International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 12 (2018) pp. 10517-10524

Using Artificial Neural Network Technique to Save Energy Consumption in HVAC Systems

Amal El Berry[1] and Haya Alaskr[2]

[1]*Mechanical Engineering Department, National Research Centre, Egypt & Information Systems Department, Faculty of Engineering &Computer Science, Prince Sattam Bin Abdulaziz University, KSA.*

[2]*Computer Science Department, Faculty of Engineering &Computer Science, Prince Sattam Bin Abdulaziz University, KSA.*

Abstract

HVAC is among the prevalent energy-consuming systems in buildings, providing a warm and cool environment. The main purpose of this study is how to forecast the future energy consumption due to cooling loads using ANN. The cooling loads resulted from the heat gain due to sensible and latent are calculated under a range of 4 months of weather data in Saudi Arabia as a case study which is the hottest area in the middle east.

To devise a model for forecasting energy consumption through the use of neural network form for time series processing (feedforward) in due to the cooling load. The theoretical analysis of cooling loads at peak months is calculated as a historical dataset. Historical cooling load data feed the neuron to simulate future energy consumption and decision-making. Simulations are performed using artificial neural network technology, which proved the stability of the results and the determination of peak times in which the optimum use of air conditioners.

Keywords: HVAC, Simulation, ANN, Energy and Consumption

INTRODUCTION

In this paper, the ANN methodology has been used to forecast energy consumption. Numerous environmental and control variables affect energy consumption and thermal comfort, demonstration problematic the improvement of calculated models among I/O. Thus, ANN has been built to forecast methodology and produce relationship within sensible determined time. The suggested methodology is applied to HVAC system, built on different weather states in KSA. Historical weather data are taken into consideration, a simulation model is handled to yield big capacity of data sets to train the consistent Artificial Neural Network as forecast machine. The trained ANN is then identified in actual situations and optimize a function as the technique to support realize energy saving goals. Numerous ANN processes has been verified with extra modification of the greatest performance ANN algorithm.

Neural network method was used by [1] to investigate the maintainability, availability, consistency, and reliability system. The trained neural network input layer had been including 80 neurons, 100 neurons in the 1st hidden layer, 10 neurons in the 2nd hidden layer and one neuron in the output layer. The suggested network had been used to consider the influence of distinct input parameters and collections of input parameters on the compound output parameter. It was established that Artificial Neural Network was valued for investigating and adjusting reliability system from the standpoint of consistency, maintainability, and availability

AI's contains regions such as ANN, genetic algorithms, expert systems, and several hybrid systems, a fuzzy logic which merge two or extra methods [2,3]. Speed was the highest benefit of Artificial Neural Network comparison to further expert systems. Easiness and facility of modeling a multivariable difficult to resolve grim relations between the variables could construct excerpt the nonlinear relations by means of training data [2, 3]. Processing by using training data in ANN has been overpowering the boundaries of expected methods by mining the requisite, which had not requisite any definite investigative equations. Artificial Neural Network model could forecast the favorite output of the system using restricted training data. For sizing of solar photovoltaic systems [4] and energy systems modeling [5, 6]. Abdul Aframa et al. [7] Concluded several approaches for modeling and performance an inclusive assessment of the artificial neural network (ANN) built model predictive control (MPC) system design was approved as an investigation in which ANN models of a residential house located in Ontario.

METHODOLOGY

The historical cooling load data set has been calculated in different latitude and longitude locations in KSA. The ANN is used to forecast energy consumption with assessment consumption of building during peak hot month's cooling load data. The network which is applied to this forecast had 20 hidden layers. The output layer involved of one neuron that provided the output.

- Number of Hours (0 to 70272)
- Longitude and latitude Location
- Outdoor design temperature
- Daily range temperature
- Indoor Air Temperature

Cooling load calculation

A cooling load estimation governs total sensible cooling load from heat gain due to:

- Transparent fenestration surfaces (glazed doors, skylights, and windows)

- Ventilation and infiltration
- Occupancy.

A cooling load estimation governs total latent cooling load from heat gain due to:

- Ventilation/infiltration
- Internal gain

The cooling load is estimated based on equations as shown in table 1 according to ASHRAE [8]:

Table 1. Cooling load sources.

Exterior transparent surfaces	$q_{fen} = A \times CF$
Partitions to unconditioned space	$q = AU\Delta t$
Ventilation/infiltration	$C_s Q \Delta t$
Occupants and appliance	$q_{fg,s} = 136 + 2.2 + 22N_{0c}$
Distribution	$q_d = F_{dl} \sum q$
Total sensible load	$q_s = q_d + \sum q$
Total latent load	$q_l = q_{vi,l} + q_{ig,l}$

Artificial Neural Network

Artificial neural networks model is approved available in 4 states as follows:

- Extract energy consumption results due to cooling
- Network taking by using theoretical forecast value
- Dataset which is not handled for training is used as Network testing with data
- Detect the greatest network construction built on statistical realization data [9, 10].

