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Prediction of residential building energy consumption: A neural network approach

M.A. Rafe Biswas [a, *], Melvin D. Robinson [b], Nelson Fumo [a]

[a] Department of Mechanical Engineering, The University of Texas at Tyler, USA
[b] Department of Electrical Engineering, University of Texas at Tyler, USA

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ABSTRACT

Some of the challenges to predict energy utilization has gained recognition in the residential sector due to the significant energy consumption in recent decades. However, the modeling of residential building energy consumption is still underdeveloped for optimal and robust solutions while this research area has become of greater relevance with significant advances in computation and simulation. Such advances include the advent of artificial intelligence research in statistical model development. Artificial neural network has emerged as a key method to address the issue of nonlinearity of building energy data and the robust calculation of large and dynamic data. The development and validation of such models on one of the TxAIRE Research houses has been demonstrated in this paper. The TxAIRE houses have been designed to serve as realistic test facilities for demonstrating new technologies. The input variables used from the house data include number of days, outdoor temperature and solar radiation while the output variables are house and heat pump energy consumption. The models based on Levenberg-Marquardt and OWO-Newton algorithms had promising results of coefficients of determination within 0.87–0.91, which is comparable to prior literature. Further work will be explored to develop a robust model for residential building application.

1. Introduction

Residential dwellings account for a considerable portion of the growing energy demand in the world today, yet this sector "is largely an undefined energy sink" when compared to the commercial, industrial, and transportation sectors [1]. According to the U.S. Energy Information Administration, the residential sector has consistently comprised 21–22% of the total energy consumption in the United States over the past decade [2,3]. Although this is a significant number, Swan and Ugursal [1] explain that the commercial, industrial, and transportation sectors have been studied extensively due to large economic and public interest from the respective industries while also identifying contributing factors for cataloging the residential sector under the 'undefined' study due to lack of financial incentive. In the residential sector, two such contributing factors are size and location of the living space. For example, small flats or apartments require less energy compared to conventional family houses since there is less thermal conditioning and heat transfer area along with lower level of human occupancy [3]. Other contributing factors that can hinder energy consumption studies include variations in building characteristics such as floorplans and size and number of windows, and different types of occupant behavior such as how often and how long appliances are used [1,3]. Moreover, privacy issues for collecting and sharing data by occupants such as their income, and high costs of sub-metering energy usage of space heating and cooling, domestic hot water, household appliances and indoor lighting in dwellings are also reasons for hindrance of such studies [1,4]. Given such factors and the substantial energy consumption of the residential sector, there are efforts geared towards comprehending energy usage to conserve energy and reduce emissions [1].

The residential sector consumes transformed energy from primary power sources provided by utility companies to become suitable for use to support the living standards of occupants [1]. Modeling and simulation of this secondary energy consumed is

* Corresponding author.
E-mail address: mbiswas@uttyler.edu (M.A.R. Biswas).

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significant in the analysis of alternative designs of new buildings, as well as for retrofits, to evaluate and decide on the most efficient and cost-effective selections. Residential energy models rely on input data based on the living standards from which to estimate and simulate energy consumption. The inconsistencies in the amount of information available for input data has yielded several different modeling techniques to compensate for such lack of information, and the various strengths, weaknesses, and capabilities of these techniques have been presented and discussed [1]. There are several popular methods used for forecasting building energy consumption that can be categorized into Engineering, Statistical and Hybrid methods [4,5]. Engineering methods "use equipment and systems and/or heat transfer and thermodynamic relationships to account for end-use energy consumption" [4]. Statistical methods use historical or collected data on building energy consumption and any kind of data analysis to identify the source of the energy consumption from particular end-uses including artificial neural networks [4]. Hybrid approaches combine elements of engineering and statistical approaches by considering both the building physical characteristics and relationships and measured historical data [4]. From these methods, the Statistical methods have gained significant ground with a growing interest and implementation of Artifical Neural Network (ANN) models, which has become an important class in empirical nonlinear modeling [1,6].

