Energy Demand Forecasting of Buildings Using Random Neural Networks

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Abstract

Energy uncertainty and ecological pressures have contributed to a high volatility in energy demand and consumption. The building sector accounts for 30 to 40% of the total global energy consumption. There is a high demand for novel techniques and viable energy strategies for reducing energy consumption in this domain. Energy prediction models have the potential to play a pivotal role in optimising energy consumption. The proposed work presents a new and accurate Energy Demand Prediction (EDP) model for large buildings. This approach leverages the Random Neural Network (RNN) prediction methodology. The proposed RNN-based EDP is compared with traditional Artificial Neural Network (ANN), Support Vector Machine (SVM) and linear regression models. A large building is modelled and simulated for one year in the Integrated Environment Solutions Virtual Environment (IES-VE). Several data inputs such as air temperature, internal gain and the number of people (occupancy) are calculated from IES-VE model and provided to traditional ANN and the proposed RNN predictor. A number of test parameters such as Root Mean Square (RMSE), Normalized Root Mean Square (N-RMSE), Mean Absolute Percentage Error (MAPE) and R provide the proposed RNN model with higher accuracy over the traditional ANN, SVM and linear regression. The proposed RNN predictor provides approximately half of the error of the ANN model. The traditional ANN model gives higher error values of 2.07×, 1.83× and 2.35× for RMSE, NRMSE and MAPE, respectively as compared to the proposed RNN model. Furthermore, the error values of SVM and linear regression were also higher than the proposed EDP scheme.

Key words: Buildings, Energy Demand, Random Neural Network, Prediction

1. INTRODUCTION

United Kingdom (UK), residential and non-residential buildings consume approximately 40% of energy [1, 2]. In non-residential buildings, Higher Education (HE) buildings are one of the most important sectors, consuming significant amounts of energy and emit greenhouse gas [1, 2]. It is outlined in reference [3] that Higher Education Funding Council of England (HEFCE) has set a target to reduce CO_2 around 43% by 2020 against the baseline year 2005. Many universities in the UK are now committed to achieving this goal. Cutting-edge cost-effective energy-saving schemes have the capacity to reduce 35% of CO_2 with at least 2 billion savings to the United Kingdom. To optimise energy consumption and reduce CO_2 emissions, it is imperative that we: (1) optimise energy expenditure in the building sector (2) invest in renewable energy projects. The implementation of building energy monitoring schemes and the analysis of their resultant consumption patterns will play a vital role in energy optimization and management.

In addition to this environmental incentive, efficient and cost-effective residential & non-residential buildings are in increasing demand due to financial and environmental pressures. The emerging solution to these constraints is to adapt convention building

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infrastructures into IT-enabled smart buildings. It is outlined by Wong et al. in the review article [4] that the early definition of smart buildings is centred around minimising unnessary human interaction with building components. However, generally smart buildings known as "automated buildings" are defined such that including smart technology or using automated methods for automating building processes such as lighting, Heating, Ventilation, Air-conditioning (HVAC) [5, 6, 7]. Smart building may also be referred to as an "intelligent building" that involves energy efficiency measures, adaptive energy system, and remote monitoring. In the review study [8], Clements outlined the exact definition of an intelligent building. According to this study [8], an intelligent building is one that is quickly reactive to the needs of occupants, society and organizations. Additionally, an intelligent building is sustainable in terms of energy consumption and also polluting in terms of waste and emissions. Such intelligent buildings enable efficient operation within the building and also enables reconfiguration to the changing environment or energy usage.

Energy consumption patterns have a critical and important role in understanding and designing of an effective energy management system for non-residential buildings. The energy management team can identify wastage of energy along with the understanding of building operational behaviour under different conditions via analysing patterns of energy consumption. Different factors such as temperature, humidity, heating set point, cooling set point, internal gain, and occupancy count information can be effectively analysed and future energy demand can be predicted. Worldwide, a swift progress in the economy has caused a rapid growing energy demand. At the same time, energy, i.e., electricity and natural gas is also considered as one of the main reason for economic progress and is thought indispensable in our daily life. Hence, energy demand prediction is one of the important topics which need researchers' attention.

Building EDP plays a crucial role in both building design alternatives and changes in operating procedures for reducing carbon emissions and minimizing energy consumption [9, 10]. Despite this, EDP remains a challenging problem due to a lack of diversity of factors that affect the consumption of energy. These include; the behaviour of occupants, the total number of occupants, and the operation of installed equipment in a building. Two major methodologies are generally adopted for EDP; physical modelling (white-box model) and data-driven approaches (black-box model). The first approach deals with the physical properties of a building which is primarily dependent on thermodynamics rules. EnergyPlus, eQuest, ESP, IES-VE, and Ecotect are examples of physical modelling tools [11]. In this approach, energy demand is calculated based on simulation of detail building construction particulars, operations schedules, weather information, and HVAC design information, etc [12]. However, some of the aforementioned input parameters might not be available to the software handling user and hence can lead to poor prediction performance. Due to the complexity and lack of input information, physical model based energy demand has serious difficulties when applying it practically [13].

On the other hand, data-driven or black-box models do not need such detailed information relating to the building. Alternatively, the black-box model learns from present and historical data relating to EDP [14]. In the past few years, data-driven based energy demand forecasting has gained a lot of attention [15, 16, 17, 18, 19, 20, 21, 22]. Research is predominantly focused on machine learning techniques such as ANN, Support Vector Machine (SVM), deep learning, etc. [13, 14, 19, 20, 21]. In the machine learning method, the system learns from data, detecting patterns which allow it to predict outcomes with minimal human intervention. In order to develop such a model, three stages are typically required: (i) data collection, (ii) model training (iii) and model testing. As a first stage, a sufficient dataset is collected such as weather conditions, energy consumption, number of occupants information, etc. Based on the input data, a model is trained in the second phase via a machine learning approach. In the third and last phase, the prediction accuracy is evaluated through some standard measures known as model testing. Standard measures in accuracy analyses are error calculations between actual and predicted distributions of data-labels. Error calculation methods include Root Mean Square (RMSE), Normalized Root Mean Square (N-RMSE), Mean Absolute Percentage Error (MAPE), etc [12]. The aforementioned parameters are generally used in model accuracy evaluation stage [12].

