Energy Demand Prediction Through Novel Random Neural Network Predictor for Large Non-Domestic Buildings

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Abstract—**Buildings are among the largest consumers of energy in the world. In developed countries, buildings currently consumes 40% of the total energy and 51% of total electricity consumption. Energy prediction is a key factor in reducing energy wastage. This paper presents and evaluates a novel RNN technique which is capable to predict energy utilization for a non-domestic large building comprising of 562 rooms. Initially, a model for the 562 rooms is developed using Integrated Environment Solutions Virtual Environment (IES-VE) software. The IES-VE model is simulated for one year and 10 essential data inputs i.e., air temperature, dry resultant temperature, internal gain, heating set point, cooling set point, plant profile, relative humidity, moisture content, heating plant sensible load, internal gain and number of people are measured. Datasets are generated from the measured data. RNN model is trained with this datasets for the energy demand prediction. Experiments are used to identify the accuracy of prediction. The results show that the proposed RNN based energy model achieves 0.00001 Mean Square Error (MSE) in just 86 epochs via Gradient Decent (GD) algorithm.**

Index Terms—**Non-domestic building, energy demand prediction, optimizations, Random Neural Network, IES-VE and building simulation**

I. INTRODUCTION

IN the United Kingdom (UK), non-domestic buildings are 10% accountable for greenhouse (GHG) emission. According to the Carbon Trust, novel cost effective measures can yield 35% reduction in CO₂ with at least £ 2 billion (bn) benefit to the UK. Through better temperature and ventilation control, workers productivity can be increased significantly [1]. Commercial buildings account for slightly less than a fifth of the energy consumption of the United States (US), with an office space, retail space, and educational institutions which represent nearly half of commercial sector energy consumption. The recession is demonstrated by a 10% decrease in energy expenditures in the commercial buildings. There is a 22% decline in value of new commercial construction which is lowest in the last 30 years [2]. Space heating, space cooling and lighting are top three end uses in commercial energy consumption. Between 1980 and 2009, the commercial floor space grew by 58% while primary energy consumption grew by 69%. According to the Energy Information Administration (EIA) plan, commercial floor space will continue to grow

at slower rates between 2009 and 2035, 28% and 22%, respectively [2]. On the other hand, average energy prices are expected to remain fairly stable [2].

The policy of improving building efficiency will not only reduce energy consumption but it will also reduce 12.6 gigatonnes (Gt) of CO_2 emissions from buildings by 2050. To reduce energy consumption, a wide range of options are available e.g., improving building envelope characteristics, updating heating systems with the latest advanced intelligent equipment, automatic lighting systems and efficient hot water provision [3], [4]. There are limitations in changing the envelope characteristics of existing buildings. In existing buildings, changing envelope material such as walls, floors, roofs, fenestrations and doors are often very costly and hence the concept of improving building fabric is limited for existing non-domestic large buildings. As a result, such solutions which are applicable in both existing and upcoming construction are needed.

One option for energy improvement is utilizing some sort of intelligent control system such as Artificial Neural Networks (ANN) [5]. Optimization of energy is a complex phenomena and dependent on many factors which are interconnected. ANN have the capability to model the complex relationships and hence can work on a causal large number of input parameters. Several papers have shown the superiority of ANN over conventional methods such as time series and regression analysis [6]–[10]. In an energy efficient building management system, ANN is not only employed for reducing energy consumption but also used for improving thermal comfort in both domestic and non-domestic buildings. Some basic algorithms used for achieving an efficient and optimized solution are: Gradient Decent (GD), Genetic Algorithms (GA), Non-dominated-and-crowding Sorting Genetic Algorithm II (NSGA-II) Particle Swarm Optimization (PSO), Simulated Annealing (SA) and Ant Colony Optimization (ACO) [11]. Hopfield et al introduced the concept of optimization based on artificial neuron and analog input information [10]. The proposed method was applied on well-defined optimization problem-the Traveling-Salesman Problem and achieved a solution in an efficient way. In the case of bounded constraints, an ANN based optimized solution was presented by Bouzerdoum et al [12] showing that a bound-constrained

quadratic optimization problem can be mapped on the neural network through the appropriate choice of the network weight matrices and neural activation functions. The system described by Bouzerdoum et al is globally convergent to a unique optimal solution. Chaotic Neural Networks (CNN) proposed in literature were analyzed by Kwok et al [13]. For optimized solutions of complex problems, CNN based models can be a better choice [13].