According to Zhao et al., ANNs are very widely used artificial intelligence models due to its effective approach in building energy applications [7]. Moreover, prediction of residential building energy consumption fits better with NN models than with the conventional statistical models such as linear regression analysis due to the ability to perform nonlinear analysis, to do parallel structures that allow uninterrupted computing, to learn and train, and to implement with flexibility and relative ease [5,8]. There are several studies that demonstrate very good approximation in energy consumption forecasting using ANN models in residential applications, some of which are discussed in Section 2. For model development in this study, data for an unoccupied research house was used and variation in energy consumption is strongly dependent on weather. Although the model developed is mainly intended for future research at this house, this approach is similar to approaches found in the literature where the impact of the occupancy is considered approximately constant and the model captures the influence of weather [9,10]. For example, Mullen et al. used an unoccupied research building at University College Cork (UCC), Ireland that has two fan assisted convectors and several furniture, but no additional heating or momentum sources such as people during the experiments for their CFD simulation study [11]. In addition, Lü used real test data from an unoccupied two-story museum house in Anjala, Finland to verify a physics-based heat and moisture transfer model [12]. Finally, Moon et al. assumed a constant value of occupant activity level for a target two-story detached residential house to incorporate into NN model prediction and control design of indoor air temperature and humidity [13]. So, without the influence of weather conditions, the energy use on a monthly basis of a house would be similar from one month to another, but the monthly energy consumption changes due to weather which is readily captured by a model as the proposed in this study. With the idea of making this paper a self-contained work for the reader regarding the use of NN for residential buildings, the outline is as follows. Section 2 reviews some studies that employ NN models in residential applications, Section 3 presents discussion on NN modeling approach, Section 4 provides experimental setup and procedure for the research house, Section 5 compares and discusses the two NN energy consumption models based on two different algorithms, and finally, Section 6 concludes on energy consumption prediction using neural network models.

2. Background on applications of neural network models

Artificial NN have been developed to generalize the nervous system of a human being into one or more mathematical models [5]. The concept of NN analysis was discovered about five decades ago, but, in the past two decades, its applications have become wider and popular due to significant advancement in technology to solve challenging problems with faster processing speed and higher computing capacity [5,7]. Artificial NN have successfully overcome the research stages to find its place in real time applications throughout various industries including aerospace, robotics, energy, medicine, economics, psychology and neurology [5,14]. The concept was applied to modeling of energy consumption in individual buildings throughout the last decade of the 20th century, starting with commercial buildings [8]. Several researchers have demonstrated that they can be more reliable at predicting energy consumption in a building than other traditional statistical approaches because of their ability to handle nonlinear patterns with high computing speed and high accuracy [7,15]. Such traditional statistical approaches, which are usually steady-state methods, include use of simple or multiple linear regression to find the relationship between the outputs and inputs parameters as well as variable-base degree-day method and change-point models [5].

Building energy consumption is a vital variable, not only in scientific analysis, but also in cost analysis. Thus, high accuracy is important in development of the energy consumption model because underestimation of energy consumption could lead to potential outages that can be detrimental to social and economic lifestyles while overestimation would lead to unnecessary idle capacity and thus wasted financial resources [16]. Therefore, there have been several studies to develop accurate prediction of energy consumption with various types of statistical models and approaches. Since conventional statistical models require significant amount of collected data and are reasonably accurate for near-linear data, NN models are able to account for nonlinear data characteristics that are observed in the varying electrical loads seen by utility meter readings [1,7,17].

Aydinalp et al. [8,18] carried out a comparison of three methods that are currently used to model residential energy consumption at the national level: the Engineering method (EM), the conditional demand analysis (CDA) method, and the NN method. The space heating (SH), domestic hot water (DHW) and appliance, lighting and cooling (ALC) energy-consumptions are modeled based on the Canadian residential sector during the year of 1993 where output variables that are estimated and simulated using NN by Aydinalp et al. [19,20]. After evaluating various approaches for the three models, the optimal NN models resulted in very high prediction performance of the energy consumption models with the coefficients of determination of 0.87 and higher, which is significantly better than the prediction performance of the EM model (the coefficient of determination below 0.8) developed using the same database [19,20]. Similarly Kialashaki and Reisel [16] compares NN and multiple linear regression models for the national residential sector in the United States where the NN model coefficients of determinations were observed to be above 0.98 while the regression model coefficients were between 0.95 and 0.98. Li and Wang

[21] have developed three different types of models where one is a single-variable hybrid model of a known first order differential equation while the other two incorporate the traditional hybrid model with NN modeling. The authors are able to successfully apply the models to forecast the electricity demand in China for the last decade of the 21st century where the hybrid models with NN approach predict maximum error of about 6% while the hybrid model estimate maximum error of almost 9% [21].

However, the NN approach is not just limited to national residential building energy forecasting, but also can be applied to individual homes. In one of the few such studies, Moon et al. developed an artificial NN model for predicting the building energy consumption to compare with other modeling approaches [22]. The authors also incorporated their optimal NN model with an advanced control strategy for creating more comfortable thermal environments in residential buildings [23]. Moon and Kim developed three NN models with an identical approach for predicting change in temperature, change in humidity, and change in Predicted Mean Vote (PMV) using the Neural Network toolbox in the MATLAB® software. The eight input variables of the models include exterior air temperature and exterior humidity to validate the amount of energy consumption and temperature profile, compared to the experimental results [13]. The experimental and training data set is taken from a typical two-story detached residential house in Detroit, MI over a period of five days. The amount of energy consumed to provide heat by the heating device in the experiment and simulation are 14.33 kWh and 14.48 kWh, respectively. The difference of 1% is considered to be an acceptable amount when compared to the other studies reviewed by the authors. The findings of the comparative studies by Moon et al. indicated that the NN method can be used to develop models with confidence to predict the energy consumption in residential houses [24,25]. Thus, NN models have distinct advantages in predicting the energy consumption and the impact of socio-economic factors on energy consumption.

