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Forecasting of Energy Demands for Smart Home Applications

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Abstract: The utilization of energy is on the rise in current trends due to increasing consumptions by households. Smart buildings, on the other hand, aim to optimize energy, and hence, the aim of the study is to forecast the cost of energy consumption in smart buildings by effectively addressing the minimal energy consumption. However, smart buildings are restricted, with limited power access and capacity associated with Heating, Ventilation and Air Conditioning (HVAC) units. It further suffers from low communication capability due to device limitations. In this paper, a balanced deep learning architecture is used to offer solutions to address these constraints. The deep learning algorithm considers three constraints, such as a multi-objective optimization problem and a fitness function, to resolve the price management problem and high-level energy consumption in HVAC systems. The study analyzes and optimizes the consumption of power in smart buildings by the HVAC systems in terms of power loss, price management and reactive power. Experiments are conducted over various scenarios to check the integrity of the system over various smart buildings and in high-rise buildings. The results are compared in terms of various HVAC devices on various metrics and communication protocols, where the proposed system is considered more effective than other methods. The results of the Li-Fi communication protocols show improved results compared to the other communication protocols.

Keywords: HVAC systems; deep learning; energy utilization; smart buildings

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1. Introduction

Automation is a technique, method or process control system using electronic devices, and it minimizes human involvement. Building an automation system for a home or office increases every day, with numerous advantages. In order to monitor and control various machines, such as lighting, ventilation and AC, on-demand, industry professionals and researchers have been developing efficiency and economic affordability automatic systems. Automation helps in utilizing the effective use of electricity, and it further reduces the cost and waste associated with any type of application [1,2].

The concept of smart buildings has been well-studied and developed in recent years and is now the ultimate concept that refers to different characteristics of human lives and has been regarded as smart living [3]. Due to the fact that a large part of people's lives are at home, smart building is one of the major smart areas. The technology provides several solutions that impact human lives. This helps raise concerns about wireless radio technology, which affects human health.

Heat Ventilation Air Conditioning (HVAC) devices are mainly concerned with, and their very resource-constrained existence mainly induces, other issues if they are integrated with the Internet of Things (IoT). They have minimal computing, memory and battery power. The devices' resources are calculated mainly by their scale, cost and implementation because of limitations in production technology [4]. It should be very thin, though a much greater part of an appliance such as a car or refrigerator [5,6]. The IoT device should occasionally be implanted within the HVAC system, since these devices differ in performance but have a significant effect on price. Another big limitation is the use of power and availability. It defines the device lifetime and limited energy efficiency. These IoT-integrated HVAC devices should be able to carry out their tasks and connect with other network devices that can have a great deal more resources. Constrained IoT devices cannot do much computing, since it sends many data with a resource-constrained communication protocol, with only basic functionalities.

The main problem associated with HVAC systems in smart building is the restricted capacity and power access for some smart building applications on HVAC systems. There are several simple sensors and actuators that play a crucial part in the home automation system that run as long as possible without replacing the batteries. The end-user may be frustrated, often finding it impossible to reach and replace batteries every day physically. The main limitation associated with the study is that the communication capabilities may be impaired due to the HVAC device limitations. The battery capacity also limits the performance and lifetime of IoT devices and the wireless communication channel.

The study thus aims to attain a reduced consumption of energy associated with HVAC systems. In this paper, energy consumptions in HVAC systems [7–25] are analyzed using a deep learning algorithm, namely the Convolutional Recurrent Neural Network (CRNN). It is designed to predict the consumption of energy under different climatic conditions, and the operations are evaluated under various communications protocols, like Bluetooth, Zigbee, Wi-Fi and Li-Fi. The model is designed to encompass constraints like reactive power loss, power loss and price management to increase the accuracy with a reduced prediction error. The consideration of such parameters develops an optimal prediction model for reducing the average energy consumption in buildings other than the existing methods.

The outline of the paper is as follows: Section 2 discusses the literature review, Section 3 proposes the model, Section 4 explains the adopted technology, Section 5 is the results and discussion that evaluate the entire work with various existing methods and with different communication protocols, and Section 6 concludes the work.

2. Literature Review

An online fuzzy control that offers a demand response based on the user Quality of Service (QoS) level was developed by Talebi and Hatami [10]. Various energy parameters, like the daily energy cost, minimum and maximum home temperatures, energy usage, energy usage during peak hours and user's comfort, are used in the study [11–13]. The effects of fixed pricing, time-of-use pricing and real-time pricing are analyzed. Homod et al. [14] used Takagi-Sugeno fuzzy in real time to meet the energy demand. A price-responsive operational model was developed for HVAC systems in smart buildings that consider distributed energy resources and inflexible loads and battery storage systems.

Ostadijafari et al. [18] carried out optimized scheduling to find the least prices estimated for HVAC controllers. The deep neural network captured the physical processes dynamics that included natural ventilation. Floor area, building material and window sizes were considered as the parameters for the study and used training data to train the Deep Neural Network (DNN) model for efficient operation.

The transfer learning model was combined with a convolutional neural network (CNN) and recurrent neural network (RNN) to have a predictive control on the natural ventilation by Chen et al. [22] and HVAC systems in smart buildings. The CNN captured the image data, and RNN found the temporal dependencies from the time series data collected from smart homes. Fekri, M. N. et al.'s [23] recurrent generative adversarial networks control the HVAC systems in smart homes. Further, a long short-term memory Artificial Neural Network (ANN) for predicting the daily consumption of HVAC systems in buildings was developed by Sendra-Arranz and Gutiérrez [26]. It uses low errors and optimal Pearson correlation coefficients between the predictions and the real consumption values to obtain real-time output which was proposed by Elnour, M. et al's [27].

Similarly, Sadeghi et al. [28] utilized DNN for predicting the energy performance in residential buildings. To extract knowledge from a trained model, a postprocessing technique called sensitivity analysis (SA) was applied for performing the best with the reference to goodness-of-fit metric on an independent set of testing data.

In the European Union (EU), renewable energy sources are promoted with high priority. The energy share of renewable energy sources in the EU has increased majorly from 2004 onwards. Gavurova et al. [29] evaluated the economic aspects of renewable energy sources used in Slovakia. In particular, the authors concentrated on analyzing the usage of different types of biomass shares used for the generation of power. It was identified that the biomass share is up to 44% of the different types of renewable energy sources. Based on the analysis, the biogas plant plays a significant role with a positive impact on the usage of renewable energy sources.

A significant role of green Gross Domestic Product (GDP) towards energy consumption was suggested by Skare et al. [30] on different sources of energy. Using the panel cointegration technique, the authors analyzed the data of nine years from 2008 onwards over 36 countries, this method was also suggested by Nguyen, P.V and Tran, K.T [31]. The analysis said that the increase in energy consumption was directly proportional to green GDP by the sectors that are damaging the environment, whereas renewable energy consumption reduces the gap between green GDP and GDP which was discussed in Khudyakova, T et al. [32].

Reinforcement Learning (RL) was developed by Azuatalam et al. [33] for scheduling and controlling the HVAC in commercial buildings. This holistic framework acts as a controller for a building model that optimizes the HVAC system for improving the thermal comfort to achieve demand response goals. A 22% energy reduction was achieved using RL with optimal thermal comfort levels within an acceptable bound.

