows a significant improvement in May due to the implemented approaches, with a decrease of 26.32%.

Furthermore, Methodology illustrates the incentives attained at various episodes throughout the model's training or assessment, exhibiting a progressive upward trend over time. The Proposed Deep Q-Network (DQN) method and the Genetic Algorithm [21] technique are thoroughly compared in Table I, which also highlights the benefits of the DQN strategy, which include a decrease in peak load, cumulative income, and total net cost. Taken as a whole, these measures highlight how well the suggested technique works to maximize energy consumption, cut expenses, and improve the overall performance of smart buildings. The study demonstrates the effectiveness of a systematic DRL framework for energy management in smart buildings. The proposed methodology integrates Min-Max normalization, reinforcement learning, and Deep Q-Networks to optimize decision-making processes. The integration of supercapacitors and lithium-ion batteries in the energy storage model is highlighted. This model aims to maximize cost-effectiveness, sustainability, and energy efficiency by strategically capturing and utilizing excess energy, addressing the intermittent nature of renewable energy sources.The study employs linear programming to develop a cost optimization model, aiming to minimize overall energy consumption costs. This model considers variables such as power rates, operating expenses, and potential fines for exceeding energy thresholds, providing a holistic approach to cost-effective energy management.

VI. CONCLUSION AND FUTURE WORKS

The energy management approach for smart buildings that is being presented demonstrates promise in terms of improving energy efficiency, cutting expenses, and efficiently controlling peak demand. It incorporates energy storage models, a Deep Q-network algorithm, and cost optimization techniques. Reinforcement learning is integrated into the system to enable dynamic adaptation to changing environmental circumstances and occupant demands. This optimizes decision-making processes related to energy storage measures, lighting management, and HVAC settings. When compared to conventional algorithms like fuzzy and genetic algorithms, the suggested DQN algorithm demonstrated notable improvements in cost reduction, peak demand management, and overall energy efficiency. The algorithm was developed on an extensive dataset from a seven-story office building in Bangkok, Thailand. Furthermore, the energy storage model improves the smart building's capacity for effective energy management and storage by cleverly using cutting-edge technology like lithium-ion batteries and supercapacitors. The linear programming-based cost optimization methodology helps to further reduce the overall cost of energy consumption. The effectiveness of the DRL technique may also be sensitive to the quality and representativeness of the dataset. Furthermore, the proposed energy storage model, while incorporating advanced technologies, simplifies the dynamics by using a basic equation, omitting factors such as round-trip efficiency and aging effects.

There are a number of directions to pursue in order to expand and enhance the suggested technique in future research. Initially, the flexibility and performance of the DQN algorithm might be improved by fine-tuning its hyperparameters and architecture to better fit the unique features of various smart buildings. Further optimizing the sustainability of the system might involve investigating the integration of renewable energy sources and implementing more sophisticated energy storage technology. Furthermore, given the dynamic nature of smart buildings, examining how online learning methods may be used to continually adjust to shifting circumstances and occupant behavior may help develop more adaptable and responsive energy management strategies. Moreover, broadening the scope of the cost optimization model to incorporate other variables like weather predictions, grid conditions, and dynamic pricing models may offer a more thorough method of reducing energy expenditures. All things considered, the approach that has been described provides a strong basis for smart building energy management. Research projects in the future can build on this foundation to tackle new problems and possibilities that arise in the quickly developing field of sustainable and energy-efficient building technology.

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