3. Modeling approach

In its simplest form, which is demonstrated in Fig. 1, an artificial NN model consists of simple individual elements, also known as neurons, where each neuron n has an input p, a weight function w and a bias function b to produce a response a

$$a = f(wp + b) \tag{1}$$

where $f(\ )$ is an activation function to scale or convert the neuron value into meaningful response values for further analysis [16,26]. The activation function can be a linear function, which can be $y = x$, or the log-sigmoid function, which can be given by Ref. [15].

$$\frac{1}{1 + e^{-x}}$$

A typical network consists of an input layer, one or more hidden layers where each layer has more than one neuron operating in parallel, and an output layer of one or more outputs that can be represented by the neurons. The number of neurons can vary for each layer independently. Fig. 2 illustrates an example of neural network containing an input layer of two independent variables, one hidden layer of three neurons, and an output layer of one neuron. As illustrated in Fig. 2, all neurons at the same level (or column) are said to belong to the same 'layer.' The input layer consists of all input variables. The neurons in subsequent layers receive a neuron response of the previous layer as their inputs. Each individual neuron is connected to all other neurons of the previous layer through a weight functions w and its response (a^{layer}_{neuron}) is generated by the activation function $f(\ )$. The example in Fig. 2 shows a building energy consumption model that has two input variables: the dry-bulb temperature T and the solar radiation SR. To arbitrarily represent the usage of electricity of different units and systems in a house, we can designate three neurons in the hidden layer: Heating, Ventilation, and Air Conditioning (HVAC) system H, lighting system L, and household appliances A. The total energy consumption E_T is the only neuron in the output layer. This arrangement of the NN model allows it to perform summation and apply activation functions to determine the values of a hidden or output layer. In the example, the summation and activation in the hidden layer would be:

$$a^1_1 = f(H) = f\left(w^1_{1,1}T + w^1_{1,2}SR + b^1_1\right)$$

$$a^1_2 = f(L) = f\left(w^1_{2,1}T + w^1_{2,2}SR + b^1_2\right)$$

$$a^1_3 = f(A) = f\left(w^1_{3,1}T + w^1_{3,2}SR + b^1_3\right)$$

where subscripts are element indices of the parameters (weight and bias) and superscripts are the layer indices of the hidden layer. The activation functions are chosen to be the linear function. The responses of the hidden layer are fed into the output layer to obtain the output response

$$a^2_1 = f(\ E_T) = f\left(w^2_1 a^1_1 + w^2_2 a^1_2 + w^2_3 a^1_3 + b^2_1\right)$$

where the activation function is also the linear function, which leaves the output neuron unchanged to give $a^2_1 = E_T$. However, the best model depends on the number of hidden layer neurons to enhance the results so an optimum number of hidden layer neurons would be based on a desired model accuracy. Hidden layer neurons may be selected using an optimized algorithm technique or using a hit-and-trial method [5]. Moreover, the optimal number of neurons could be established using a formula [22].

$$n_h = 2n_i + 1 \tag{2}$$

where n_h is the number of neurons in the hidden layer and n_i is the number of input variables.

After the layers and neurons of the NN model are determined and set in order, a collected dataset is randomized and divided into three sets for the model: training, validation and testing. A training set is a group of matched input and output patterns used for training the NN model, usually by suitable modification of the weight functions to minimize the error. A suggested minimum number of data sets can be calculated using [22].

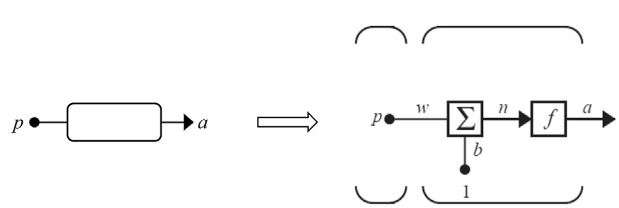

Fig. 1. Example of simple element called a neuron with an input layer of one variable [15].