Yu et al. [34] proposed an online energy management scheme using Lyapunov optimization to predict the HVAC parameters. It stabilizes four queues integrated with electric vehicle charging, indoor temperature and energy storage by offering feasible designs over the models.

Tittaferrante and Yassine [35] demonstrated Multi-Advisor RL feasibility to adapt a proper control to balance the objectives' underweighting function. It further offered a better demand response by optimally balancing the temperature setpoint tracking, thereby providing optimal energy consumption.

Javed, A. et al. [36] used the RNN model to estimate the occupant population to predict the setpoints in order to control the HVAC systems in smart buildings. It uses the help of the Internet of Things (IoT) and cloud computing technologies to achieve this task. The effective integration shows the effective control of HVAC systems in the smart building with prominent energy consumption.

Likewise, Yu et al. [37] investigated the problems associated with energy and cost minimization for smart homes without a thermal dynamics model in a comfortable temperature range. The method considers the problem of controlling energy consumption as the Markov decision process using deep deterministic policy gradients. It avoids using prior knowledge on parameters. It has uncertain values and offers the effective consumption of energy.

Javed et al. [38] presented a random neural network controller integrated with the IoT and cloud processing to train the controller to improve the energy consumption in smart buildings. The results show that the accuracy of the hybrid RNN occupancy estimator is 88%.

On the other hand, Bui et al. [39] accommodated the effectiveness of artificial neural networks to evaluate the heating load (HL) and cooling load (CL) using two given datasets. The datasets were obtained by monitoring the façade system effect and building dimensions on energy consumption.

Zou et al. [40] used a RNN algorithm to achieve optimal control over HVACs. These control frameworks build training environments with HVAC information and building geometrics. It achieves optimal control over Air Handling Units with long short-term memory networks in real-world HVAC operations. Zhang et al. [41] developed a fine-grained in-depth learning approach to model the relationship between thermal comfort and controllable building operations. It determined the thermal comfort using multiple comfort factors with training on an exclusive model for each factor.

3. System Model

The commercial building was designed with thermal zones (N) with multiple HVAC systems [42] to control the indoor temperature across all the thermal zones, as in Figure 1. Each HVAC system had an air handling unit and a set of variable air volumes across each zone within a commercial building. The air handling unit was designed with a variable frequency drive fan, cooling/heating coil and dampers. The dampers mix the fresh air from the outdoor environment with the returned air across each zone inside the building to fulfil the ventilation conditions. The variable frequency drive fan at each zone is useful in delivering the mixed air to the variable air volume box. The cooling/heating coil is used for cooling or heating the mixed air. The thermal characteristics (Figure 1) in the building parameters consider the climate inside and outside the building.

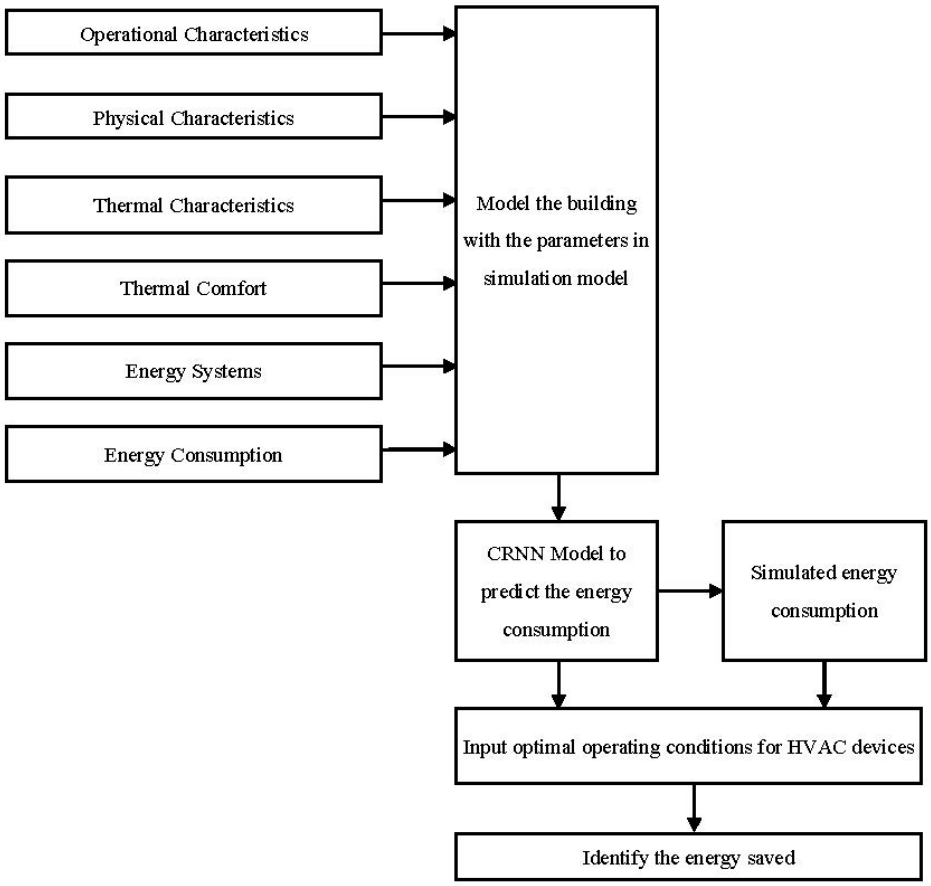

Figure 1. Overall architecture of the energy consumption prediction model. HVAC: Heating, Ventilation and Air Conditioning and CRNN: Convolutional Current Neural Network.

This study focused on all zones for thermal comfort by operating the HVAC devices in the defined time slots t = {1, 2, . . . , L}. The following subsection provides the details of the energy cost minimization formulation.

3.1. Control Model

In the study, the adjustment of damper positions is carried out in the air handling unit and air supply rate to maintain the indoor air quality and thermal comfort (i.e., comfortable temperature range). The model considers $T_{i,t}$ as the temperature of the indoor zones i over the time period t, and then, the following equation is established:

$$T_i^{\min} \leq T_{i,t} \leq T_i^{\max}, \forall i, t,\ K_{i,t} > 0 \tag{1}$$

where

$K_{i,t}$ is defined as the total occupants within a region or zone i over time slot t,
$T_i^{\min}$ is the minimum indoor temperature at an acceptable level over the zone i and
$T_i^{\max}$ is the maximum indoor temperature at an acceptable level over the zone i.