In order to optimize a chiller systems, ANN and GA are integrated in [14]. A Stochastic Simulated Annealing (SSA) method was introduced by Wang et al [15] to highlight some drawbacks in previous Chaotic methods that did not find a globally optimal solution. Large data inputs can be reduced to small data inputs using the method proposed in [16]. In Hinton et al algorithm, better results are achieved if initial weights are equal to good solution. Simulation results are compared to principle component analysis (PCA) and all results were quite promising [16]. ANN based hourly prices forecasting method was introduced in [17] by Gareta et al. Error between estimated prices and actual prices are quite small and hence provide application in real time scenarios [17].

The energy estimation of two blocks in administration building of the University of São Paulo were analyzed [18]. An ANN based model and EnergyPlus based model were compared for energy calculations. Another EnergyPlus based model was developed by Wong et al in which day lighting energy was analysed via ANN [19]. An ANN based controller was also designed to achieve a higher thermal comfort for residential buildings [20]. Gelenbe proposed a new class of ANN, known as RNN in literature [21]. Many applications of RNN based model are reported in research field such as pattern recognition, image processing, video compression, texture generation and classification problems [22]. Kumar et al discussed the potential of RNN based techniques in energy modelling and came to a conclusion that RNN can be employed in many areas of building services engineering [23]. Researchers had developed many techniques using RNN, however some flaws were also reported in [24], [25].

The main contributions of this paper are:

- A model for a large non-domestic building is developed in IES-VE with accurate real settings data
- Essential data for energy demand prediction is measured via IES-VE simulation for a period of a year
- RNN based model for energy demand prediction is developed, and the energy demand prediction from simple RNN based model and complex IES-VE model are critically analysed.

The rest of paper is organized as follows. In Section II, a brief overview of RNN, GD and IES-VE is given. The proposed RNN based prediction model and IES-VE model is given in Section III. Conclusion and future work is presented in Section IV.

II. RELATED KNOWLEDGE

This section presents the fundamental knowledge related to RNN, GD algorithm and IES-VE.

A. Random Neural Network (RNN)

In RNN, the potential of a neuron is represented by integer. Neurons in RNN interact by probabilistically exchanging excitatory and inhibitory spiking signals. In RNN model, +1 represents excitation spike and -1 represents inhibition spike, respectively. These spiking signals travel from one neurons to other neuron as impulses. In a given time t, a neuron i has a potential $k_i(t)$ which is a non-negative integer. When $k_i(t) < 0$, neuron i is considered in an idle state. If neuron i has a positive amplitude ($k_i(t) > 0$), it can randomly transmit signals according to the exponential distribution with rate r_i. The transmitted signals can reach neuron j as a positive signal (excited) with probability $p^+(i,j)$ or as negative signal (inhibited) with probability $p^-(i,j)$, or can leave the network with probability $l(i)$. Mathematically, the aforementioned statement can be written as:

$$\sum_{j=1}^{n} p^+(i,j) + p^-(i,j) + l(i) = 1, \forall i, \quad (1)$$

where n is total number of neurons. In Eq. 1, the sum of all probabilities must be equal to 1. In RNN model, $\Lambda(i)$ represents the arrival rate of external excitation (positive) signals and $\lambda(i)$ is the arrival rate of external inhibition (negative) signals. According to these definitions, the probability of excitation of neuron i is [22]:

$$q(i) = \frac{\lambda^+(i)}{r(i) + \lambda^-(i)}, \quad (2)$$

where,

$$\lambda^+(i) = \sum_{j=1}^{n} q(j)r(j)p^+(j,i) + \Lambda(i), \quad (3)$$

$$\lambda^-(i) = \sum_{j=1}^{n} q(j)r(j)p^-(j,i) + \lambda(i). \quad (4)$$

Here the output $q(i)$ is a activation function of positive inputs ($\lambda^+(i)$) divided by negative inputs ($\lambda^-(i)$) and firing rate $r(i)$. $w^+(i,j)$ and $w^-(i,j)$ indicates positive and negative rates, respectively, when neuron i is in excited state. Mathematically:

$$w^+(i,j) = r(i)p^+(i,j) \geq 0, \quad (5)$$

$$w^-(i,j) = r(i)p^-(i,j) \geq 0, \quad (6)$$

Expression for rate $r(i)$ can be derived by combining Eqs 1, 5 and 6:

$$r(i) = (1 - l(i))^{-1} \sum_{j=1}^{n} [w^+(i,j) + w^{-1}(i,j)]. \quad (7)$$

In [26], it is has been shown that for any system based on RNN, Eq 8 is enough for the existence of a unique solution.

$$\lambda^+(i) < [r(i) + \lambda^-(i)] \quad (8)$$

B. Gradient Descent Algorithm

This section presents a standard GD algorithm for training RNN. Let x_p be pth training pattern which is represented by vectors $\Lambda_p = [\Lambda_{1p}, \Lambda_{2p}..., \Lambda_{Np}]$ and $\lambda_p = [\lambda_{1p}, \lambda_{2p}..., \lambda_{Np}]$. Mathematically, pth data input x_{ip} training pattern can be written as:

$$\begin{cases} \Lambda_{ip} > 0, \ \lambda_{ip} = 0 & \text{If } x_{ip} > 0 \\ \Lambda_{ip} = 0, \ \lambda_{ip} > 0 & \text{If } x_{ip} \leq 0 \end{cases} \qquad (9)$$

In order to guarantee the network stability, the values of non-zero elements must be $|x_{ip}|$ or some constant value Λ and λ. The error cost function for GD algorithm can be expressed as:

$$E_p = \frac{1}{2} \sum_{i=1}^{n} \beta_i (q_j^p - y_j^p)^2, \ \beta_i \geq 0. \qquad (10)$$

where $\beta_i \in (0,1)$ indicates whether neuron i is an output neuron, q_j^p is differentiable function and y_j^p is desired value. The role of GD algorithm in any ANN model is to minimize the cost function described in Eq 10. Consider a connection between neurons u an v. Weights $w^+(u,v)$ and $w^-(u,v)$ are updated according to the expression:

$$w_{u,v}^{+t} = w_{u,v}^{+(t-1)} - \eta \sum_{i=1}^{n} \beta_i (q_j^p - y_j^p)[\frac{\partial q_i}{\partial w_{u,v}^+}]^{t-1}, \qquad (11)$$

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

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

$$\frac{\partial q_i}{\partial w_{u,v}^+} = \Gamma_{u,v}^+ q_u [I - W]^{-1} \qquad (13)$$

$$\frac{\partial q_i}{\partial w_{u,v}^-} = \Gamma_{u,v}^- q_u [I - W]^{-1}, \qquad (14)$$

where 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 $\dfrac{\partial q_i}{\partial w_{u,v}^+}$ and $\dfrac{\partial q_i}{\partial w_{u,v}^-}$, respectively which can be defined as:

$$\Gamma_{u,v}^+ = \begin{cases} \frac{-1}{r_i + \lambda^-} & \text{if } u = i, v \neq i \\ \frac{1}{r_i - \lambda^-} & \text{if } u \neq i, v = i \\ 0 & \text{elsewhere} \end{cases} \qquad (15)$$

$$\Gamma_{u,v}^- = \begin{cases} \frac{-1 + q_i}{r_i + \lambda^-} & \text{if } u = i, v = i \\ \frac{-1}{r_i + \lambda^-} & \text{if } u = i, v \neq j \\ \frac{-q_i}{r_i + \lambda^-} & \text{if } u \neq i, v = i \end{cases} \qquad (16)$$