In machine learning-based EDP, SVM is one of the effective models used in non-linear problems. Dong et al used SVM as a prediction model and forecasted electricity consumption. The cooling load for the non-residential building was predicted through SVM in Li et al work [23] and accuracy was compared with an

ANN. The annual energy consumption in a residential building using SVM was forecasted in [24]. The accuracy and performance results in [24] indicate that SVM can predict energy demand with high accuracy. Subodh et al [25] selected an Ecole des in Mines de Nantes (EMN) building consisting 120 rooms located in France as a case study and predicted heating and cooling energy consumption. Results in [25] reveals that a relevant dataset as an input to SVM can lead to higher accuracy. In Yangyang et al study [26], a short-term load was predicted using 24 SVM models (one model per hour). Through RMSE and Mean Bias Error (MBE) analysis, authors proved that SVM based predictor has the least mean errors when compared to other methods [26]. Despite the pros of SVM based energy prediction, SVM has some limitations. It requires higher computations and hence needs a longer time during the training phase when finding a non-linear relationship between inputs and outputs.

In contrast to SVM, ANN models are fundamentally inspired by the human brain. Such models are used to find hidden or unknown patterns in data and a complex relationship between inputs and outputs are calculated. An ANN model is typically organized in three layers: input, hidden and an output layer. These layers contain input, hidden and output neurons, respectively that are interconnected with each other as shown in Fig. 1. Input data is given to the neural network through "input layer", which communicates with "hidden layer" (one or more than one hidden layers) where further processing is carried out through a structure of weighted "connections". The hidden layer (or last hidden layer) is linked to the "output layer" which produces the output in response to the input data. Among artificial intelligence based energy forecasting methods, ANN is one of the most popular black-box used in recent years.

Researchers have used ANN and numerous machine learning methods for EDP. However, such methods are computationally extensive and not accurate. As compared with ANN and other machine learning method, RNN-based can provide a robust solution for EDP. According to our best of knowledge, many authors has not explored the relationship between energy consumption and humidity, temperature and occupancy etc. In this paper, different variables such as humidity, temperature and human-traffic are collected, their relationship with energy consumption were explored and future energy demand can be predicted.

A simpler, computationally efficient and accurate forecasting energy demand model can help building managers in optimising energy resources and discover inefficiencies quickly. A reliable energy budget can be prepared via a robust energy prediction model. Furthermore, energy prediction systems play a key role in the successful and optimum energy management system. Building energy management uses the results of energy predictions system in energy-related decision-making. The financial manager can then set-up their priorities and strategic goal once energy demand is accurately predicted.

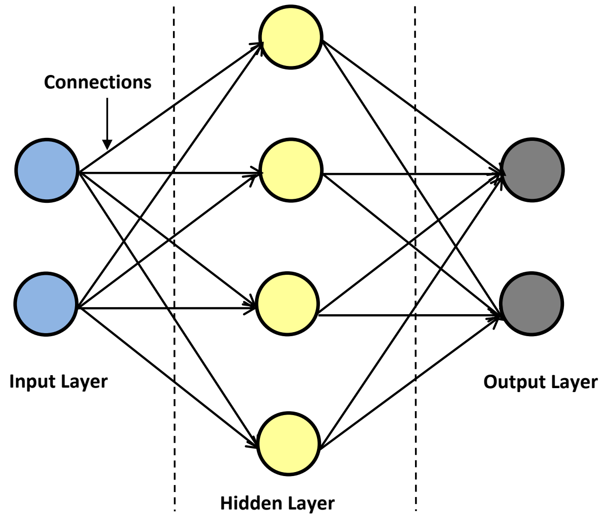


Figure 1: A typical example of ANN network.

Main Contributions:

A real building and its accurate setting in Glasgow Caledonian University, UK is simulated in IES-VE for EDP.

For a period of one year, essential data inputs for EDP models are calculated.

A novel energy demand model is developed using RNN and gradient decent algorithm, and the results obtained through the proposed model are analysed.

The proposed RNN-based method is highly accurate and computationally efficient when compared with other machine learning-based methods.

As compared to other scheme, RNN-based scheme has better generalisation capability.

The rest of the paper is structured as follows. The case study building modeled in IES-VE tool is described in Section 2.1. Section 2.2 discusses the traditional ANN method. The proposed RNN-based EDP model is outlined in Section 2.3. In Section 3, results of the proposed RNN-based model are discussed and compared with traditional ANN-based method. Conclusion of the paper is presented in Section 4.

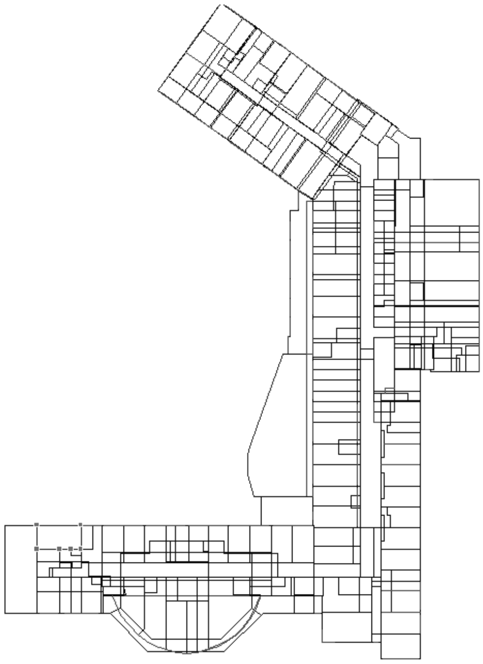
2. Preliminaries

This section discusses the necessary information related to the proposed scheme.