The indoor temperature $T_{i,t+1}$ over a zone i at time slot t+1 is given by Equation (2):

$$T_{i,t+1} = F\left(T_{i,t},\ T_{z,t}|_{\forall z \in N_i}, T_t^{out}, m_{i,t}, \varsigma_{i,t}\right) O_{i,t} \leq O_i^{\max}, \forall i, t,\ K_{i,t} > 0 \tag{2}$$

$$O_{i,t+1} = \left(1 - \frac{m_{i,t}\tau}{\kappa\vartheta_i}\right) O_{i,t} + \left(\frac{m_{i,t}\tau}{\kappa\vartheta_i}\right) O_t^{mix} + \frac{K_{i,t}\tau\chi}{\vartheta_i} \tag{3}$$

$$\sigma_t \in \left\{\sigma^1, \sigma^2, \ldots, \sigma^Z\right\} \forall t \tag{4}$$

where

$T_{\ i,t}$ is indoor room zone temperature i,
$T_{z,t}$ is adjacent zones at the time slot t,
T_t^{out} is the outdoor temperature over the time slot t,
$m_{i,t}$ is the rate of air supply at the zone i over the time slot t,
$\varsigma_{i,t}$ is the thermal disturbance over zone i over the time slot t,
N_i is defined as the neighboring set across zone i,
$O_{i,t}$ is the CO_2 level (ppm),
τ is the time slot duration (ms),
κ is the density of air (kg/m^3),
ϑ_i is the volume of zone i (m^3),

$$O_t^{mix} = (1 - \sigma_t) O_t^{out} + \sigma_t \frac{\sum\limits_i O_{i,t} m_{i,t}}{m_{i,t}} \tag{5}$$

is the level of concentration of CO_2 in the mixed air at the time slot t, with $m_{i,t} \in \left\{m_i^1, m_i^2, \ldots, m_i^M\right\} \forall i, t$,
χ is the generation of CO_2 level per person and
σ_t is the damper position in the air handling unit.

3.2. HVAC Energy Cost Model

The energy cost of the HVAC is divided into two parts, i.e., cooling coil and supply fan. The consumption of power is mainly due to the supply fan $\mu\left(\sum\limits_{i=1}^{N} m_{i,t}\right)^3$, considering μ as a temperature coefficient.

Therefore, the cost of energy-related to the fan supply is defined as follows:

$$\Phi_{1,t} = \mu \left(\sum_{i=1}^{N} m_{i,t} \right)^3 \lambda_t \tau, \ \forall t \tag{6}$$

where λ_t is defined as the cost of electricity at time slot t.

Similarly, the consumption of power by the cooling coil p_t is defined as:

$$p_t = \frac{C_a \sum_i m_{i,t} \left(T_t^{\mathrm{mix}} - T_s \right)}{\eta COP}, \ \forall t \tag{7}$$

where

C_a is defined as the specific heat of the air at 300 Kelvin,

η is defined as the efficiency of the coolant,

Coefficient of Performance (COP) is defined as the coefficient of performance of the cooling unit,

$$T_t^{mix} = \sigma_t \frac{\sum_i m_{i,t} T_{i,t}}{\sum_i m_{i,t}} + (1 - \sigma_t) T_t^{out} \tag{8}$$

is defined as the temperature of the mixed air and

T_s is defined as the temperature of the supply air at the variable frequency drive fan.

Substitute T_t^{mix} into p_t as in Equation (7), and then, it is rewritten as below:

$$p_t = \sum_i p_{i,t} \tag{9}$$

where

$$p_{i,t} = m_{i,t} \frac{C_\alpha}{\eta COP} \left(\sigma_t T_{i,t} + (1 - \sigma_t) T_t^{out} - T_s \right) \tag{10}$$

Finally, the cost of the energy related to the coolant is given by

$$\Phi_{2,t} = p_t \lambda_t \tau, \ \forall t \tag{11}$$

3.3. Energy Cost Minimization Problem

Depending on the energy cost model and control model, a stochastic program is formulated to minimize the energy cost at HVAC devices, and it is given as below:

$$f1 = \min_{m_i, t, \sigma_t} \sum_{t=1}^{L} E\{\Phi_{1,t}, \Phi_{2,t}\} \tag{12}$$

where E is defined as the random system parameters that include outdoor temperature, electricity price and a total number of occupants. $m_{i,t}$ and σ_t are the decision variables.

4. Proposed CRNN Model

The architecture of the model is given in Figure 1, which assesses the energy-saving and thermal comfort in the case of commercial buildings with the HVAC system. The energy conservation investigates the thermal comfort and energy savings from the commercial buildings. The energy model in the commercial building uses a CRNN deep learning model that acts as an energy optimization tool in terms of the physical, operational and thermal features. This model is adjusted for achieving the rate of prediction between the original and predicted energy consumption.

4.1. Hybrid CRNN for Prediction of Energy Consumption

In this section, the hybrid deep learning model (Figure 2) is designed with the combination of a CNN and RNN. The hybrid CNN with RNN is developed with recognition and prediction, respectively, for energy-efficient systems.

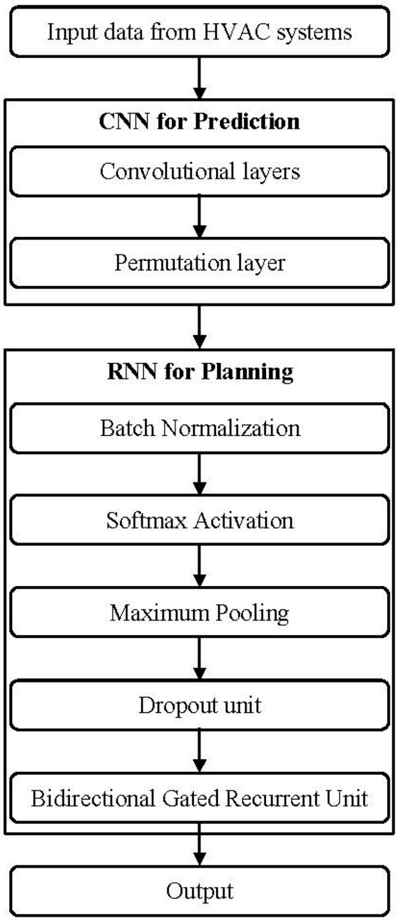

Figure 2. Deep learning model with automated detection module. CNN: Convolutional Neural Network and RNN: Recurrent Neural Network.

Algorithm 1 shows the prediction of energy demands in the smart building using a CRNN. Initially, the recognition and prediction modules estimate the power loss, reactive power loss and energy consumption cost from the surroundings and sends the output to the prediction module. The CNN in the recognition module updates at frequent intervals to recognize the behavior of the HVAC energy consumption. The RNN in the prediction module interacts with the indicated task and makes predictions based on the recognized consumption of energy from the HVAC devices. The prediction operations take place based on three parameters, as mentioned in step 1.

Algorithm 1: Prediction Using the CRNN

1: Recognition and prediction module estimate all three parameters
2: Parameters are power loss, reactive power loss and cost of energy consumption from the surroundings.
3: It sends the output to the prediction module.
4: Recognition module using the CNN classifies predictable and unpredictable classes (behavior).
5: It updates continuously in an iterative manner to achieve the task of accurate predictive behavior.
6: Prediction module using the RNN interacts actively to the changes (predictable and unpredictable classes) to the indicated task.
7: RNN makes the planning of future prediction, where the model incorporates the results of the classification (high-energy consumption or low-energy consumption devices for optimal operation of the HVAC devices).
8: The prediction models handle the objective function (with power loss, reactive power loss and cost of energy consumption) in a time-variant mode.
9: It achieves optimal high-quality prediction using the RNN model.

4.1.1. Recognition

In the recognition model, the objects in the external environments are extracted during the testing phase. The redundant frames like objects not on the trajectories are considered as redundant and eliminated as input data. The residual data with objects is sent as an input to the CNN classifier.

4.1.2. Prediction Using CNN

The object in movement is extracted with increasing convolutional layers with more solidity. After the training, the convolution layer extracts the log details of each HVAC device in real time. In addition, it extracts the log details of devices in non-real time and other devices in the building to compensate the power stability.