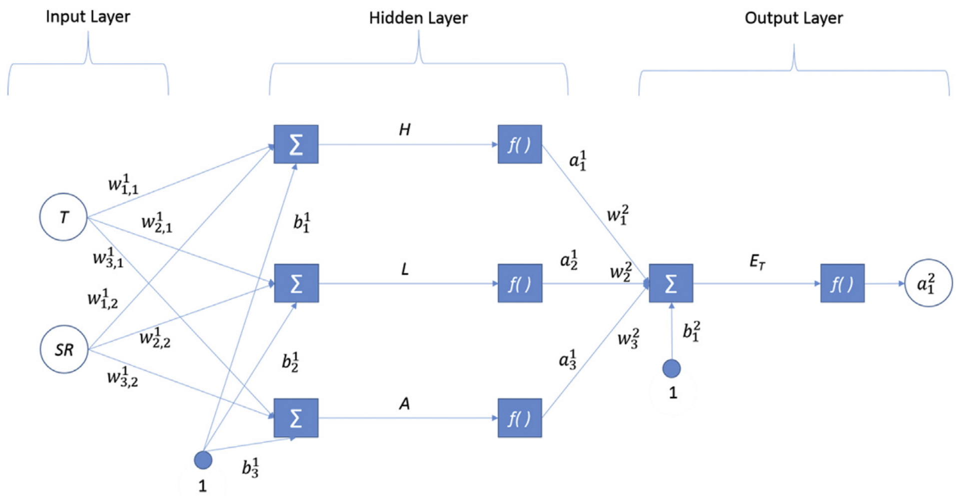

Fig. 2. Neural network model example of building energy consumption with an input layer, one hidden layer and an output layer.

$$n_d = \left(n_h - \frac{n_i + n_o}{2}\right)^2 \tag{3}$$

where n_d is the minimum number of data sets and n_o is the number of neurons in the output layer. The outputs are the dependent variables that the network generates as a result of the relevant input. For training, the input data is passed through the neural network to estimate the value of the output variable. When each pattern is analyzed, the network uses the input data to result in an output that can be compared to the training pattern for consistency and error minimization. After the network has run through all the input patterns, if the error is still greater than the maximum desired tolerance, the NN model runs again through all the input patterns repeatedly until all the errors are within the required tolerance [17,23]. The NN is considered to complete training after the NN holds the estimated weight and bias parameters constant to be used to in the next step of validation, which utilizes the validation data set to determine if the model is adequate [6]. After the model is validated, the untrained input data or training data set is employed to make decisions, identify patterns or define associations depending on the objective of the model.

The model is achieved by minimizing the error values between the target or actual data values and the predicted data values based on the pattern given. The error minimized in the model can be of different types, including the sum of squares error (SSE) and the mean squared error (MSE), and depends on the user preference. The SSE can be defined as

$$\mathrm{SSE} = \sum (Z - Y)^2 \tag{4}$$

where Z is the set of predicted values, and Y is the set of experimental data values. The MSE can be similarly defined as

$$\mathrm{MSE} = \frac{1}{n}\mathrm{SSE} \tag{5}$$

where n is the number of data points in the set [15]. These errors can then be used in different statistical analysis including the coefficient of determination. This coefficient can be described as

$$R^2 = [Cor(Z, \mathrm{Y})]^2 = 1 - \frac{\mathrm{SSE}}{\sum (Y - \overline{Y})^2} \tag{6}$$

where $Cor(Z,\mathrm{Y})$ is the correlation coefficient, $\overline{Y}$ is the mean of the data and $\sum (Y - \overline{Y})^2$ is total sum of squares. The value of R^2 varies between 0 and 1; a value of R^2=0.9 indicates that 90% of the total variability in the response variable is accounted for by the predictor variables, which is a reasonable indicator for good fit, but further analysis may be required to ensure robust fit.

Since the training speed and accuracy of error minimization are important to obtain a reliable model, optimization is key, and thus different algorithms can be employed and evaluated. The backpropagation algorithm is a common algorithm used in artificial NN approach. First order techniques feature the venerable backpropagation algorithm. Though this algorithm is tried and true, it is often plagued by slow convergence and getting stuck in local minima. For fast convergence, we would like to use Newton's method to train our MLP, but the Hessian matrix for the whole network is singular [27]. An alternative to overcome this problem is to modify the Hessian matrix as in the Levenberg-Marquardt (LM) algorithm.

The LM algorithm adds a small term $\mu\mathbf{I}$ to the Hessian matrix to improve the conditioning. Extensive research has been done in finding good initial values for μ [28]. Small values of μ allow the performance to approach Newton's algorithm whereas large values of μ are identical to gradient descent or backpropagation algorithm

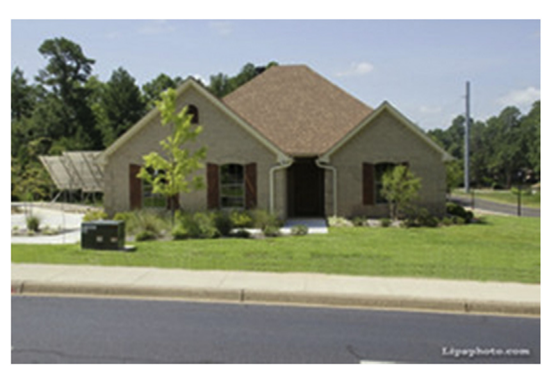

Fig. 3. Photo of the TxAIRE research and demonstration House # 1 [34].