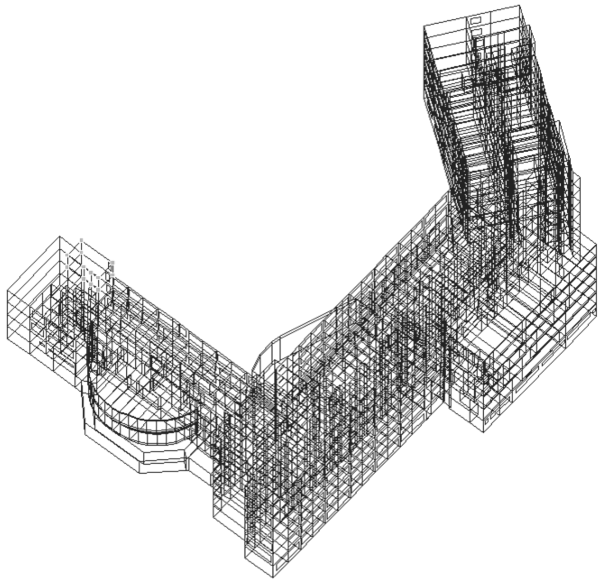
2.1. IES-VE Building Model

The case study building shown in Fig. 2 is an 8 storeys building known as GM at GCU, UK. Total number of larger and smaller rooms in GM building is 562 and hence the energy demand is a complex problem for such a large building. Volume and floor area of the case study building is 13769 m^3 and 8104 m^2, respectively. Real front view of GM building shown in Fig. 2 is modelled in the IES-VE software package. One can see plan and axonometric view in Figs. 3(a), and (b) which were generated from IES-VE model. Furthermore, the total number of rooms such as lecture rooms and meeting rooms, etc., can be seen in Fig. 3(c). The output from model viewer II shown in Fig. 3(d) highlights that IES-VE model is closer to the original building shown in Fig. 2. The case study building is simulated in IES-VE for one year and a number of output were saved in a database. The reporting interval was one hour and 9 important parameters such as room temperature, heating set point, cooling set point, plant profile, relative humidity, moisture content, heating sensible plant load, internal gain and number of people were calculated in IES-VE (Apachesim module). For each individual parameters, for example humidity, 8736 values were saved in the database. The total number of rooms were 562 and hence the total number of values were 8736×562 for each individual parameter. The energy consumption on 25th January is shown in Fig. 4. It is clear from Fig. 4 that most of the energy consumption is between 0900 and 1700 with peak at 0900 hours when Heating Ventilation and Air-conditioning (HVAC) etc., was turned on for room conditioning.

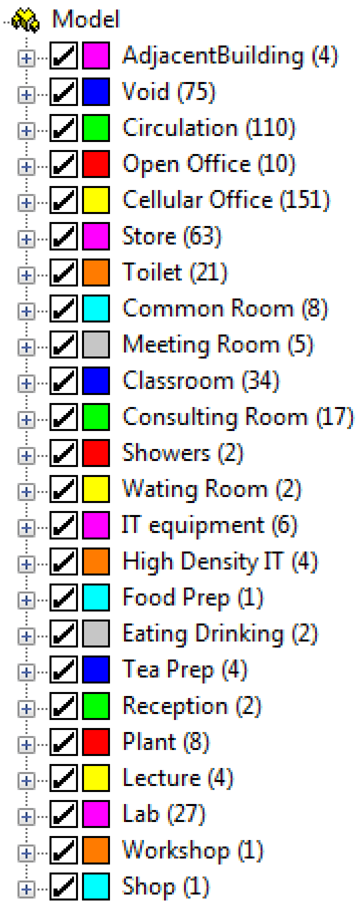
Figure 2: Govan Mbeki a.k.a GCU Health Bulding - A Front View.



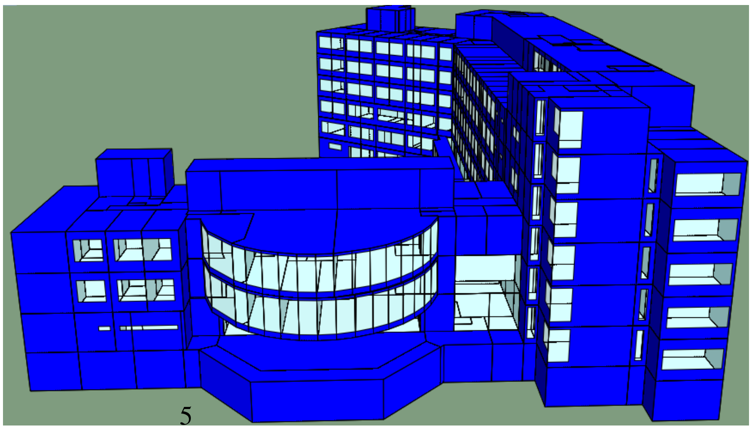
(a) GCU Health Building- A Plan View.



(b) GCU Health Building - An Axonometric View.



(c) Space activities.



(d) Model Viewer II output.

Figure 3: IES-VE Model of Govan Mbeki Building at Glasgow Caledonian University UK.