- Convolutional layers perform the processing operation that is a linear operation when a series of weights is multiplied using the video input data array. A filter is used to scan the entire image, which is referred to as a translation invariance, to detect the saliency from the input image. Since filters are repeatedly used with the input array, a two-dimensional feature map is created.
- Permutation layers confirm the device classified for optimal energy consumption by the convolution layer, which lists the reference objects in the order in a permutation-based representation. The similarity is estimated by using the two permutations rather than using the distance function between the reference object and the ground truth.

4.1.3. Planning Using RNN

The regular operations of RNN for planning to drive the HVAC devices are thus given below:

- Batch normalization reduces the number of hidden layers required for processing the input features from the CNN. It adjusts the scaling and activation functions to speed up the learning process.
- The batch normalization lowers the number of hidden layers necessary for processing the CNN inputs. It adapts the activation and scaling function to speed up the process of learning.
- Softmax Activation produces a vector that shows a list of potential outcomes in the probability distribution.
- Maximum pooling is a packing process that calculates the maximum or largest value in each patch of every feature map, where the packing and permutation layers are processed.
- Dropout unit ignores a number of hidden units on the forward pass, which are likely to drop the individual nodes so that a reduced network is left; the entry and output

edges of a dropped node, on the other hand, are also removable. These operations are performed to prevent overfitting.

- To address the gradient problem, the Bidirectional Gated Recurrent Unit is used to make the operation more rapid and efficient.

With feedback loops, the learning strategy is increased, as the network can remember past data. This, however, leads to a memory space limit, as the amount of video data increases. The corresponding functions are updated, and the past sequences are ideally remembered. This shows a significant observation between the energy consumption of devices in past and present.

5. Results and Discussion

In this section, various HVAC devices are used to find the effectiveness of the proposed method that includes Heating and Cooling Split Systems, Hybrid Split System, Duct Free (Mini-Split), Packaged Heating and Air, Window Through-the-Wall Air Conditioner, Packaged Terminal Heat Pumps, Unit Heaters, Packaged Rooftop Unit, Packaged Rooftop Heat Pump and Humidifiers. The proposed method is compared with other existing methods that include RNN [43–46], ANN [39,46] and CNN [47–50] algorithms and with other communications protocols, including Li-Fi, Wi-Fi, Zigbee and Bluetooth. The datasets are collected from large size units, as in [51], and the simulations are conducted in a python anaconda complier with 16GB RAM usage requirements.

The CNN and RNN algorithms individually undergo a 10-fold cross-validation. Here, RNN is trained with 2,249,880 trainable parameters and GRU with 2,545,056 parameters and long short-term memory (LTSM) in RNN with 1,644,064 parameters. Similarly, CNN has 27 convolutional layers with 1024 fully connected layers with 128 hidden nodes. The CNN is trained with 4,725,344 network parameters and 3,228,864 untrained parameters. The training loss reduces at the initial 10 iterations, and then, it reduces slowly with 10 iterations, and finally, the training loss reaches 0 at the 50th iteration.

Load Balancing Accuracy: It is defined as the ratio of a controllable load of a device like a light switch with a total number of loads in a smart building.

$$\text{Load balancing Accuracy} = \text{Controllable load of a device}/\text{Total Loads} \tag{13}$$

Energy Efficiency: Energy efficiency is calculated as the ratio of energy obtained (useful energy or energy output) by the initial energy (energy input).

$$\text{Energy Efficiency} = \text{Energy Output}/\text{Energy Input} \tag{14}$$

Transmission Rate: Transmission rate is defined as the volume of data transmitted over a transmission channel. The transmission rate of Li-Fi is in the order of 1 GBPS and Wi-Fi with 5 MBPS. Here, the transmission capacity is

$$\text{Transmission rate} = 2 \times (\text{processing delay} + \text{packet delivery time}). \tag{15}$$

- Li-Fi: Li-Fi is a wireless communication technology that utilizes light to transmit data and the positions between devices.
- Wi-Fi: Wi-Fi is a wireless networking technology that allows devices such as computers, mobile devices and other equipment to interface with the Internet.
- Zigbee: Zigbee is a low-cost, low-power, wireless mesh network standard targeted at battery-powered devices in wireless control and monitoring applications. Zigbee operates on an IEEE 802.15.4 physical radio specification and operates in unlicensed bands including 2.4 GHz, 900 MHz and 868 MHz. The data rate of 250 kbps is essentially be suited for two-way data transmission between the sensors and controllers.
- Bluetooth: Bluetooth is a wireless technology standard used for exchanging data between fixed and mobile devices over short distances using UHF radio waves in the industrial, scientific and medical radio bands, from 2.402 GHz to 2.480 GHz,

and building personal area networks. Bluetooth signals are transmitted over short distances, typically between 30 feet, and low-cost transceivers support this in the devices. It further supports the 2.45-GHz band for such data transmission and can support up to 721 KBps along with three voice channels.

5.1. Case Study: Comparison with Different Communication Protocols

This section explains the implementation of various elements of HVAC systems via the Wi-Fi/Zigbee/Bluetooth communication protocols. A user can connect to a home automation device terminal using user interfaces. Messages between the server and devices are transmitted via communication protocols using internet gateway devices. Messages are forwarded to the home gateways on the local communication protocols through an Asymmetric Digital Subscriber Line (ADSL) modem. Similarly, contacts between HVAC systems are communicated via the communication protocols. Li-Fi/Wi-Fi/Zigbee/Bluetooth controllers directly send messages to end devices through the communication protocols. The cloud server controls the security of sent/received messages, and the authenticated messages are transmitted via the home network to the destination HVAC systems. All device responses (e.g., receipts, device logs and sensor readings) are also transmitted via Home Gateway to the server to control the home automation system.

Figure 3 displays the effects of a communication delay in the domestic automation network between the devices and gateway communication. To verify the feasibility of a delay between them, two separate derivatives are considered. The findings are contrasted with the networking systems Wi-Fi and Li-Fi. The results show that Li-Fi communications are less time-consuming than Wi-Fi.

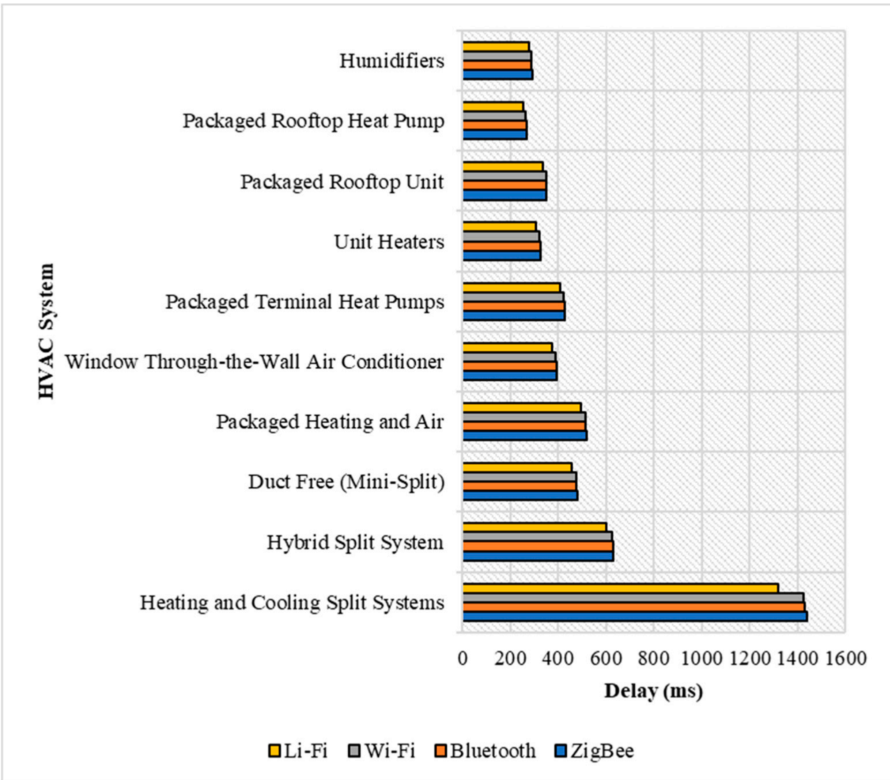

Figure 3. Delays (ms) between various communication protocols using the Convolutional Recurrent Neural Network system.