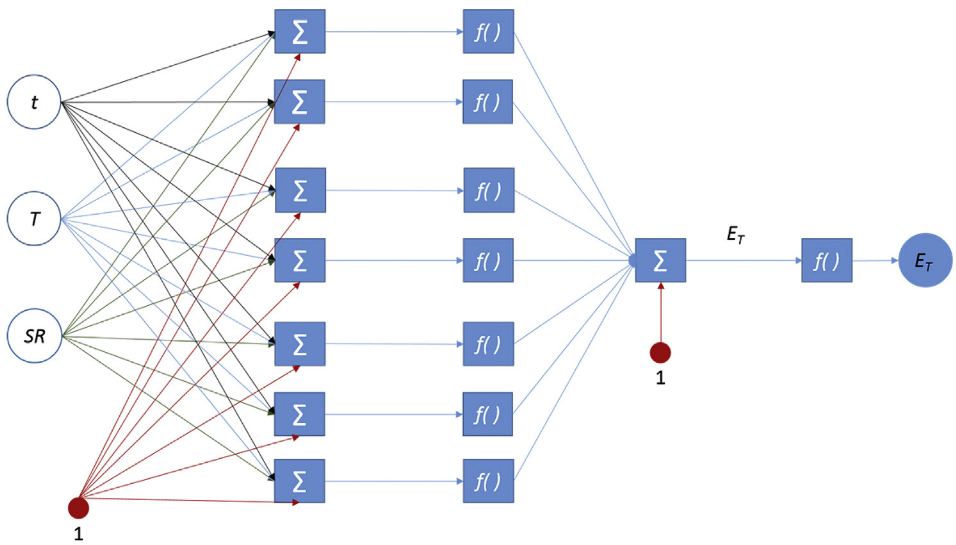

Fig. 4. Neural network model of total (house) energy consumption with an input layer, one hidden layer and an output layer.

performance.

Initialization is important in neural network modeling and there are several methods to do this. One simple method that can be easily used in feedforward networks is the Output Weight Optimization (OWO) algorithm [29]. OWO calculates the output weight matrices, which are concatenated into a vector $\mathbf{w}_o$ column by column after the input weight matrix $\mathbf{W}$ determined in some fashion, usually by random initialization. OWO minimizes the error function

$$E(\mathbf{w}_o) = \mathbf{w}_o^T \mathbf{R} \mathbf{w}_o - 2\mathbf{w}_o^T C + E_t \tag{7}$$

where $\mathbf{R}$ and $\mathbf{C}$ are estimates for the auto- and cross-correlations of the underlying random process, and E_t is sum of average squares of the target vector elements. Equation (7) is minimized by the solution to the linear equations $\mathbf{RW} = \mathbf{C}$. These equations can be solved using any number of methods, but special care must be taken when $\mathbf{R}$ is ill-conditioned. In this paper, we use orthogonal least squares [30]. OWO is merely Newton's algorithm for the output weights since Equation (7) is quadratic. A modern descendant of OWO is the Extreme Learning Machine [31] training.

Newton's algorithm is the basis of a number of popular second order optimization algorithms including Levenberg-Marquardt [32]. Newton's algorithm is iterative where each iteration

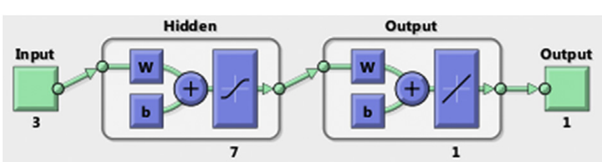

Fig. 5. Feedforward Levenberg-Marquardt back-propagation algorithm NN model [37].

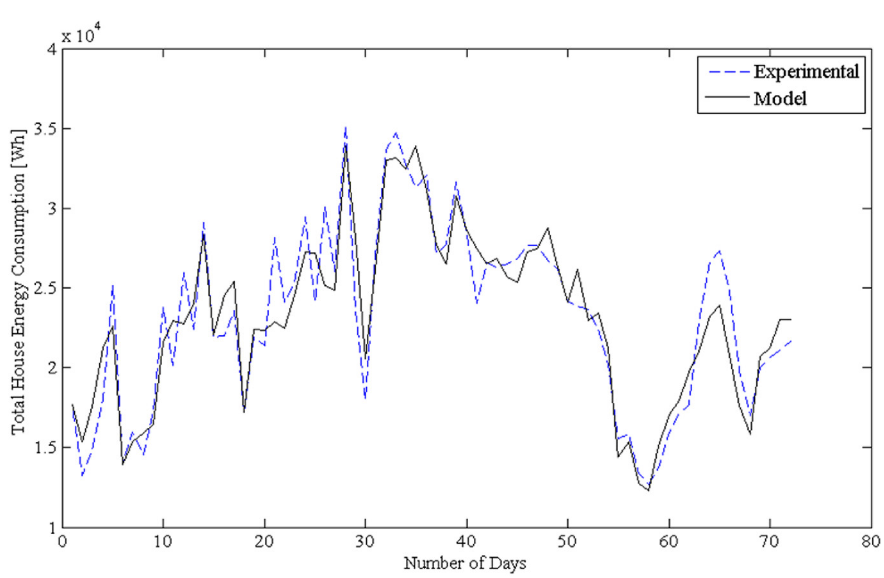

Fig. 6. Plot of the total (house) energy consumption data and model using LM algorithm after training, validating and testing the NN.