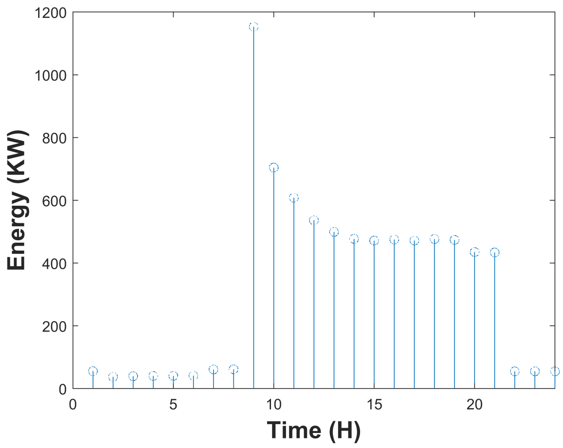


Figure 4: Energy Demand Analysis During January 25th.

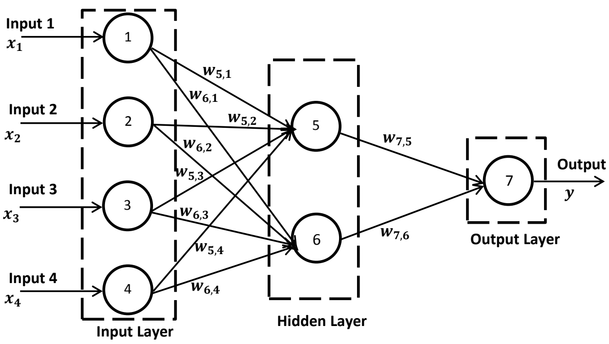


Figure 5: An example of FFNN: 4 inputs, 2 hidden and 1 output neuron.

2.2. Artificial Neural Network (ANN)

A Feed-Forward Neural Network (FFNN) is a biologically inspired ANN in which the decision flow is unidirectional. FFNN is one of the most widely used black-box learning model which has been used to solve non-linear difficult problems in machine/deep learning. In a FFNN, information flow is acyclic and network connections have no feedback. Each node known as a neuron in the input, hidden and /or output layers is the basic processing unit in Neural Networks (NNs). Figure 5 show an example of one hidden layer (2 hidden neurons) FFNN. FFNN tries to produce the output of network closer to the target value. Weights associated with each neuron and bias given to input neurons are trained by the NNs in such a way that the predicted output $\bar{y}$ is close to the actual output y. Mathematically, the network output $\bar{y}$ is calculated as:

$$\bar{y}_i = f(\sum_{j=1}^{n} x_j w_{ij} + b_i), \tag{1}$$

where x is the input to the network, w is the connection weight and b is the bias or constant term of the network. During the training phase, the network has to learn weights w associated with neuron and constant term b. In the testing phase, the network predicts outputs $\bar{y}$ via the learned weights and biases. Results from traditional ANN and the proposed RNN model are compared in results section. In this paper, the terms ANN and FFNN are meant to be the same.

2.3. The Random Neural Network (RNN) Model For Energy Demand Prediction

Flow chart of the proposed RNN-based energy demand prediction is shown in Fig. 6. In Random Neural Networks (RNN), the neurons exchange information by positive and negative signals which occur due to the excitation or inhibition process at each node. The excitation stage is described as +1 while -1 represents the inhabitation of signals [27, 2]. The information flows between neurons in time t as an impulse. In case of neuron i, the state $U_i(t)$ is defined as non-negative integer [27].

Based on the signal received at neuron i, the following possibilities can occur:

- It would remain in idle state if $U_i(t) < 0$.
- It would change its state, if $(U_i(t) > 0)$ and then fires the information towards a neighbouring neuron j with transmission rate $d(i)$ upon reception of a positive signal.

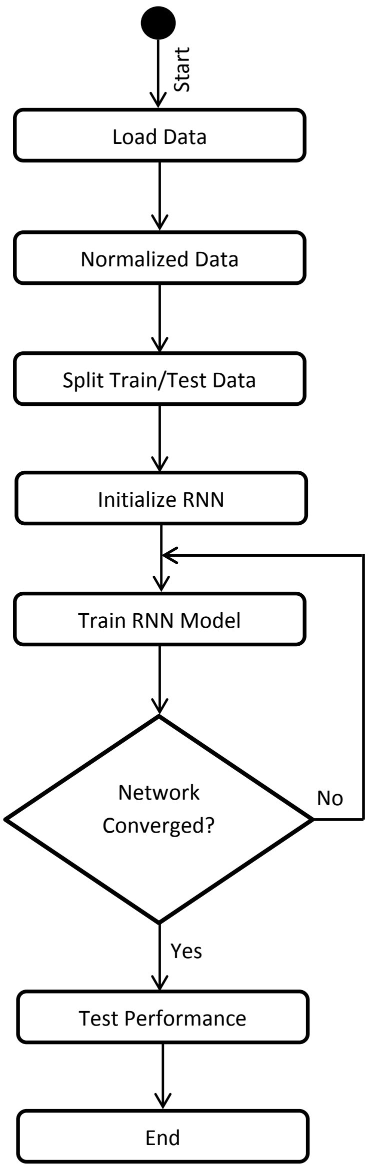


Figure 6: Flow chart of the proposed scheme.

During the transmission of information from neuron i to neurons j, the following probabilities are possible:

- It may attain probability of $p^+(i,j)$ due to an excitation signal.
- It may attain probability of $p^-(i,j)$ due to an inhibition signal.
- It may never reach the destination node and leave the network by the probability of $\Delta(i)$.