A flow chart for steps involved in GD algorithm are summarized in Fig. 1. All steps are repeated until convergence.
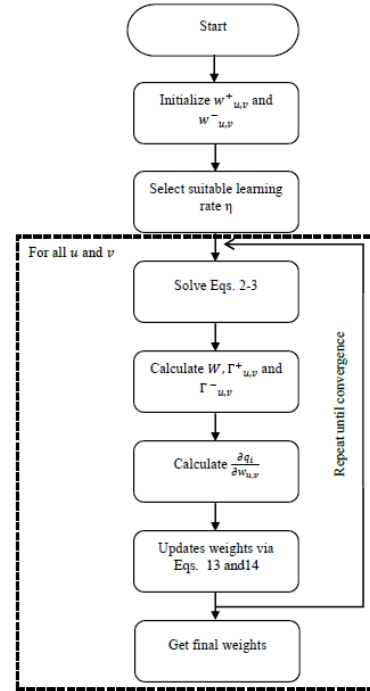

Fig. 1: Steps involved in GD algorithm for weight calculation

C. IES-VE (Integrated Environment Solution-Virtual Environment)

We have selected IES-VE in our research as a simulation tool which can be utilized for both renovated and new buildings. Analytically the IES-VE simulation tool provides a variety of variables for the building designers and architects. All results obtained through IES-VE are easy to visualize and provide significant details and technical information about a building [27]. IES-VE allows interaction with other software tools such as Sketchup [27] for better analysis. There are various important modules in IES-VE such as solar, light, HVAC, global compliance, climate, UK and Ireland regulations, value/cost impact, energy/carbon, airflow and LEED (Leadership in Energy and Environmental Design) tool. Basically, these modules share one central integrated model. In IES-VE, ApacheSim tool evaluates heat transfer processes of buildings which is used in the evaluation of energy and consumption costs. Keeping in view, both energy and human comfort, IES-VE imparts detailed knowledge based on some intensive physical characteristics of buildings. For the analysis of natural ventilation, natural lighting and shading, ApacheSim tool can be linked to Suncast and Macro Flo dynamic tools. The results obtained via IES-VE simulation tools can be automatically saved as CSV files in a machine and be further applied in ANN based systems [28]–[30].

III. Proposed Methodology Based on RNN

The Govan Mbeki (GM) building in Glasgow Caledonian University (GCU) (Glasgow campus) was selected as a case study. This building contains 562 rooms including smaller and larger rooms. Total floor area and volume of GM building is 8104 m^2 and 13769 m^3, respectively. Figure 2 shows a real

Fig. 2: Front view of real Govan Mbeki (Health) building.

front side of GM building. To implement the geometry of the GM building, a complex model was developed in IES-VE. Plan and axonometric views of the GM building in IES-VE can be seen in Figs. 3(a), and (b), respectively. Fig. 3(c) shows this model contain total 562 (large number of) rooms. It can be seen from Fig. 3(d), when changing the orientation of model and using model viewer II, the GM building is now much closer to the real building when compared with Fig. 2. The GM building model was simulated from January to December for an year with a reporting interval of one hour. Ten important parameters: such as room temperature, dry resultant temperature, heating set point, cooling set point, plant profile, relative humidity, moisture content, heating sensible plant load, internal gain and number of people are calculated for in ApacheSim module. Since we generated data for one year, 8640 values for each individual parameter were obtained. Against each individual parameter, we have total 8640×562 values. At a time t_1, E_1 is a single value of energy consumption for the GM building in that specific one hour duration (here time t_1 indicates, one hour duration). The complete year was divided into equal length of time from $t_1, t_2, ...t_{8640}$. Figure 4 shows energy consumption on 1st January with the reporting interval one hour. It is clear from Fig. 4 that most of energy consumption is from 09:00 to 17:00 hour.