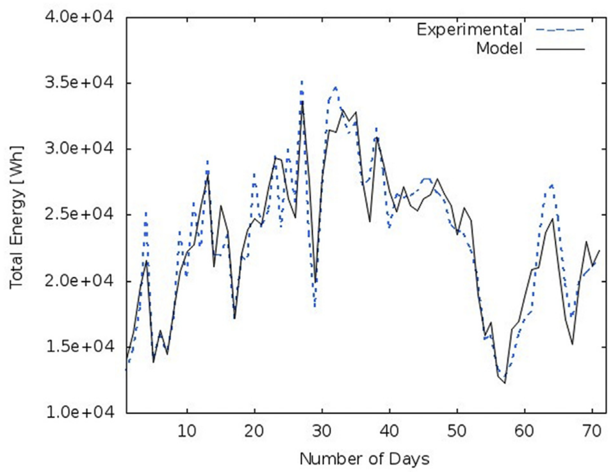

Fig. 7. Plot of the total (house) energy consumption data and model using OWO-Newton algorithm after training, validating and testing the NN.

calculates the Newton direction **d** and updates variables with direction **d**. The vector **d** is calculated by solving the linear equations

$$\mathrm{Hd} = \mathrm{g} \tag{8}$$

where **H** is the Hessian matrix and **g** is the gradient of the objective function, which is the error. The variables are then updated as

$$\mathbf{w} \leftarrow \mathbf{w} + \mathbf{d} \tag{9}$$

Non-quadratic objective functions require a line search. This results in **w** being updated as

$$\mathbf{w} \leftarrow \mathbf{w} + z\mathbf{d} \tag{10}$$

OWO-Newton iteratively trains output weight using OWO and the input weights using Newton's method. This is done until a specified tolerance is reached or for a fixed number of iterations. Much of the content presented about the OWO-Newton algorithm and its building blocks are taken from Robinson et al. [33].

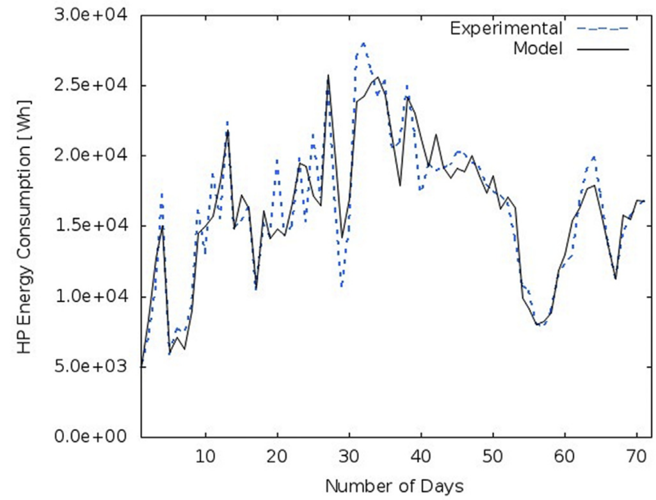

Fig. 9. Plot of the heat pump energy consumption data and model using OWO-Newton algorithm after training, validating and testing the NN.

4. Experimental environment: TxAIRE research house

A case study was carried out to assess the capabilities and potential implementation of a NN-based models using a similar approach used in Ref. [13]. The selected data used for the NN method analysis presented corresponds to the energy consumption and weather parameters recorded at the TxAIRE Research and Demonstration House #1 [34] during the months of June, July, and August 2013. A photo of the house is shown in Fig. 3. The house is unoccupied and all energy systems are electric, *i.e.* no natural gas is used [35]. The TxAIRE Research and Demonstration Houses have been designed to serve as realistic test facilities for developing and demonstrating new technologies related to energy efficiency, indoor air quality, and sustainable construction materials and methods. Two TxAIRE houses were constructed on the UT Tyler campus. The TxAIRE Houses are fully instrumented testbeds,