Mathematically, it is computed as:

$$\sum_{j=1}^{n} p^+(i,j) + p^-(i,j) + \Delta(i) = 1, \ 1 \leq i \leq n, \quad (2)$$

where n represents the total number of neurons in RNN nodes. According to the empirical rules of probability distribution, the sum of all probabilities in a function must be equal to 1, as mentioned in Eq. 2. The arrival rate of positive and negative signals in random neural network model is represented by $\Lambda(i)$ and $\lambda(i)$ respectively. Hence, the output activation function $f(i)$ upon excitation of neurons i is calculated as [28]:

$$f(i) = \frac{\lambda^+(i)}{\lambda^-(i) + d(i)}, \quad (3)$$

where,

$$\lambda^+(i) = \sum_{j=1}^{n} f(j)d(j)p^+(j,i) + \Lambda(i), \quad (4)$$

$$\lambda^-(i) = \sum_{j=1}^{n} f(j)d(j)p^-(j,i) + \lambda(i). \quad (5)$$

It is evident from Eq 3, 4 and 5 that output activation function $f(i)$ is the product of firing rate $d(i)$ as well as the positive ($\lambda^+(i)$) and negative ($\lambda^-(i)$) inputs at neurons. In case of excitation and inhabitation, the weights on the neurons are calculated as:

$$w^+(i,j) = d(i)p^+(i,j) \geq 0, \quad (6)$$

similarly

$$w^-(i,j) = d(i)p^-(i,j) \geq 0, \quad (7)$$

Combining Eqs 2, 6 and 7, the transmission rate of neurons $d(i)$ is derived as follows:

$$d(i) = (1 - \Delta(i))^{-1} \sum_{j=1}^{n} [w^+(i,j) + w^-(i,j)]. \quad (8)$$

Also, [29] summarize the unique behaviour of RNN for positive and negative signals as shown in Eq 9:

$$\lambda^{+}(i) < [\lambda^{-}(i) + d(i)] \tag{9}$$

Gradient Descent Algorithm for RNN

ANN and RNN can be trained using numerous training algorithms such the Gradient Descent (GDA), Newton Method, Conjugate Gradient, and Levenberg-Marquardt (LM) algorithms. However, due to faster convergence and saving computational time, GDA can be preferred over other training algorithms. In the proposed method, GDA is used during training the RNN model. Let the training patterns $\mathbf{\Lambda_p}$ and $\boldsymbol{\lambda_p}$ be the pth training patterns for x_p. The vector form of training patterns can be written as: $\mathbf{\Lambda_p} = [\Lambda_{1p}, \Lambda_{2p}..., \Lambda_{Np}]$ and $\boldsymbol{\lambda_p} = [\lambda_{1p}, \lambda_{2p}..., \lambda_{Np}]$. Mathematically, pth data input x_{ip} training pattern can be written as:

$$\begin{cases} \Lambda_{ip} > 0,\ \lambda_{ip} = 0 & \text{If } x_{ip} > 0 \\ \Lambda_{ip} = 0,\ \lambda_{ip} > 0 & \text{If } x_{ip} \leq 0 \end{cases} \tag{10}$$

The value of Λ and λ should be non-zero or some constant value for the network stability. The means square error cost function in gradient decent algorithm is written as follows:

$$E_p = \frac{1}{2}\sum_{i=1}^{n} \beta_i (q_j^p - y_j^p)^2, \beta_i \geq 0. \tag{11}$$

where q_j^p is the activation function which is a differentiable function, y_j^p is the actual value and $\beta_i \in (0,1)$ specifies that neuron i is an output neuron or not. The cost function shown in Eq. 11 is minimized via GD. Let u and v be the two neurons and the weights between them are $w^{+}(u,v)$ and $w^{-}(u,v)$ which are updated using below equations as:

$$w_{u,v}^{+t} = w_{u,v}^{+(t-1)} - \eta \sum_{i=1}^{n} \beta_i (q_j^p - y_j^p)[\frac{\partial q_i}{\partial w_{u,v}^{+}}]^{t-1}, \tag{12}$$

$$w_{u,v}^{-t} = w_{u,v}^{-(t-1)} - \eta \sum_{i=1}^{n} \beta_i (q_j^p - y_j^p)[\frac{\partial q_i}{\partial w_{u,v}^{-}}]^{t-1}, \tag{13}$$

where $\frac{\partial q_i}{\partial w_{u,v}^{+}}$ and $\frac{\partial q_i}{\partial w_{u,v}^{-}}$ are defined as:

$$\frac{\partial \boldsymbol{q_i}}{\partial w_{u,v}^{+}} = \Gamma_{u,v}^{+} q_u [\boldsymbol{I} - \boldsymbol{W}]^{-1} \tag{14}$$

$$\frac{\partial \boldsymbol{q_i}}{\partial w_{u,v}^{-}} = \Gamma_{u,v}^{-} q_u [\boldsymbol{I} - \boldsymbol{W}]^{-1}, \tag{15}$$

where $\boldsymbol{I}$ is the identity matrix. W depends on current values of q^p and $w(u,v)$. The parameters $\Gamma_{u,v}^{+}$ and $\Gamma_{u,v}^{-}$ are associated with $\frac{\partial \boldsymbol{q_i}}{\partial w_{u,v}^{+}}$ and $\frac{\partial \boldsymbol{q_i}}{\partial w_{u,v}^{-}}$, respectively which can be defined as:

$$\Gamma_{u,v}^{+} = \begin{cases} \frac{-1}{r_i + \lambda^{-}} & \text{if } u = i, v \neq i \\ \frac{1}{r_i - \lambda^{-}} & \text{if } u \neq i, v = i \\ 0 & \text{elsewhere} \end{cases} \tag{16}$$

$$\Gamma_{u,v}^{-} = \begin{cases} \frac{-1+q_i}{r_i + \lambda^{-}} & \text{if } u = i, v = i \\ \frac{-1}{r_i + \lambda^{-}} & \text{if } u = i, v \neq j \\ \frac{-q_i}{r_i + \lambda^{-}} & \text{if } u \neq i, v = i \end{cases} \tag{17}$$

The steps used in the GD algorithm are shown in Fig. 7. Steps in Fig. 7 are repeated until convergence.