A database from the simulated results was created and all parameter values (i.e., temperature etc) and energy values were stored in a CSV file for further processing in MATLAB R2015b. As discussed in Section II, training patterns are needed for RNN based model, hence the database can be utilized for both training as and testing purpose. To avoid complex scenarios, each parameter is considered as an input neuron in the proposed methodology. On hourly basis, mean values of room temperature, dry resultant temperature, heating set point, cooling set point, plant profile, relative humidity, moisture content, heating sensible plant load internal gain and number of people are calculated. In such a scenarios, instead of 562 different values of for a parameter at time t_1, the model has one mean value. An Output neuron is the energy in killowatts (kW) at each time step t_1. Hence at time t_1, we have only ten inputs as a dataset which is utilized in RNN. The proposed RNN based solutions for energy prediction is shown in Fig 5. Out of the total 8640 time steps, half of the mean values were used for training an the other half were used for
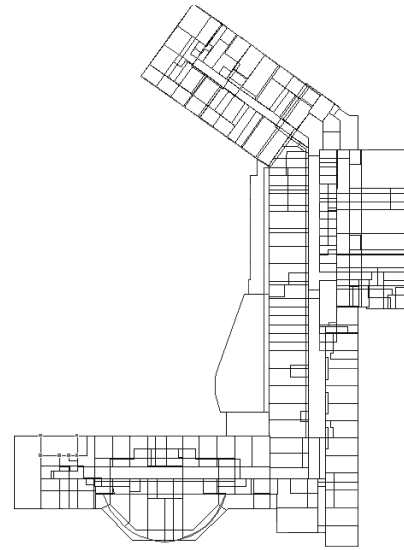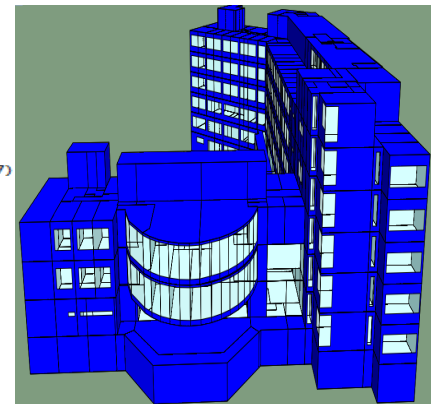

(a) Plan view of health Building.
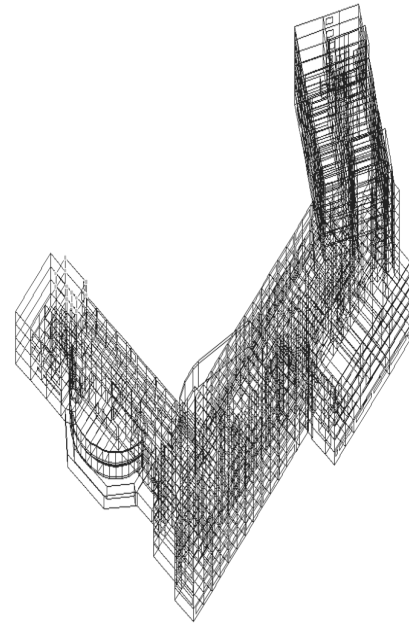
(b) Axonometric view of model.
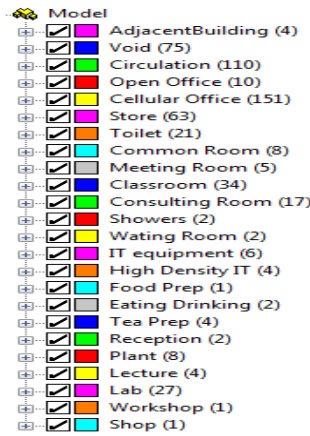
(c) Space activities.

(d) Changing the orientation of Govan Mbeki building Model.