Artificial neural networks (ANN) reflect the brain jobs in a computer method by retrieving the machine learning as the based-on behavior of the human. ANN can run similar to "black box model", which needs no complete data nearly the HVAC system. ANN could learn the connection amongst output and input built on the training data. The output of the model have been expressed as follow [11]:

$$Y_t = \alpha_o + \sum_{i-1}^{q} \alpha_j\, g\big(\beta_{oj} + \sum_{i=1}^{p} \beta_{ij}\, y_{t-i}\big) + \varepsilon_t, \forall t \quad (1)$$

Where

p , $y_{t\,a}$ are input & output respectively

"$Y_{t-i}(i = 1,2, \dots \dots, p)$"

p, q is the integer of hidden and input nodes respectively.

Connection weights are α_j, β_{ij}

Where:

$j = 0,1,2, \dots \dots \dots, q$

$i = 0,1,2, \dots, p; j = 0,1,2, \dots \dots q$

ε_t Random shock

α_o, β_{oj} favor expression

Regularly, the function of logistic sigmoid shown as follow:

$$g(x) = \frac{1}{1+e^{-x}} \quad (2)$$

Activation functions, such as Gaussian could also be handled [12]. Feedforward ANN model (3) achieves a non-linear functional mapping from the historical time series data to next value:

$$y_t = f(y_{t-1}, y_{t-2}, \dots \dots y_{t-p,W) + \varepsilon_t} \quad (3)$$

Where

w is an all vector parameters

f w is a function resolved by the connection weights and construction of network [13, 14].

To assessment the non-linear least square, connection weights, processes are handled, which are built on the error function minimization [15, 12]:

$$F(\varphi) = \sum_t e_t^2 = \sum_t (y_t - \hat{y}_t)^2 \quad (4)$$

The universal forecast equation might be transcribed as [15]:

$$\hat{x_t} = \emptyset_o + \left(w_{co} + \sum_h w_{ho}\, \emptyset_h\big(w_{ch} + \sum_i W_{ih}\, x_{t-j_i}\big)\right) \quad (5)$$

Where

Input term= $x_{t-j_1}, x_{t-j_2}, \dots \dots, x_{t-j_k}$

w_{ch} Connections weights between the constant input & hidden neurons.

w_{co} Direct connection weight between the constant input & the output

W_{ih}, w_{ho} Connections weights between the (input, hidden neurons) & between the (hidden, output neurons) respectively.

$\boldsymbol{\emptyset_h}, \boldsymbol{\emptyset_o}$ Where the hidden and output layer activation functions respectively.

Faraway and Chatfield [16] handled the notation NN ($j_1, j_{2,} \dots \dots j_{k;} h$) to signify the inputs at delays. Hidden neurons ($j_1, j_{2,} \dots \dots j_{k;} h$) . In our model, the monthly factor s was handled to govern the input and output neurons' number. This study builds a simple model for considerate and application. In this model, the monthly factor *s is* used to govern the input and output neurons' number. The i^{th} and *(i+1)* the monthly period historical data are separately handled as the values of input /output neurons in this network construction. To each monthly epoch was collected from a number of historical data.

Mathematical Output Model is [17]:

$$Y_{t+1} = \alpha_l + \sum_{i=1}^{m} w_{il}\, f\big(\theta_j + \sum_{i=0}^{s-1} v_{ij}\, Y_{t-i}\big) \forall t; l = 1,2,3, \dots \dots, s. \quad (6)$$

Forecasts for the future s days is $Y_{t+1}(l = 1, 2, 3 \dots s)$

Previous day's observations s is $Y_{t-i}(i = 0,1,2, \dots \dots, s-1)$

Connections weights from input nodes to hidden nodes are $v_{ij}(i = 0,1,2, \dots \dots, s-1; j = 1,2,3, \dots \dots, m)$

and

$$w_{il}(j = 1,2,3, \dots\dots, m; l = 1,2,3, \dots\dots s)$$

Connections weights from hidden nodes to output nodes are:

$$\alpha_l(l = 1,2,3, \dots\dots, s)$$

and

$$\theta_j(j = 1,2,3, \dots\dots., m)$$

Favor connection weights of and *f is* the motivation function.

The valid number of hidden nodes could be estimated by acting conveniently on the training dataset.