The values (such as humidity and temperature etc.,) obtained after IES-VE simulation is stored in a CSV file. The obtained values were given as an input parameters for further processing in MATLAB R2017a software. In order to train the network, 70% of the input parameters were given to both ANN and RNN-based EDP models. Each parameter i.e, room temperature, heating set point, cooling set point, plant profile, relative humidity, moisture content, heating sensible plant load internal gain and a number of people are used as an input to the neural network. A Linear activation function is employed in the ANN model. The mean value of each input parameter is calculated and hence; at time t_1 we have one value instead of 562 values for each room. This strategy avoids the complexity of the network. At each hourly time step, the output neuron is the EDP of building. Initially, the total number of inputs to both ANN and RNN models were 9. Out of the total data, about 70% values were used for training and 30% were used for testing purpose. The number of hidden neurons is computed via adding output and inputs neuron and then divided by 2. In the proposed RNN model, we are using $\frac{I_N + O_N}{2}$ hidden neuron, where I_N and O_N are number of inputs and outputs neurons, respectively. The model depicted in Fig. 8 is a 9-5-1 RNN model, where 9 are inputs, 5 are hidden and 1 is output neuron(s). The model shown in Fig. 8 is used as an energy demand predictor.

3. Results and Discussions

The proposed random neural network based model is shown in Fig. 8. The dataset used for the evaluation of

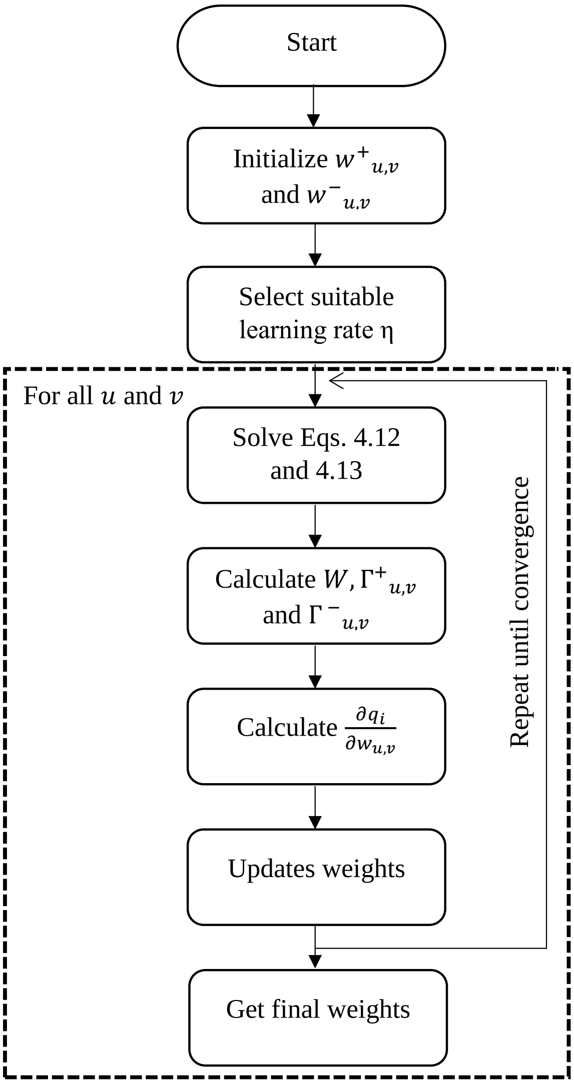


Figure 7: Weight calculation in RNN via GD algorithm.

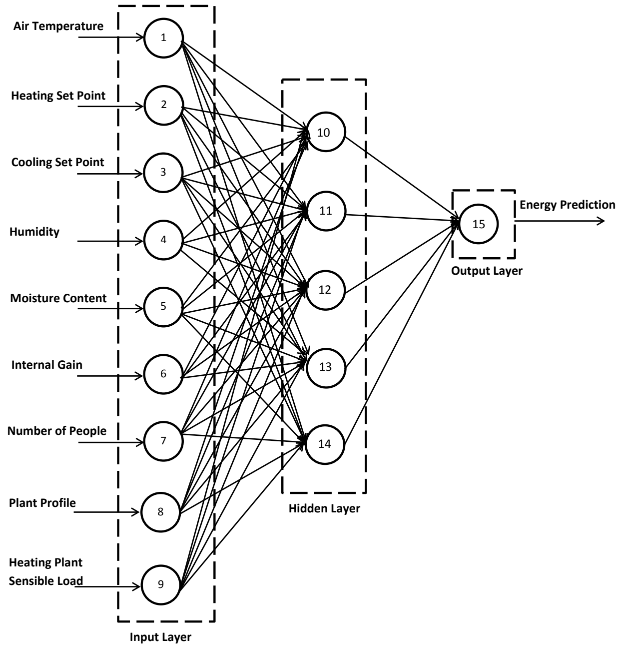


Figure 8: Proposed RNN architecture: 9 inputs.

system is divided into Train Data and Test Data with ratio of 70:30. Fig. 9 depicts the results upon comparison with seen (train data) and unseen patterns (test data) simultaneously. The results gathered after simulation as shown in Fig. 10 and Fig. 11 justifies the accuracy of proposed scheme where the simulated energy demand using IES-VE is very close to the prediction of RNN based model.