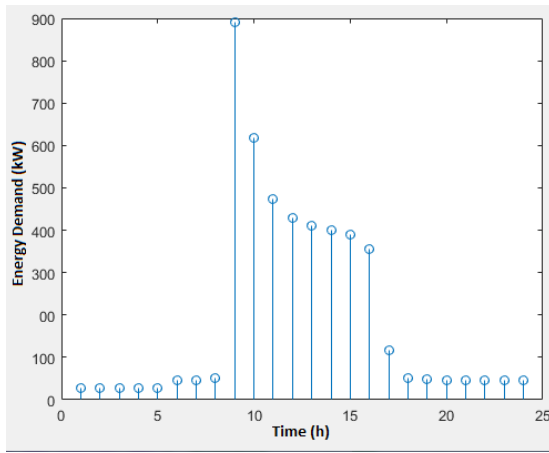Fig. 3: IES-VE model of Govan Mbeki building located in GCU.
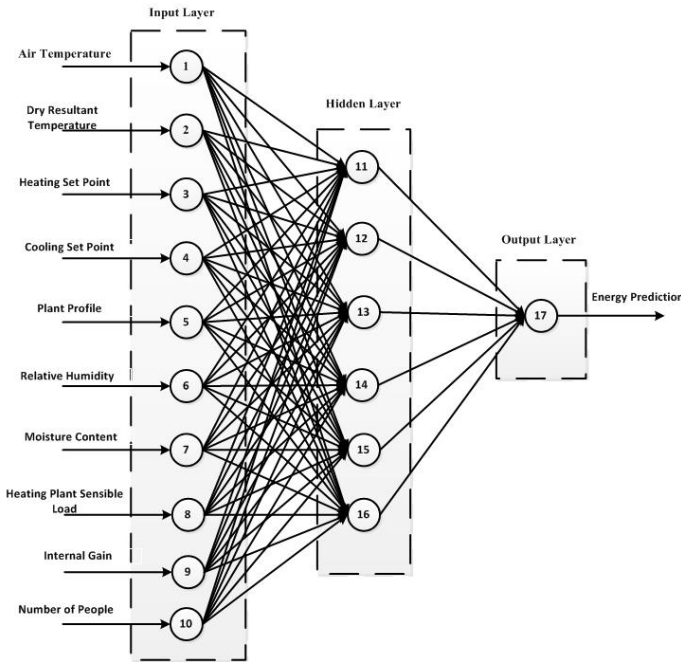
Fig. 4: Energy demand profile on 1st January.

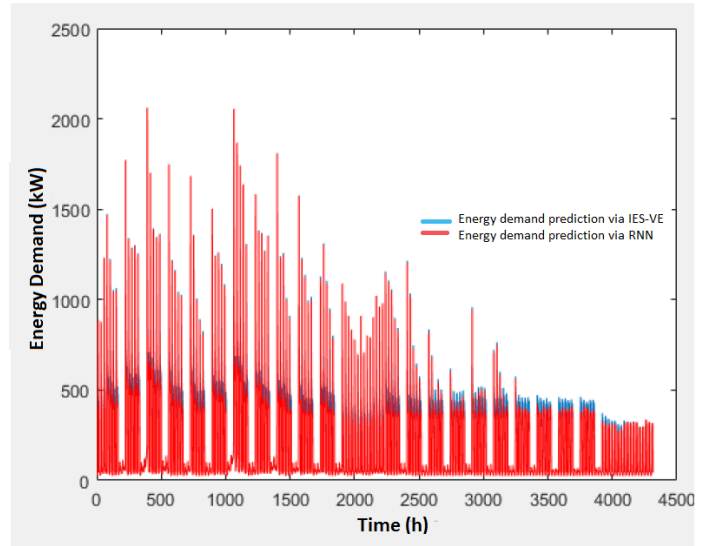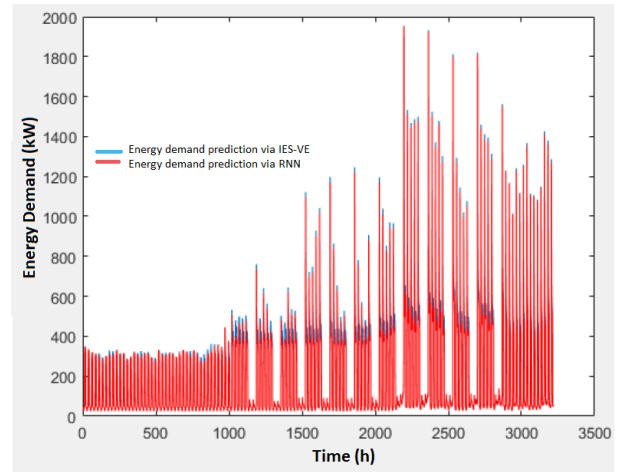Fig. 5: Proposed RNN architecture.