Prediction Models

Performance measures and their significant characteristics will be discussed in this part of the study. In each of the approaching descriptions, y_t is the definite value, $_{it}$ is the predicted value, $e_t = y_t - f_t$ is the prediction error and n is the test data size. Also,

$$\text{Test mean} \quad =\bar{y} = \frac{1}{n}\sum_{t=1}^{n} y_t \tag{7}$$

$$\text{Test variance} \quad =\sigma^2 = \frac{1}{n-1}\sum_{t=1}^{n} (y_t - \bar{y})^2 \tag{8}$$

The Mean Forecast Error (MFE)

"This measure was definite as [18] MPE"

$$MFE \quad = \frac{1}{n}\sum_{t=1}^{n} e_t \tag{9}$$

Mathematical definition of this measure was [17] MSE

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \tag{10}$$

The Root Mean Squared Error (RMSE) [11] mathematically, expressed as:

$$\sqrt{\mathrm{MSE}} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2} \tag{11}$$

RESULTS AND DISCUSSIONS

Outdoor weather situations have an influence on cooling loads. Historical outdoor design temperature, daily range, and indoor air temperature are the base to calculate the cooling load. This data is taken for a 122-day (4 peak months) at different locations in KSA. The temperature at MAKKAH as an example, May, June, July, and August, with values of 94.4, 97.4, 97.1, and 97.2°F. Various solar fluxes are capable of using different components of the total irradiation which indicates that from 7 am to 5 pm solar flux is very high. Solar-air temperature (Tsol-air) is a variable used to calculate the cooling load of a building; the heat gained by conduction through the walls and defines the total heat gain through external surfaces. It has been shown that along 24 hours, the heat gained during the day reaches about 2400 at 1:00 pm this is a peak time. The heat gained is obtained from 7:00 am to 5:00 pm (high cooling load). Total heat, enthalpy (h) can be calculated by summation of latent and sensible heat. Outside air presented for ventilation by the air-conditioning equipment can also be calculated by the same equation of infiltration cooling load resulted from latent and sensible heat. Lights, appliances, and occupants are also caused by heat.

Divided the axes and then using the Surf, three-dimensional forms of different cities are obtained in the four months of summer 24 hours. Figure (1) shows how the energy consumption curve changes due to cooling loads in 24 hours in May. Note that the energy consumption reaches the peak from 7:00 am to 5:00 pm. There is an increase in cooling loads in cities with hot climates and high humidity such as Jeddah and Dammam because these cities are close to the water surfaces.

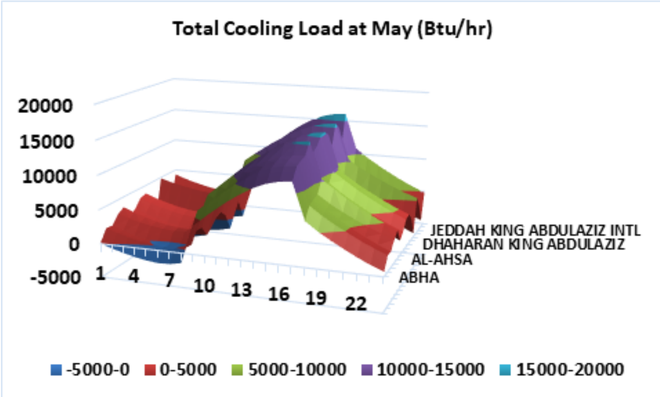

Figure 1. 24-hour total cooling loads ((Btu/hr.) in May at different locations (KSA**)**

A prediction is a type of dynamic filtering, in which historical calculated energy consumption data due to cooling load of one or more time series were handled forecast forthcoming values. Predictive models were also handled for system identification (or dynamic modeling), in which you build dynamic models of physical systems. Forecast series **y (t)** specified **d** previous values of **y (t)** and another series **x (t)**. Input-output time series problems involve of forecasting the future value of 1 time-series specified extra time-series. Historical data of both series (for greatest accurateness) and only one of the series (for a simpler system) might be handled to forecast the target series. NN can be trained to make forecasts. The number of hidden neurons is 20. The parameter for neural network training performance was evaluated at 3 different months (May, June, and July). The mean square error for May, June, and July datasets as learns sequentially from the training data for August data set as a target. An approximation error is calculated from the test data provided and learn the function around (174,313and 437 epochs) at different months. The defaulting achievement feed-forward networks function is the computing of the mean square error MSE an average squared error between the networks outputs and the target outputs. In the figures (2), (3) and (4), it can be seen the development of the MSE during, testing and validation steps. In this graph, the MSE is going down towards the best results expected. At the (174,313and 437) epochs we get the minimum MSE which are 2.6218e-05, 7.1296e-05 and 3.7882e-07).