The energy efficiency networks Li-Fi and Wi-Fi in the home automation framework with the CRNN algorithm, which is designed in accordance with the control model, energy cost and energy cost minimization problem and the results are presented in Figure 4. It is found that the energy efficiency in Li-Fi is high compared to Wi-Fi.

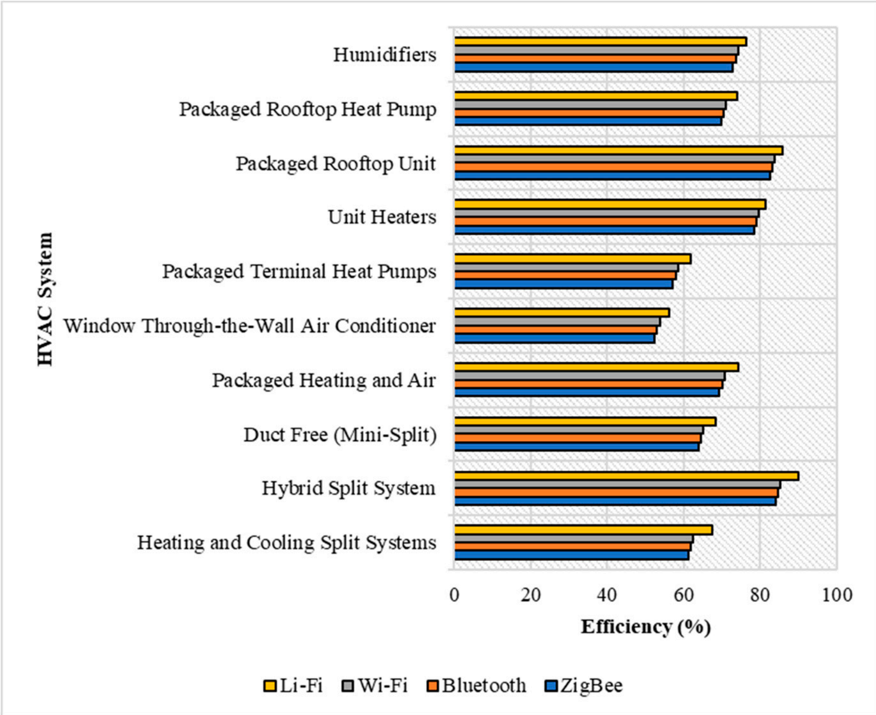

Figure 4. Energy efficiency (%) between various communication protocols using the CRNN system.

Figure 5 displays the effects of computational time in the automation network between the devices and gateway communication. The findings show that the proposed Li-Fi module offers a reduced computational time compared to Wi-Fi communication protocols due to its faster computational speed in carrying out the data packets between the cloud server and gateway.

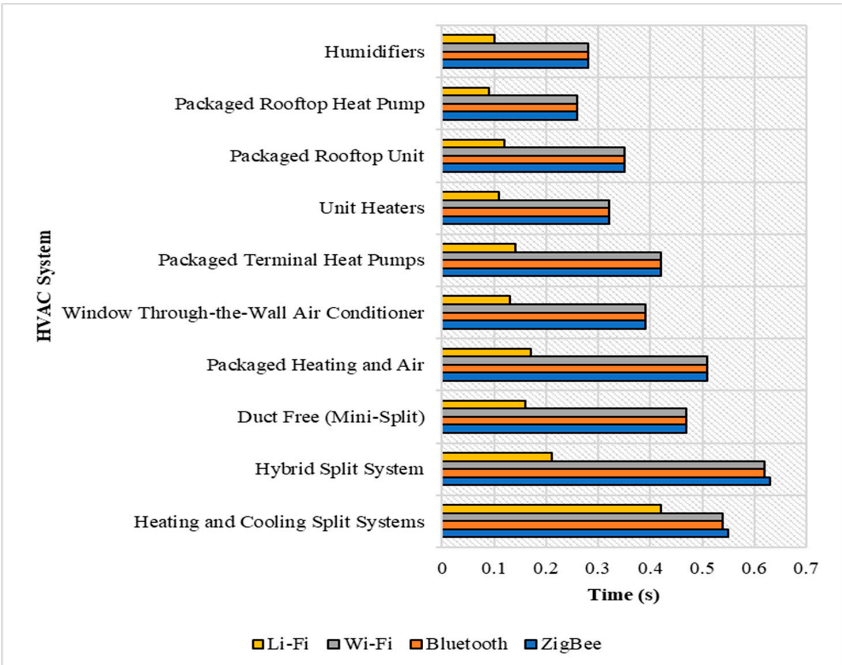

Figure 5. Computational times (s) between various communication protocols using the CRNN system.

Figure 6 displays the effects of communication costs in the home automation network between the devices and gateway communication. The findings show that the proposed Li-

Fi module offers reduced communicator costs compared to Wi-Fi communication protocols due to its higher computational speed in carrying out the data packets between the cloud server and gateway.

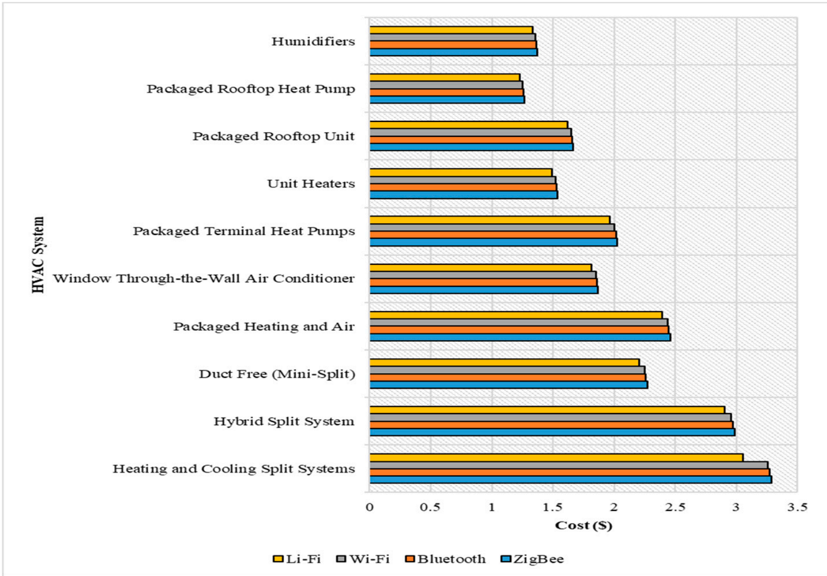

Figure 6. Communication costs ($) between various communication protocols using the CRNN system.