To show the strength of RNN model, four important metrics i.e., Root Mean Square (RMSE), Normalized Root Mean Square (N-RMSE), Mean Absolute Percentage Error (MAPE) and R are calculated. Accuracy of RNN model is computed through the aforementioned tests. The average magnitude of error is calculated through RMSE metric. N-RMSE is the normalized square root of the average of squared differences between actual and predicted data and MAPE is the percentage of the mean value of the sum of absolute differences between actual and forecasted data. Mathematically, these performance metrics are written as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(E_{Aj} - E_{RNNj}\right)^2} \tag{18}$$

$$N\text{-}RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(\frac{E_{Aj} - E_{RNNj}}{E_{Aj}}\right)^2} \tag{19}$$

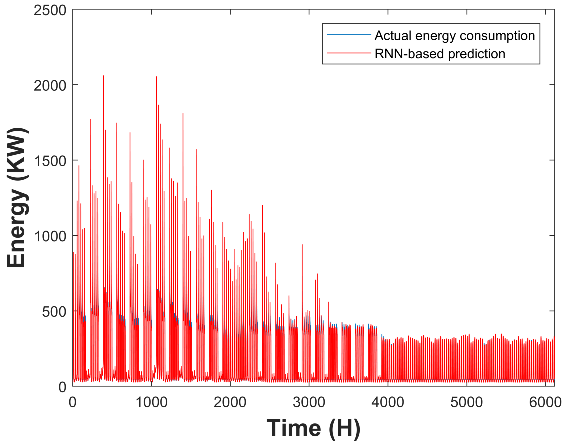


Figure 9: Comparison of actual energy consumption with RNN-based energy prediction (Training data)

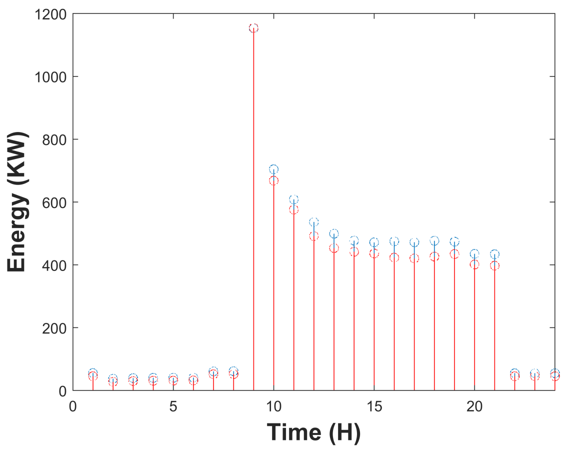


Figure 10: Comparison of energy demand prediction on 1st January.

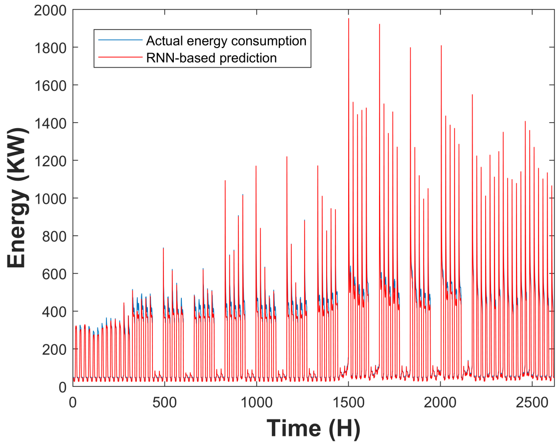


Figure 11: Comparison of actual energy consumption with RNN-based energy prediction (Test data).

$$MAPE = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{E_{Aj} - E_{RNNj}}{E_{Aj}}\right| \times 100\% \tag{20}$$

$$R = 1 - \left(\frac{\sum_{j=1}^{n}(E_{Aj} - E_{RNNj})}{\sum_{j=1}^{n} E_{Aj}}\right)^2 \tag{21}$$

where n is the total number of samples, E_A and E_{RNN} are simulated and predicted energy at time j, respectively. A lower value of RMSE, N-RMSE and MAPE indicates a good prediction model. Closer the value of R to a value of 1, closer is the prediction to the actual value. ANN and RNN are trained for a fixed time of 200 seconds with same learning rate ($\eta = 0.05$) and the same number of hidden neurons (hidden neurons = 5). In case of ANN, MSE reached to 5.59×10^{-5} in total 71939 epochs. In the RNN model, MSE reached to 1.47×10^{-5} in just 84 epochs. From Table 1, one can see that values of all performance metrics are in favour of the proposed RNN model. In RNN-based training, values of RMSE, N-RMSE, and MAPE are least when compared to ANN training. In the training and testing phase, the percentage error in the RNN model is less as compared to the ANN model. RMSE and Normalised RMSE in RNN is 48.30% and 54.79% less in comparison to the ANN model. One can see from the table that MAPE in RNN-based model is 42.62% less than in ANN model. Furthermore, R values of RNN-based EDP model is much closer to the ideal value of 1. Additionally, RMSE is graphically depicted in Fig. 14 which also indicates a lower RMSE for the proposed scheme. In order to carry out speed analysis, we fixed the value

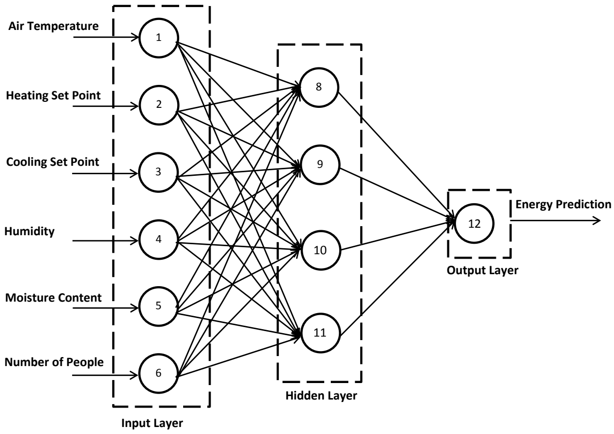


Figure 12: Proposed RNN architecture: 6 inputs.

of MSE to 4×10^{-5} for both RNN and ANN models. RNN achieved the aforementioned MSE in just 59 seconds with 25 epochs while ANN took 1113 seconds and achieved the desired MSE in 198358 epochs. Hence, RNN speed is 18.86 times faster than ANN.