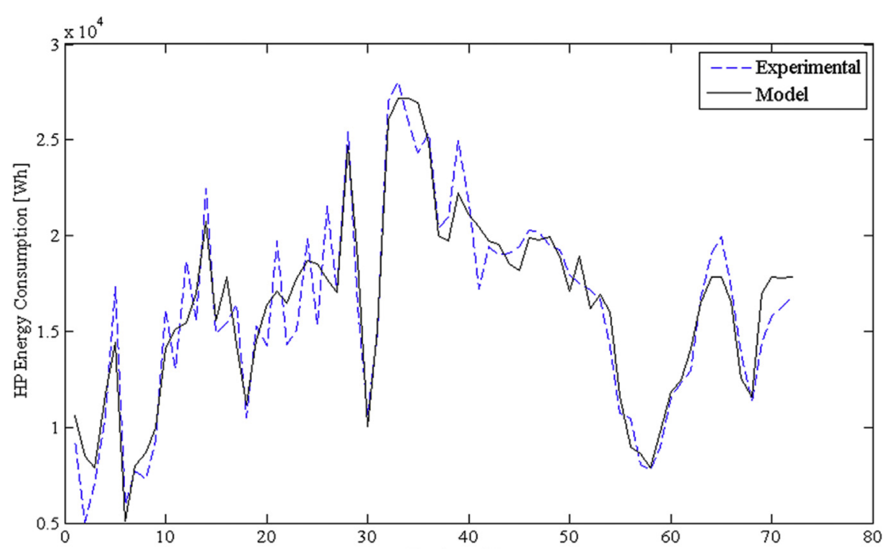

Fig. 8. Plot of the heat pump energy consumption data and model using LM algorithm after training, validating and testing the NN.

making possible full testing and analyses of roof, wall, window, and slab building envelope components [34]. All mechanical systems are also fully instrumented, and include multiple systems to facilitate comparison of performance. A wide range of energy efficiency projects are being scheduled for the TxAIRE Houses. The house used to experimentally observe in this study demonstrates a wide range of energy efficiency renovation features that result in a house that will consume only 50% of the energy used by an average home. The house uses only electricity and energy consumption is recorded every 5 min for the total electricity and HVAC equipment. Weather data is recorded also every 5 min by a weather station located at the research site. For this analysis, the data is compiled to obtain the daily energy consumption and weather parameters given in the Appendix. The total (house) and the heat pump (HP) electrical energy consumptions E_T and E_{HP} are given in Wh, the number of days in summer t, the outdoor dry-bulb temperature T is given in °C and the global horizontal radiation SR is giving in Wh/m^2.

5. Results and discussion

As mentioned in the previous section, the house is unoccupied and therefore the influence of behavior and preferences of occupants is not present in the recorded data. Future research will include controlled loads due to occupancy to investigate how the individual loads impose modifications on the NN models.

Fig. 4 illustrates the NN of the total energy consumption as the output. The same NN is developed for another model that has the HP energy consumption as output. These two feedforward NN models are identically developed to consist of a set of input terms, a hidden layer, and an output layer. The output layer is the key distinction between the models. The three input variables in both models are the number of days (t), the dry-bulb temperature (T) and the solar radiation (SR). Using Equation (2), the hidden layer is determined to have 7 neurons that represent the different units and systems of the house that contribute to energy consumption. This NN model was verified to be optimal in another paper comparison of models with various number of hidden neurons [36]. The hidden neurons are followed by log-sigmoid functions. The responses of the hidden layer enter as inputs to the output layer of a single neuron followed by a linear function to produce the output response. Fig. 5 shows setup diagram of the model using in MATLAB® and its Neural Network toolbox [37]. Based on Equation (3), the 50 training data set from the Appendix exceeds the minimum number for the data set. The rest (30%) of the data set is used for validation and testing. The models are set to training goals of zero for house and HP energy consumptions, respectively. Given successful use in prior studies, the LM algorithm with a maximum 1000 epoch is permitted for the training to converge the model rapidly by minimizing the MSE. The quality of fit of the model to the given target data of the house and HP energy consumptions can be judged by using the coefficient of determination R^2.

Fig. 6 shows the experimental data and NN model using LM algorithm of the total energy consumption over the summer days. The x-axis is the selected number of days in summer of 2013 and the y-axis is the total energy consumption in Wh. The dashed line is labeled as the experimental data while the solid continuous line represents the model obtained after training, validating and testing the data set from the Appendix. Fig. 7 shows the experimental data and NN model using OWO-Newton algorithm of the total energy consumption, which has the same axes and lines as found in Fig. 6.

Fig. 8 shows the experimental data and NN model using LM algorithm of the HP energy consumption data over the summer days. The x-axis is the selected number of days in summer of 2013 and the y-axis is the HP energy consumption in Wh. The dashed line is labeled as the experimental data and the solid line is represented as the model obtained after training, validating and testing. Similarly Fig. 9 is plotted where the NN model is an OWO-Newton-based algorithm. The energy consumption for all models are in the order of 10^4. The plots shown are representative of the overall results where each model is a function of all three inputs. The results are plotted against one input variable for easy visual reference.