Figure 7 displays the effects of a packet delivery rate in the home automation network between the devices and gateway communication. The findings show that the proposed Li-Fi module offers an increased packet delivery rate compared to Wi-Fi communication protocols due to its faster delivery of data packets between the cloud server and gateway.

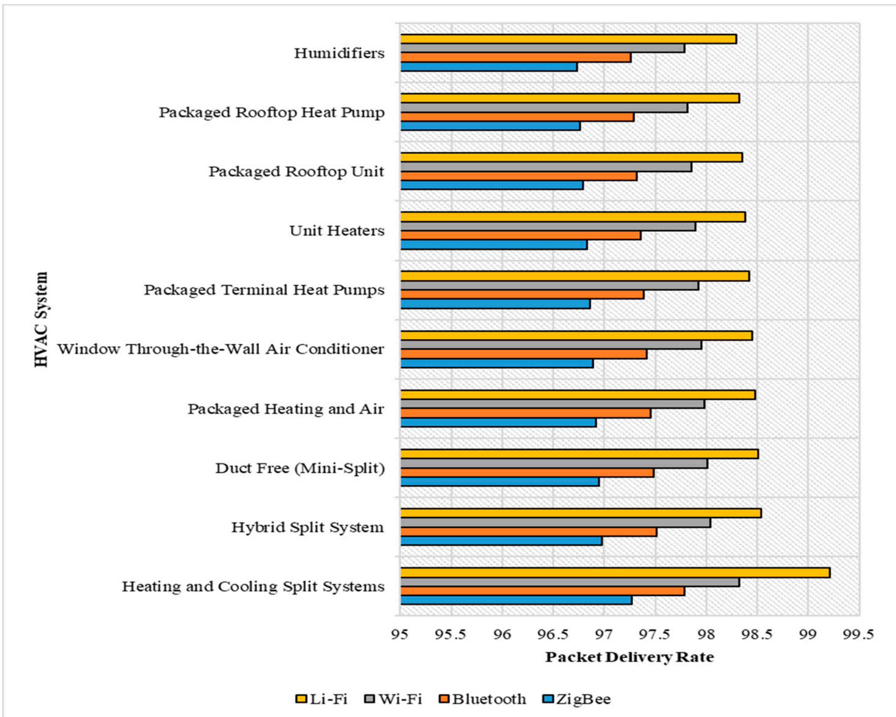

Figure 7. Packet delivery rate between various communication protocols using the RNN system.

The home gateway also links the machine interface with different networks to access the system. Facility and suitability are tested successfully by the experimental method, and the testing is done suitably in creating low, scalable and safe devices. The test demonstrated the stability and lowest effect on the device efficiency. Li-Fi systems showed a potential solution with coexistence and interoperability on the home automation system.

With HVAC device installation and low interoperability, the Li-Fi communication protocols for home automation systems show reduced complexity compared to the other protocols. Li-Fi communication technology increased the rate of transmission in the home automation system. It facilitated faster data transmission with reduced latency and increased energy efficiency between the devices and a gateway. The comparison with other communication protocols like Wi-Fi showed improved communication with reduced latency and operation. This helps the HVAC devices in the home automation network to reduce the energy consumption due to its faster communication processing ability.

5.2. Comparison with Existing Deep Learning Methods on HVAC Systems

This section provides the validation for testing using four different metrics that include load balancing, energy efficiency, low latency and transmission rate. The estimations in this section are carried out with by considering the control model, energy cost and energy cost minimization problem.

5.2.1. Load Balancing Accuracy

In the case of multiple buildings, the average of all the loads' balancing accuracy is estimated. The performance shows the results of controllable loads (Heating and Cooling Split Systems, Hybrid Split System, Duct Free (Mini-Split) and Window Through-the-Wall Air Conditioner) in Figure 8, and it measures the current balancing among the supply phases. It is seen that, with an increasing number of controllable loads, the balancing increases and makes the system stable. In Figure 8, the study evaluates the load balancing stability for a three-storied commercial building that uses HVAC systems with Li-Fi communication protocols.

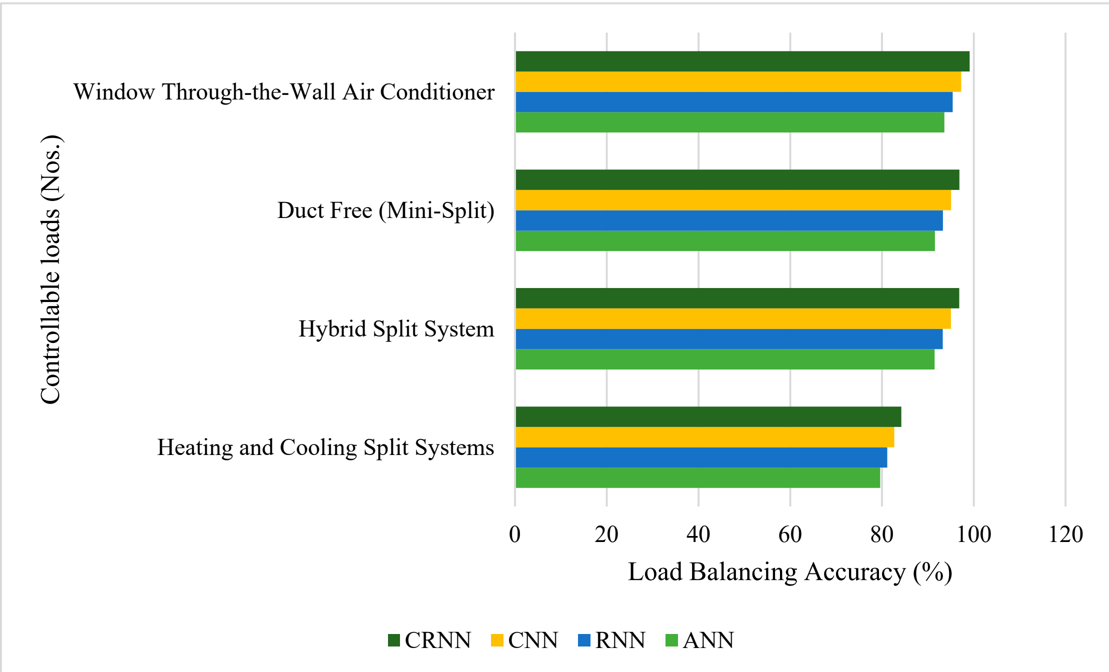

Figure 8. Load balancing accuracy (%) in a single smart building. ANN: Artificial Neural Network.

Figure 9 shows improved load balancing accuracy on uncontrollable loads (Packaged Terminal Heat Pumps, Unit Heaters, Packaged Rooftop Unit and Packaged Rooftop Heat

Pump and Humidifiers) by Li-Fi technology for smart commercial three-storied buildings with multiple HVAC devices over the RNN [43–46], ANN [39,46] and CNN [40,47–50] algorithms. The results show that an increased number of counts for single device lags the stability due to the reduced load balancing accuracy compared to those with fewer device counts. Figure 9 shows an improved load balancing accuracy by the CRNN method for a smart building with multiple devices over the ANN, CNN and RNN algorithms. Further, it shows that an increasing number of homes tend to reduce their load balancing accuracy, and it further reduces the reduced bandwidth in the communication protocol used.