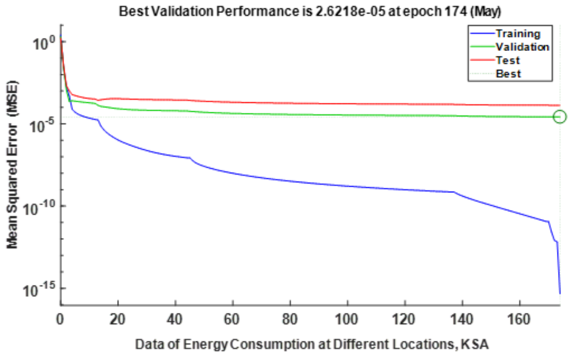

Figure 2. Neural Network Training performance (plot perform), Epoch 174 (May)

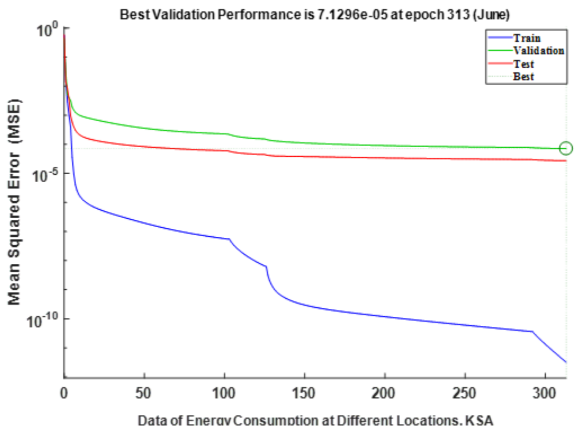

Figure 3. Neural Network Training Performance (plot perform), Epoch 313(June)

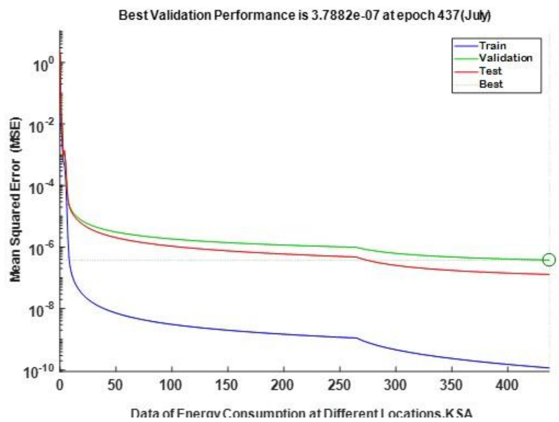

Figure 4. Neural Network Training Performance (plot perform), Epoch 437(July)

Figures (5), (6) and (7) show 3 graphs, the first one up describes the results of the gradient value in every iteration. The higher the gradient value is near to 0, the higher the performance of our network is going up.

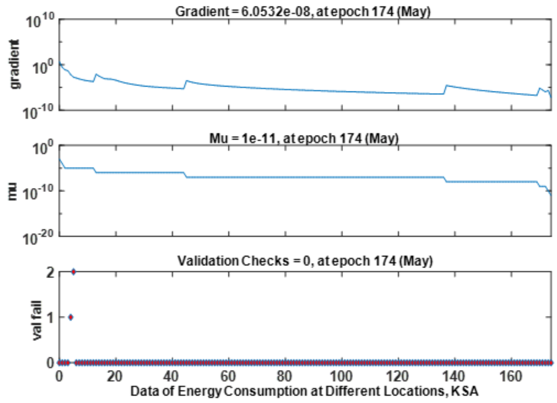

Figure 5. Neural Network Training State Epoch 174 (May)

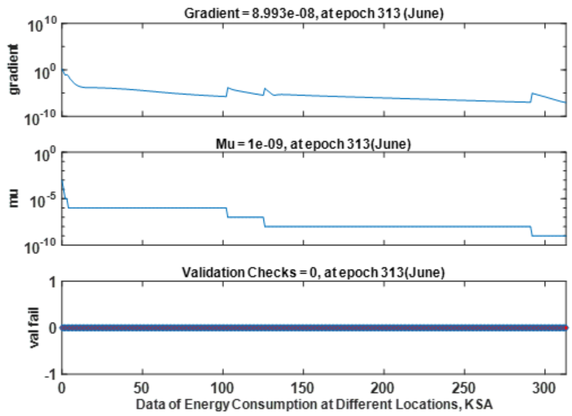

Figure 6. Neural Network Training State Epoch 313(June)