Fig. 6 demonstrates the LM-based model output E_T to able to match the experimental data with R^2 of 0.878. Fig. 7 also demonstrates the OWO-Newton-based model output E_T to match the experimental data with R^2 of 0.871. Fig. 8 illustrates the LM-based model output E_{HP} that can match the empirical data with R^2 of 0.906. Fig. 9 also illustrates the OWO-Newton-based model output E_{HP} to match the empirical data with R^2 of 0.886. The results are satisfactory and the coefficients of determination are comparable to prior studies [18,13]. The plots also illustrate the nonlinearity and fluctuations in the energy consumption, noted in earlier works. The lower R^2 and the higher nonlinearity of the house energy consumption data than those of the HP energy consumption data can be observed from the results. Since the heat pump only accounts for a specific portion of the house, the fluctuations in energy consumption is less than that of the whole house. In the figures of the results, one can also observe some regions where there are significant differences between the model and the data. This could be the neural network model parameters being over constrained and thus lead to larger errors in regions with more noise or more variation than expected. The LM-based model was slightly better than the OWO-Newton-based model. However, such comparison may not be significant due to the limited number of data points used. In the future, more data points will be collected for improved accuracy and further analysis of NN in residential building energy application.

6. Concluding remarks

The need for reliable and consistent prediction of residential building energy consumption is of importance, but has little focus compared to the other sectors like transportation and industry. However, recent studies has led to significant advancement in developing models with high accuracy and convergence. One such advancement has been the inclusion of artificial NN methods to the estimation of energy consumption, which typically fluctuates and is nonlinear in nature. The NN method is able to address nonlinear data effectively and quickly using various algorithms to minimize the error including back-propagation algorithms. The results from previous studies have shown the NN models perform very well with typical coefficient of determination above 0.9. The promising results of NN models inspired the data analysis and model development of the TxAIRE research house for different approaches; LM algorithm is common and conventional while OWO-Newton algorithm is unique and different. The results were satisfactory for the given data set and was comparable in terms of statistical analysis with prior literature. Further analysis will be carried with a wider range of data to assess the performance and accuracy of the NN model to predict the outputs of the TxAIRE house.

Acknowledgements

The authors would like to thank TxAIRE for providing the data and support. The authors would also like to thank the undergraduate research students including Daniel Lackey and John Henken for their contribution.

Appendix. Case study's daily energy consumption and weather parameters

Days	Electricity (Wh)		T (°C)	SR (Wh/m^2)
	Total	HP		
1	17541	9329	27.6	5953
2	13275	5017	23.2	6858
3	14825	7042	23.3	8315
4	18047	10693	25.7	7794
5	25176	17311	26.5	7380
6	14016	5922	22.5	1736
7	15952	7722	22.2	7999
8	14529	7326	23.1	7524
9	17311	9363	24.6	5975
10	23745	16161	27.1	8348
11	20179	13036	27.2	7837
12	25935	18715	27.7	8073
13	22401	15552	28.8	8223
14	29081	22448	29.8	7490
15	21950	14893	28.4	5013
16	21977	15426	28.5	7806
17	23534	16422	26.5	5563
18	17190	10480	25.5	2924
19	21893	15275	25.9	6375
20	21408	14254	27.9	8086
21	28159	19715	28.1	7979
22	24124	14338	27.9	7989
23	25370	15050	28.2	7607
24	29461	19844	28.4	7239
25	24116	15330	28.6	7381
26	30060	21520	29.2	7919
27	26042	17104	29.4	8090
28	35197	25403	31.1	7614
29	23573	16282	30.1	7893
30	17980	10656	26.9	8130
31	27025	14913	26.7	7421
32	33705	27091	28.6	7069
33	34686	28028	28.7	7079
34	32704	26036	27.5	5193
35	31265	24353	27.5	6419
36	32061	25375	27.5	5285
37	27126	20398	24.6	4645
38	27724	20971	26.1	7505
9	31645	24984	28.3	6516
40	28310	21638	28.8	7093
41	24011	17201	29.3	7375
42	26539	19424	29.4	7546
43	26303	18969	29.4	7251
44	26475	19081	29.4	7455
45	26814	19449	29.5	7505
46	27668	20285	30.2	7550
47	27676	20196	30.4	7583
48	26708	19516	30.6	7348
49	26181	19291	30.1	7422
50	24180	17959	29.5	7366
51	23826	17478	29.7	6318
52	23620	17170	28.9	6779
53	22410	16681	29.0	6534
54	20240	14198	28.1	5346
55	15590	10749	26.3	4494
56	15861	10455	25.5	7101
57	13399	8075	24.3	5214
58	12721	7758	23.8	7367
59	13744	8959	25.7	6430
60	15986	11591	27.3	7391
61	17136	12304	27.7	7180
62	17686	12924	28.0	6381
63	22900	16698	28.5	6134
64	26634	19115	29.6	6341
65	27331	19955	29.9	6614
66	24826	17273	28.7	6563
67	19819	13856	27.4	6491
68	17018	11350	26.5	6014
69	19985	14416	28.9	6598
70	20625	15783	30.1	6075
71	21101	16264	30.0	6717
72	21656	16821	30.4	6631

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