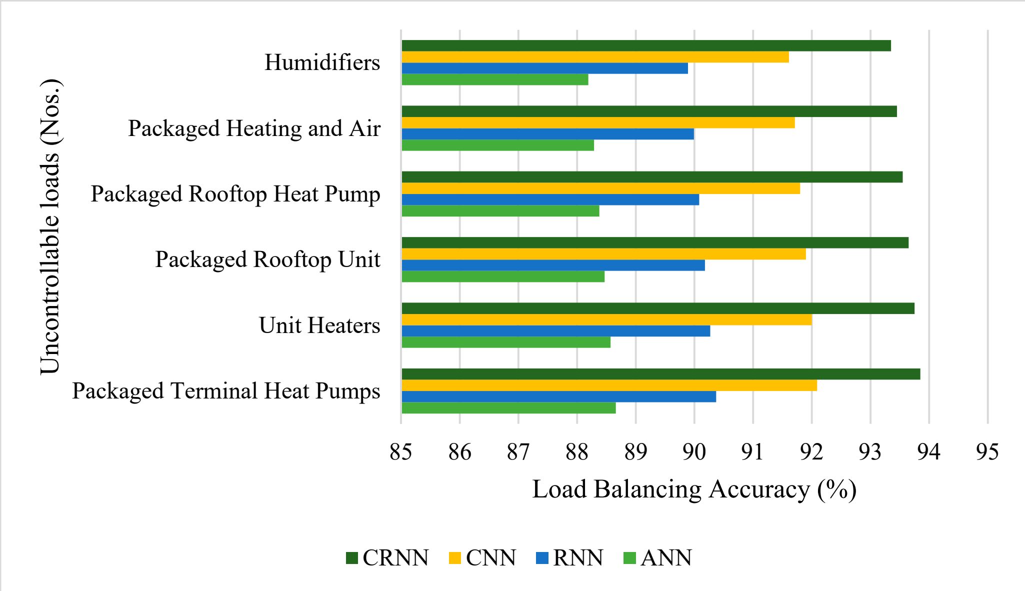

Figure 9. Load balancing accuracy (%) with more smart buildings.

5.2.2. Energy Efficiency

Figure 10 shows improved energy efficiency by the CRNN method for a smart building with multiple devices over the ANN, CNN and RNN algorithms.

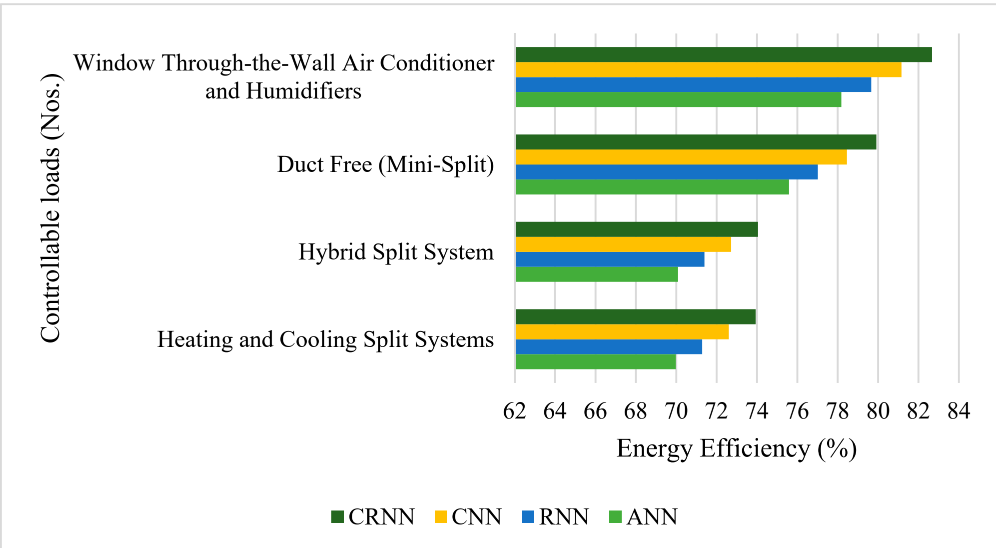

Figure 10. Energy efficiency (%) over various deep learning algorithms with controllable loads.

Figure 10 shows an improved energy efficiency by the CRNN method for a smart building with multiple devices over the ANN, CNN and RNN algorithms. With an increasing number of devices of the same type, it shows a reduced energy efficiency compared to the reduced number of devices with the same type.

Figure 11 shows an improved energy efficiency by the CRNN method for a smart building with multiple devices over the ANN, CNN and RNN algorithms. Further, it shows an increasing number of homes that tend to reduce their energy efficiency, and it further reduces the reduced bandwidth in the communication protocols used. The Li-Fi technology with the CRNN method offers a higher bandwidth compared to the other technologies, with a slightly lesser bandwidth allocation.

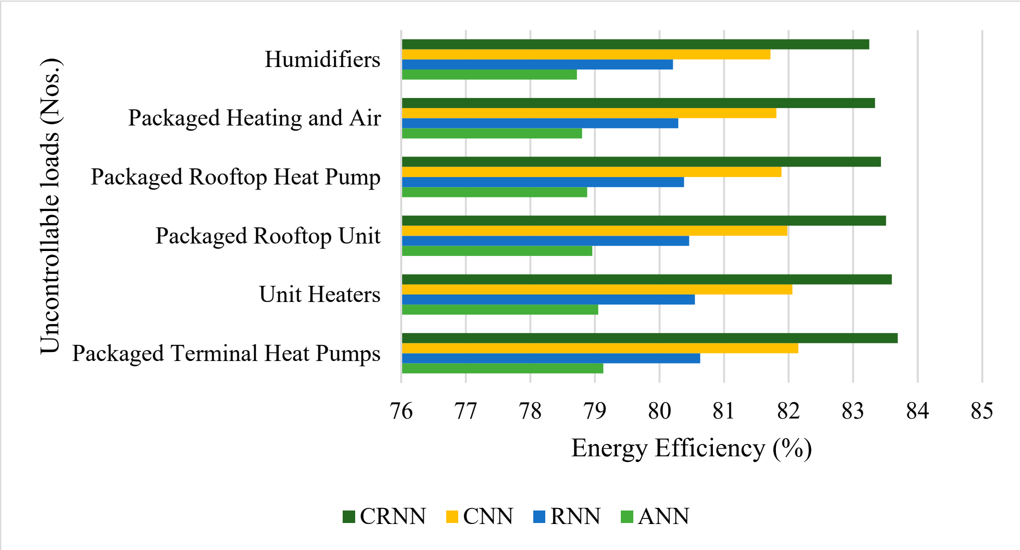

Figure 11. Energy efficiency (%) over various deep learning algorithms with uncontrollable loads.

5.2.3. Latency

Latency is defined as the time it takes for data or a request to go from the source to the destination. Latency in networks is measured in seconds.

Figure 12 shows a reduced latency by the CRNN algorithm for a commercial building with multiple devices over the ANN, RNN and CNN. With an increasing number of devices of the same type, it shows an increased latency compared to the reduced number of devices with the same type.