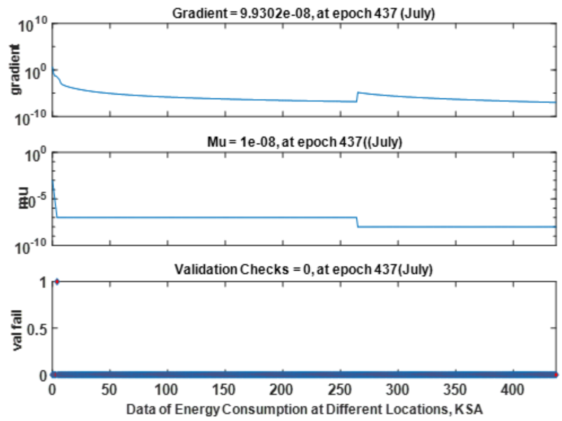

Figure 7. Neural Network Training State Epoch 437(July)

Learning algorithm training built artificial neural network model has been presented a recovering achievement for the specified topology. Further analysis will be approved built on the factor modification for this algorithm to realize the best performance for the future usage scenario /case. The structure of ANN has been selected input 70% training 15% validation and 15% testing with the hidden layer: 20, a number of neurons: number of an epoch: 174,313and 437. During the factor alteration, the "transfer functions" are different with the function specified. From the three forecast diagrams presented in Figures (8), (9) and (10), comparison between figures clarifies real and forecasted data for the energy consumption series. Forecasting important variation between the tested and forecasted data can be observed. Due to the occurrence of potent seasonal differences, the energy consumption data some time was non-stable. This data are handled during and validation and training stage and are used to evaluate the real overview and forecast power of the models. The predicted HVAC energy consumed via these three models, the absolute comparative errors between forecasted and real energy consumed values, comparison of expected, forecasted, energy consumed. The achieved diagram of percentage error is demonstrated. Moreover, data have been tested by handling regression models and Artificial Neural Network models were compared, it was obvious that Artificial Neural Network achieved slightly better. We observed training regression models with the different gradient that R near 1 at different states (lower RMSE and higher R values). “MSE is the average squared difference between outputs and targets. Lower values are better”. Zero signified no error.

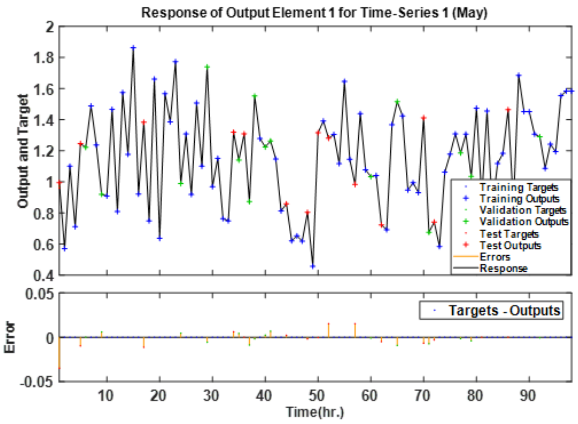

Figure 8. Response Neural Network Training Time Series, Epoch 174(May) gradient reached

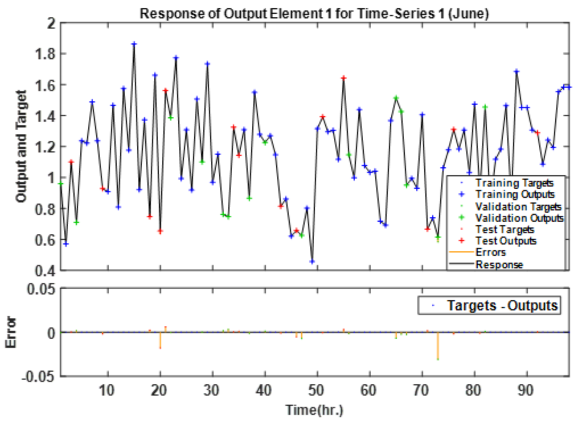

Figure 9. Response Neural Network Training Time Series, Epoch 313(June) gradient reached

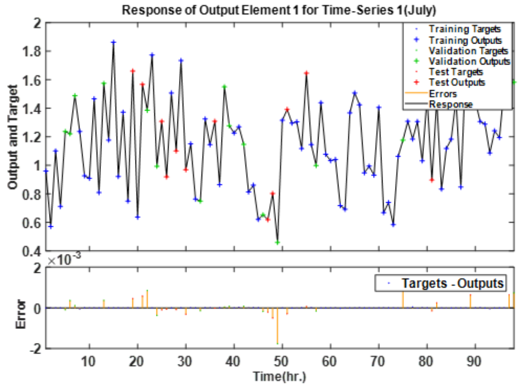

Figure 10. Response Neural Network Training Time Series, Epoch 437(July) gradient reached