RNN and ANN models are tested for a reduced number of input parameters. Figure 12 shows the RNN model for 6 inputs only. For a fixed training time (200 seconds), RNN and ANN models were trained with 6 inputs, 4 hidden and 1 output neurons with a slow learning rate $\eta = 0.05$. The scatter plot of predicted vs actual energy demand for RNN model with only 6 input parameters is shown in Fig. 13 which indicates that predicted values are following the energy demand trend. The scatter plot for RNN based prediction shows positive correlation. MSE values for ANN and RNN were 1.69×10^{-3} and 1.36×10^{-3}. The difference between MSE value is only 0.3×10^{-3}. It seems that MSE values have a minor difference but it has larger effects on error values as shown in Table 2. During MAPE tests, the percentage error between the ANN test and RNN test data is 57.30%. Furthermore, the results of the proposed RNN shown in Tables 3 and 4 are compared with SVM and linear regression. All test parameters indicates that the proposed RNN-based prediction is close to actual values and hence the proposed model can be employed for building EDP.

4. Conclusion

Energy demand prediction for large non-domestic buildings is a complex problem. Currently, accurate energy forecasting mainly focuses on machine learning and neural network-based techniques. In this work, a novel RNN-based EDP is presented for a non-domestic

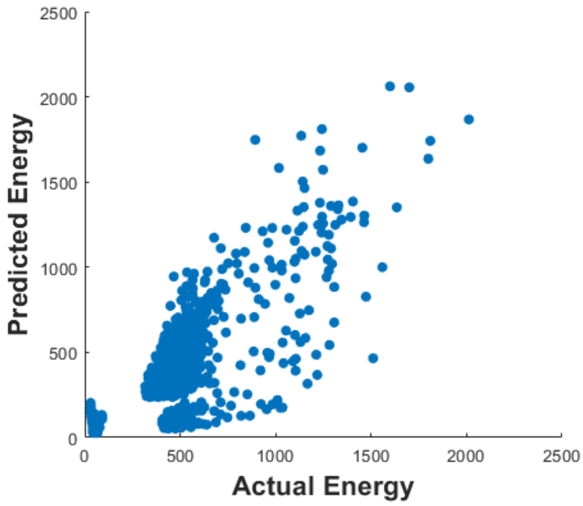


Figure 13: Scatter plot of actual vs predicted energy: RNN Model.

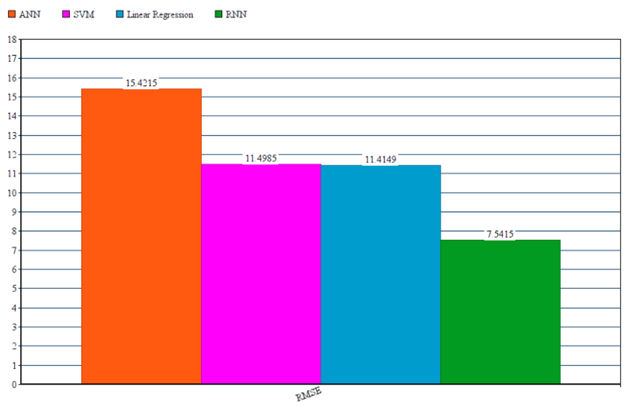


Figure 14: Graphical comparison of RMSE.

Table 1: Error comparison of the proposed RNN model with ANN: 9 inputs.

Error	ANN Train	ANN Test	RNN Train	RNN Test
RMSE	15.4217	15.6121	7.0101	7.5415
N-RMSE	0.0073	0.0073	0.0037	0.0040
MAPE	8.3912%	8.3733%	3.4893%	3.5716%
R	0.9972	0.9974	0.9994	0.9994

Table 2: Error comparison of the proposed RNN model with ANN: 6 inputs.

Error	ANN Train	ANN Test	RNN Train	RNN Test
RMSE	86.4779	82.0269	71.8444	74.2903
N-RMSE	0.0600	0.0611	0.0406	0.0395
MAPE	34.2021%	36.3880%	21.8205%	19.6281%
R	0.9057	0.9133	0.9350	0.9350

Table 3: Error comparison of the proposed RNN model with other regression models: 9 inputs.

Error	SVM	Linear Regression	RNN
RMSE	11.4985	11.4149	7.5415
N-RMSE	0.0057	0.0062	0.0040
MAPE	14.4658%	13.4855%	3.5716%
R	0.9982	0.9983	0.9994

Table 4: Error comparison of the proposed RNN model with other regression models: 6 inputs.

Error	SVM	Linear Regression	RNN
RMSE	120.9384	111.6564	74.2903
N-RMSE	0.0657	0.0640	0.0395
MAPE	27.0552%	27.0287%	19.6281%
R	0.8213	0.8418	0.9350

large building located at Glasgow Caledonian University, UK. An RNN based model is proposed and successfully developed for nine and six input parameters. The proposed model provides half the error in predicted energy values for a large non-residential building under test as compared to the other prediction models such as ANN, SVM and linear model. For nine input parameters, the RNN model provides an MSE of 1.47×10^{-5} with 84 epochs, while an ANN gives an MSE of 5.59×10^{-5} with 71939 epochs. The simulation results show that the proposed model is computationally efficient and highly accurate when compared to traditional machine learning-based methods. The difference between MSE seems very low, however, it has a greater impact on predicted outputs that leads to an accurate model. Moreover, the RNN model also has better results with six input parameters. RMSE, NRMSE, MAPE and R results prove the superiority of the proposed RNN model. Due to faster computation, the proposed model can be embedded in energy simulation tools, such as the IES-VE. In future work, the proposed model will be implemented in an embedded system for real-time prediction of energy consumption and a deep RNN model with also be analysed with multiple hidden layers for higher accuracy and real-time applications. Furthermore, a sensor fusion-based real-time occupancy will be implemented and the impact of occupancy on energy demand will be investigated.

Conflict of Interest

There is no conflict of interest.

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