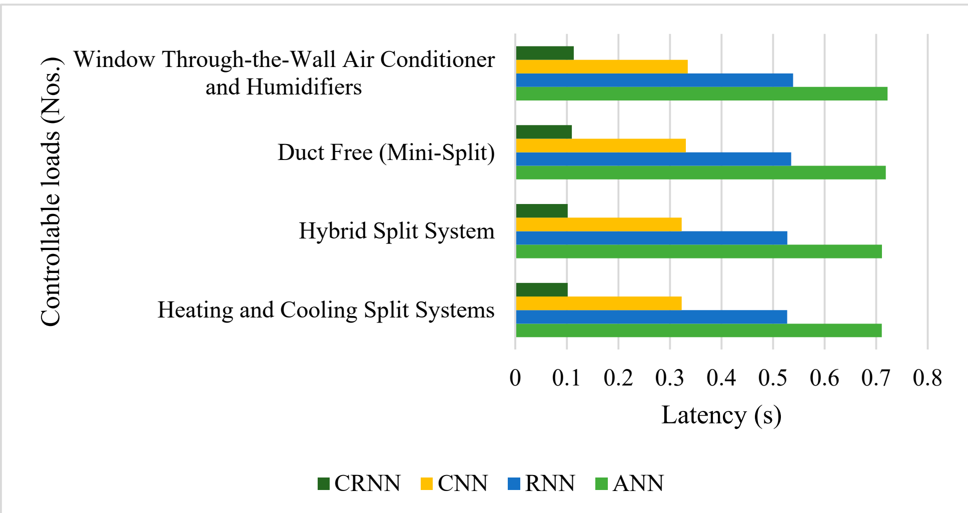

Figure 12. Latency (s) over various deep learning algorithms with controllable loads.

Figure 13 shows a reduced latency by the CRNN method for a smart building with multiple devices over the ANN, CNN and RNN. Further, it shows an increasing number of uncontrollable devices in smart commercial buildings; there is an increase in the latency. It further increases with a reduced bandwidth in the communication protocol used. On the other hand, the Li-Fi technology with the CRNN offers a higher bandwidth than the other technologies, where those offer only a limited bandwidth allocation.

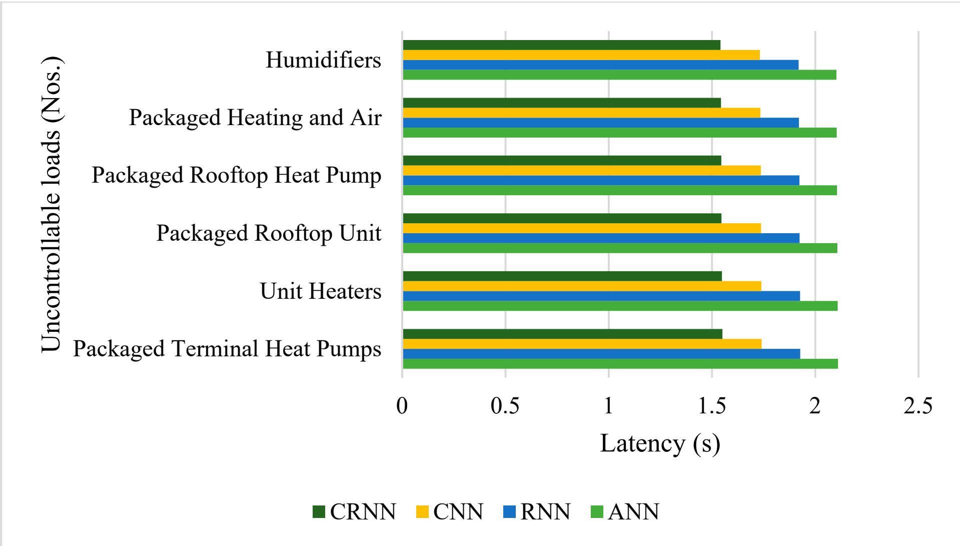

Figure 13. Latency (s) with more smart buildings.

5.2.4. Transmission Rate

Table 1 shows the increased data rate by the CRNN technology for smart commercial buildings with multiple HVAC devices over the CNN, RNN and ANN. With an increasing number of devices of the same type, it shows a reduced data rate compared to the reduced number of devices with the same type.

Table 1. Transmission rate (MBPS) in a single smart building.

Controllable Loads (Nos.)	ANN	RNN	CNN	CRNN
Heating and Cooling Split Systems	53.89	64.14	67.12	940
Hybrid Split System	52.81	62.85	65.77	921
Duct Free (Mini-Split)	52.81	62.85	65.77	921
Window Through-the-Wall Air Conditioner and Humidifiers	53.04	63.12	66.06	925

Table 2 shows increased data rate by the CRNN for a smart building with multiple HVAC devices over the CNN, RNN and ANN. Further, it shows that an increasing number of HVACs tends to reduce its data rate and increases with the reduced bandwidth in the communication protocols used. The Li-Fi technology CRNN method offers a higher bandwidth than the other technologies, with a slightly lesser bandwidth allocation.

The results show the validation for testing and improving the operating speed of the network to achieve the load balancing, energy efficiency, low latency and transmission rate. The results show that the proposed CRNN method with a Li-Fi system has an increased load balancing accuracy, energy efficiency and transmission rate with reduced latency compared to the CNN, RNN and ANN since reduced fluctuations in the HVAC load energy efficiency tend to get increased in CRNN systems compared to the other methods.

Table 2. Transmission rate (MBPS) with more smart buildings.

Uncontrollable Loads (Nos.)	ANN	RNN	CNN	CRNN
Packaged Terminal Heat Pumps	53.32	64.15	66.63	931
Unit Heaters	53.17	64.16	66.15	930
Packaged Rooftop Unit	53.34	64.31	66.31	929
Packaged Rooftop Heat Pump	53.50	64.47	66.46	928
Packaged Heating and Air	53.67	64.62	66.61	927
Humidifiers	53.84	64.78	66.77	926

5.2.5. Training Loss

Table 3 shows the results of the training and validation losses between the proposed CRNN with the CNN, RNN and ANN models. The results show that the proposed CRNN has a reduced training loss compared to the existing methods.

Table 3. Training and validation losses in terms of the mean square error (MSE).

	ANN	RNN	CNN	CRNN
Input nodes	11	11	11	11
Hidden nodes	45	45	45	53
Output nodes	1	1	1	1
Learning rate	0.38	0.39	0.41	0.45
Momentum	0.55	0.57	0.60	0.65
Training loss (MSE)	2.1×10^{-5}	5.2×10^{-6}	4.1×10^{-6}	1.5×10^{-7}

6. Conclusions

In this paper, the CRNN balances well all the fitness components, namely power loss, price management and reactive power. The multi-objective function offers an improved solution using the CRNN that finds the power loss components, price management factors and reactive power losses compared to the other existing deep learning algorithms. The solution using the CRNN optimization algorithm provides an optimal operation of an HVAC device that compensates the losses and price factors specific to HVAC systems. The simulation with various communication protocols offers an effective solution with Li-Fi technology compared to the other communication protocols on the HVAC systems. There are reduced fluctuations in the HVAC load energy efficiency that tends to become increased in CRNN systems compared to the other methods. In the future, studies intend to address various other limitations associated with non-HVAC devices and on household appliances.

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