Figures (11), (12) and (13) show the correlation between the target (measured 3- months strength) and output (estimated 1-month compressive strength) values for both the training and validation, created in MATLAB software. According to these figures, both the training and validation show desirable correlation coefficients (R values). The correlation coefficient shows how strong the association between two variables are. Regression R Values measure the correlation between outputs and targets is measured by regression R-value. If R equal 1 a relationship is close. If R= 0 a relationship is random. ANN outperforms the regression models at different tested data. Still, regression models model can efficiently handle any lost data during the testing and training stages. A set is a group built on an algorithm. It can precisely forecast when some of the input data are lost. Moreover, less precise results do not signify that regression models have not concluded the input and output’ relation-ships variables. Regression models results are within the suitable domain and can moreover be utilized for forecasting purposes and carry out recovers in forecasting the lower data. Artificial Neural Network is achieving improvement in forecasting the high values of the energy consumption. Both regression models and Artificial Neural Network have valued “machine learning’ tools to forecast building’s energy consumed. It is observed that, Training Regression Models with different Gradient that R near 1 in different states.

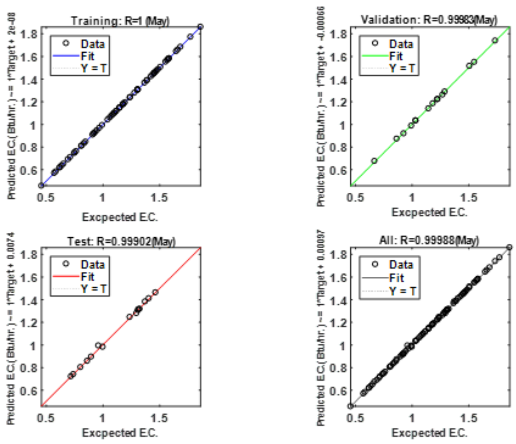

Figure 11. Training Regression Models with different Gradient. Epoch 174(May)

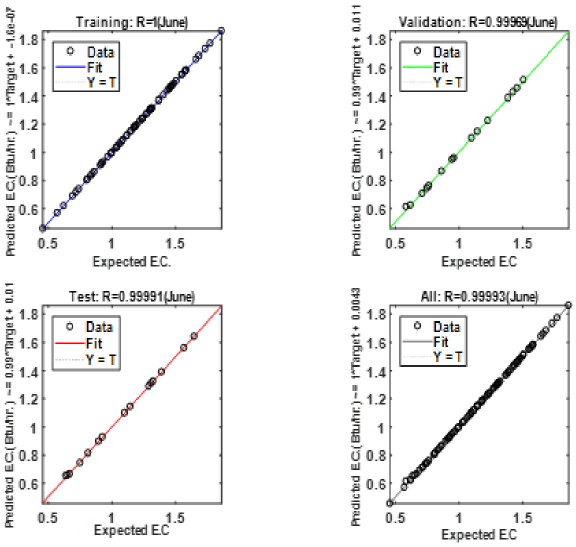

Figure 12. Training Regression Models with different Gradient. Epoch 313(June)

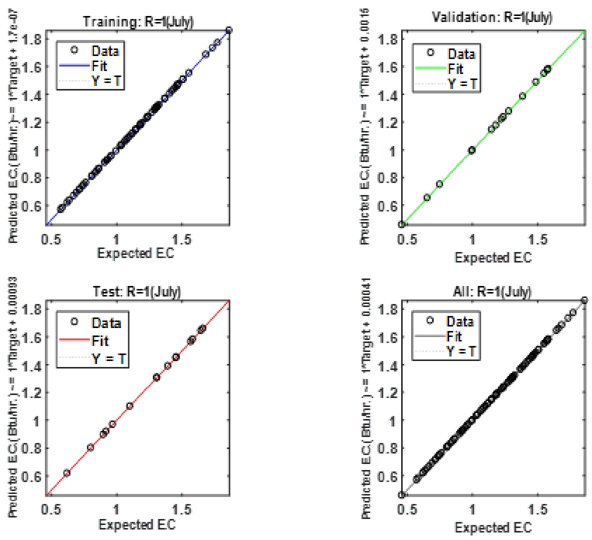

Figure 13. Training Regression Models with different Gradient. Epoch 437(July)

Figures (14), (15) and (16) show that there are significantly Neural Network Training Error Autocorrelation, Epoch 174(May), 313(June) and 437(July) gradient reached values at the growing lags, which do not reduce rapidly. This indicates some time the non-stable of the energy consumption data. Regardless of the model, the performance is evaluated by how well it can be generalized. About the cross-validation – this is the data set that is used to evaluate the model during our process of improving the model. This training dataset is used to identify what are problems the model is having; under fitting, over fitting.