Fig. 6: Comparison of predicted and simulated energy results for six months data.

(a) Energy prediction for all unseen data points.

(b) Energy prediction for last month.

Fig. 7: RNN based prediction of energy for untrained (unseen) data.

testing purpose. As there is no specific formula for selecting the optimum number of hidden layer neurons, we selected 6 neuron in the proposed RNN based model which can be seen in Fig 5. A rule of thumb for hidden layer neurons is to add output and input neurons and divide the result by 2.

IV. RESULTS AND DISCUSSIONS

Initially, RNN was trained for 6 months data via the proposed model shown in Fig. 5. Results for training (seen) patterns are shown simultaneously on a single graph in Fig. 6. In order to carry out important comparison for unseen patterns, last six months are selected in our analysis. From Fig. 7(a) and Fig. 7(b), it can be seen that RNN based model prediction is very close to the simulated energy demand. Figure 7(b) highlights the output for last month data which make a clear pictorial representation of prediction. To show the strength of the proposed scheme, two important tests i.e., MSE and
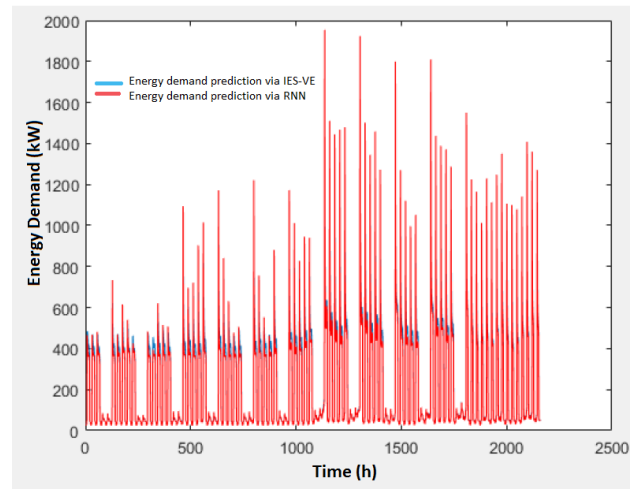
correlation coefficient analyses are also carried out. MSE can be defined as:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (E_{RNN} - E_s)^2 \qquad (17)$$

where E_{RNN} is predicted RNN based energy and E_s is simulated energy. Correlation between RNN based energy and simulated energy can be written as:

$$CC = \frac{\sum\limits_{X} \sum\limits_{Y} (E_{RNN} - \overline{E_{RNN}})(E_s - \overline{E_s})}{\sqrt{\left(\sum\limits_{X} \sum\limits_{Y} (E_{RNN} - \overline{E_{RNN}})^2\right)\left(\sum\limits_{X} \sum\limits_{Y} (E_s - \overline{E_s})^2\right)}}, \qquad (18)$$

where CC is correlation coefficient, $\overline{E_{RNN}}$ and $\overline{E_s}$ indicates mean values of RNN based energy and simulated energy, respectively. A lower value of CC indicates good prediction model. In case of trained data, values obtained for both MSE and CC are 9.96×10^{-6} and 0.9965, respectively. For unseen data, MSE and CC values are 8.96×10^{-6} and 0.9969, respectively. It is clear from aforementioned discussion that both MSE and correlation values are in favour of the proposed methodology.

V. Conclusion

This paper proposes a novel energy predication demand from several data parameters of Govan Mbeki building located in Glasgow Caledonian University, Glasgow, United Kingdom. A RNN based model successfully developed which predicts total energy consumption with a low MSE and a higher correlation between estimated and actual energy. In testing process, targeted MSE was 1×10^{-5} which was achieved within 86 epochs. Due to these small number of iterations, the processing time to achieve low MSE makes the system feasible for practical applications in real-time. The proposed methodology can replace various complex and time consuming traditional artificial neural network based prediction models. The proposed model can also be embedded in IES-VE simulation tool that will calculate annual energy consumption. In future work, the proposed model will be utilized in the process of energy optimization and designing better control strategies while maintaining an acceptable thermal comfort for occupants. We also intend to compared predictions with actual BMS collected data.

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