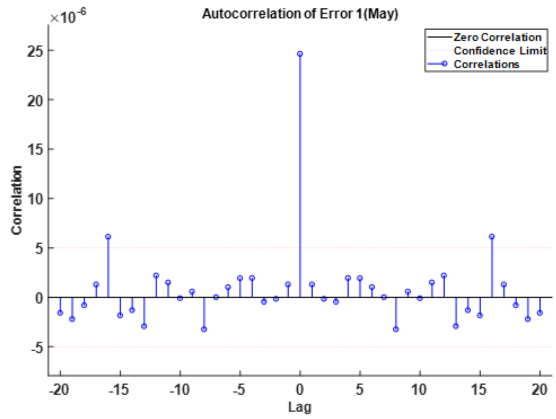

Figure 14. Neural Network Training Error Autocorrelation, Epoch 174(May) gradient reached

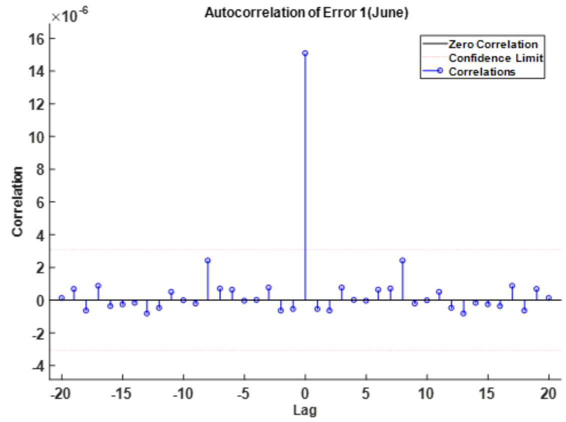

Figure 15. Neural Network Training Error Autocorrelation, Epoch 313(June) gradient reached

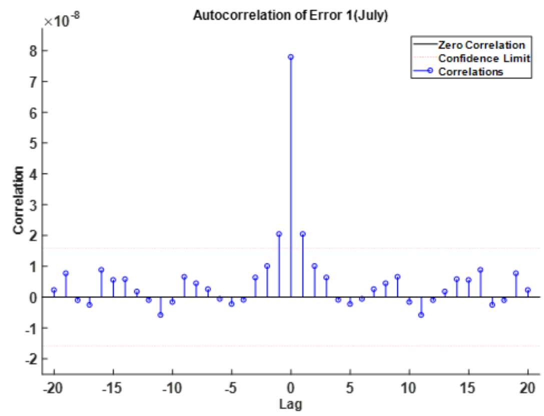

Figure 16. Neural Network Training Error Autocorrelation, Epoch 437(July) gradient reached

CONCLUSIONS AND RECOMMENDATION

For assessing cooling loads, one has to study the unstable state procedures. The outside situations also differ considerably during the day as result of solar radiation. In adding, Heat gains are affected by solar effects, outdoor air loads conduction, and internal heat loads. Residential buildings, Heat is gained from outside weather through (Roofs, Walls Glazing, Ventilation, and Infiltration. Internal Heat Gains (Heat is caused inside buildings by occupants, lights, and appliances). Latent heat results from evaporation and exhaled moisture. Energy forecast has been the significant effect to take decisions by energy estimate the future from historical data. This study compares the performance of the widely-used feed-forward back ANN with arbitrary predict. For forecasting HVAC energy consumption, when their performance is compared to assess the ability for forecasting energy consumption. The defaulting achievement feed-forward networks function built on mean square error MSE, the average squared error between the networks outputs and the target outputs. At the (174,313and 437) epochs the minimum MSE is obtained which are 2.6218e-05, 7.1296e-05 and 3.7882e-07. The comparison between regression models and Artificial Neural Network models are considered, it is obvious that Artificial Neural Network achieves slightly better. It is detected training regression models with the different gradient that R near 1 at different states (lower RMSE and higher R values). MSE is the average squared difference between outputs and targets. Lower values are better. The correlation between the targets (measured 3-months' strength) and output (estimated 1-month compressive strength) values for both the training and validation are computed under MATLAB platform. Both the training and validation show desirable correlation coefficients (R values). Artificial Neural Network achieved improved in forecasting the higher values of the energy consumption. In future, the heating load application and the nonresidential cooling load should be calculated. Both future models use different data sets. For the quantifiable assessment, it must identify dataset, which had better to insurance all probable accurate scenarios.

ACKNOWLEDGMENT

This paper is supported by King Abdulaziz City for Science and Technology (KACST) under the research (small grant number 37-70). The investigators would like to express their gratitude and appreciation to King Abdulaziz City for Science and Technology. The investigators also extend thanks to Prince Sattam Bin Abdulaziz University for providing facilities and support to carry out this research.

Nomenclature

ANN: Artificial Neurons Network

q_{fen}: Exterior transparent surfaces cooling load, Btu/h

A: net surface area, ft^2

CF: surface cooling factor, Btu/h·ft^2

U: construction U-factor, Btu/h·ft^2·°F

Δt: cooling design temperature difference, °F

C_l: air latent heat factor, 4840 Btu/h·cfm at sea level

C_s: air sensible heat factor, 1.1 Btu/h·cfm·°F at sea level

C_t: air total heat factor, 4.5 Btu/h·cfm·(Btu/lb) at sea level

Noc: number of occupants (if unknown, estimate as Nbr + 1)

q: Heating or cooling load, Btu/h

Q: air volumetric flow rate, cfm

t: temperature, °F

ΔW: indoor-outdoor humidity ratio difference, lb$w$/lbda

F_{dl}: distribution loss factor

F_p: heat loss coefficient per unit length of perimeter, Btu/h·ft·°F

Greek Symbols

Δ Increment of variable

Subscripts

avg average

s sensible or solar

cf conditioned floor

oc occupant

opq opaque

ig internal gain

dl distribution loss

d diffuse, distribution

l latent

REFERENCES

[1] P.S. Rajpal, K.S. Shishodia and G.S. Sekhon, 2006, "An artificial neural network for modeling reliability, availability, and maintainability of a repairable system" Reliability Engineering and System Safety 91 pp.809–819.

[2] Kalogirou SA., 2003, "Artificial intelligence for the modeling and control of combustion processes: a review." Progress in Energy and Combustion Science; 29:105–66.

[3] Mellit A, Kalogirou SA., 2008, "Artificial intelligence techniques for photovoltaic applications: a review." Progress in Energy and Combustion Science; 34, 164–632.

[4] Mellit A, Kalogirou SA, Hontoria L, Shaari S., 2009, "Artificial intelligence techniques for sizing photovoltaic systems: a review. Renewable and Sustainable Energy Reviews"; 13 pp.406–419.

[5] Kalogirou S.,1999, "Applications of artificial neural networks in energy systems: a review. Energy Conversion and Management"; 40 pp.1073–1087,.

[6] Kalogirou SA.,2001, "Artificial neural networks in

renewable energy systems applications: a review. Renewable and Sustainable Energy Reviews"; 5, pp. 373–401.

[7] Abdul Afram, Farrokh Janabi-Sharifi, Alan S. Fung and Kaamran Raahemifar,2017, "Artificial neural network (ANN) based model predictive control (MPC) and optimization of HVAC systems: A state of the art review and case study of a residential HVAC system"Energy and Buildings 141 pp.96–113.

[8] *ASHRAE handbook fundamentals*, 2017.

[9] I. Zajic, T. Larkowski, M. Sumislawska, K.J. Burnham, D. Hill, 2011, "Modelling of an air handling unit: a Hammerstein-bilinear model identification approach", in: 21st International Conference on Systems Engineering (ICSEng), IEEE, Las Vegas, NV, USA pp.59–63.

[10] A. Beghi, L. Cecchinato, F. Paggiaro, M. Rampazzo, 2011, "VAVAC systems modeling and simulation for FDD applications", in International Conference on Control & Automation(ICCA), IEEE, Santiago, Chile pp.800–805.

[11] G.P. Zhang, (2007), "A neural network ensemble method with jittered training data for time series forecasting", Information Sciences 177 pp.1229–1246.

[12] Joarder Kamruzzaman, Rezaul Begg, Ruhul Sarker, 2006, "Artificial Neural Networks in Finance and Manufacturing", Idea Group Publishing, USA.

[13] G. Zhang, B.E. Patuwo, M.Y. Hu, 1998, "Forecasting with artificial neural networks: The state of the art", International Journal of Forecasting 14, pp.35-62.

[14] G.P. Zhang, 2003, "Time series forecasting using a hybrid ARIMA and neural network model", Neurocomputing 9 pp.159–175.

[15] J.M. Kihoro, R.O. Otieno, C. Wafula, , 2004, "Seasonal Time Series Forecasting: AComparative Study of ARIMA and ANN Models", African Journal of Science and Technology (AJST) Science and Engineering Series Vol. 5, No. 2 pp.41-49.

[16] J. Faraway, C. Chatfield, 1998, "Time series forecasting with neural networks: a comparative study using the airline data", Applied Statistics 47231–29.

[17] C. Hamzacebi, 2008, "Improving artificial neural networks' performance in seasonal time series forecasting", Information Sciences 178 pp.4550-4559.

[18] L.J. Cao and Francis E.H. Tay, 2003, "Support Vector Machine with Adaptive Parameters in Financial Time Series Forecasting", IEEE Transaction on Neural Networks, Vol. 14, No. 6, November pp. 1506-1518.