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Development of Hybrid Artificial Neural Network for Quantifying Energy Saving using Measurement and Verification

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Abstract

This paper presents a Hybrid Artificial Neural Network (HANN) for chiller system Measurement and Verification (M&V) model development. In this work, hybridization of Evolutionary Programming (EP) and Artificial Neural Network (ANN) are considered in modeling the baseline electrical energy consumption for a chiller system hence quantifying saving. EP with coefficient of correlation (R) objective function is used in optimizing the neural network training process and selecting the optimal values of ANN initial weights and biases. Three inputs that are affecting energy use of the chiller system are selected; 1) operating time, 2) refrigerant tonnage and 3) differential temperature. The output is hourly energy use of building air-conditioning system. The HANN model is simulated with 16 different structures and the results reveal that all HANN structures produce higher prediction performance with R is above 0.977. The best structure with the highest value of R is selected as the baseline model hence is used to determine the saving. The avoided energy calculated from this model is 132944.59 kWh that contributes to 1.38% of saving percentage.

Keywords: *Neural Network, Energy Saving, Evolutionary Programming, Measurement and Verification.*

1. Introduction

Malaysia is a rapidly developing country in Asia. The Gross Domestic Product (GDP) in Malaysia grew by 20% from the year 2010 to 2013 and expected to increase over the years [1]. Due to that, the number of commercial and residential area will also increase in parallel with the GDP growth. The increasing number of commercial and residential area in Malaysia has increased the energy demand and supply.

In 2014, it is reported that the number of electricity consumption in Peninsular Malaysia increased by 7.5% from 2012 to 2014 and 56% was from commercial and residential sectors [2]. The electricity cost was the largest contributor to the total operating cost of a building [3]. The needs to reduce energy consumption while maintaining productivity are important due to the rising of electricity cost nowadays. This situation has prompted Malaysian government to take several actions including energy efficiency to manage these problems. By implementing the energy efficiency, the electrical power demand can be reduced and thus assist in creating an overall cost reduction.

Energy efficiency (EE) implementation remains far cheaper than investing in an additional generation [4]. Regards to this factor, the energy efficiency of energy conservation measures (ECM) projects have been introduced by the Malaysian government. ECM projects have been implemented with the aim to reduce energy consumption in the building. In order to evaluate the impact of ECMs in EE, the reduction in energy consumption and energy saving must be determined. The evaluations are very dependent on Measurement and Verification (M&V) activities.

M&V method is a tool to determine, quantify and verify the savings on energy use. M&V is the process of using measurements to reliably determine actual saving created within an individual activity by an energy management program [5]. There are several protocols and guidelines for M&V but the most common and widely used is IPMVP [2]. In order to properly

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report saving in M&V, the baseline energy use pattern before ECM implementation must be first studied and developed to determine the relationship between energy use and input variables. Then, after ECM implementation, this baseline energy model is used to estimate how much energy would have used if there had been no ECM implementation. This estimation is referring to adjusted baseline energy in post-retrofit phase. Energy saving can be determined by comparing the adjusted baseline energy with the post-retrofit measured energy. Recently, regression analysis is the most common method in formulating the baseline energy [6], [7]. However, this M&V regression model is less accurate especially for non-linear characteristic hence contributes a large standard error [6], [7]. The M&V process involves modeling, metering and sampling process and these activities create uncertainty in reporting energy savings. It is important to precisely considering the accuracy hence to develop an accurate M&V baseline energy model to overcome these issues.

Recently, Artificial Neural Networks (ANN) has been one of the most popular forecasting techniques and used to solve various engineering and technology problems [8], [9]. The main advantage of ANN is the ability to perform complex processing task in order to find the relationship between inputs and outputs [10]. In other words, ANN is an accurate prediction tool that is used to predict or forecast future output based on previous data. Generally, ANN consists of the interconnected elements processing devices known as neurons. ANN is trained through the adjustment of weight and biases parameters between neurons. Figure 1 shows Multilayer Feedforward Neural Network architecture that consists of three types of layer, an input layer, a hidden layer and an output layer. Each layer consists of number of neurons which is connected to the other neurons in the next layer. Each neuron receives a signal from the neurons in the previous layer and both are connected to each other by a set of synaptic weights and biases. As can be seen in Figure 1, W_{ji} is a synaptic weight between input and hidden layer, W_{kj} is a synaptic weight between hidden and output layer meanwhile b is the bias. Each neuron in the previous layer is multiplied with its own associated weight value. Then, the weighted inputs and bias are summed and passed through transfer function, f which normally modelled as a pure linear (purelin) or log sigmoid (logsig) function. The predicted output may obtain after applying transfer function to the weighted input and bias.

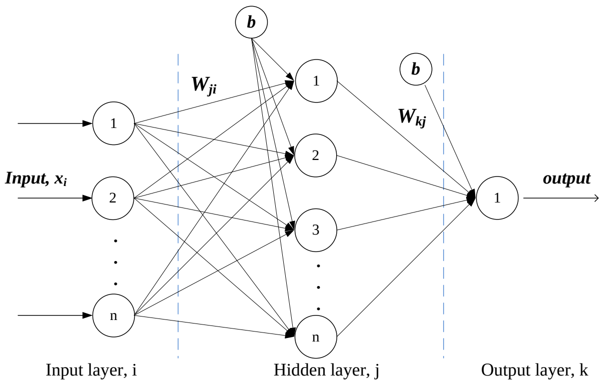

Figure 1. Multilayer Feedforward Neural Network architecture

Most of the researchers implemented the trial and error technique to determine an optimum ANN parameters [11], [12]. Therefore, to get a better accuracy of ANN prediction, appropriate ANN parameters selection using optimization technique need to be formulated. This was done by hybridizing various optimization techniques with ANN model to automatically find the optimum ANN parameters as opposed to the trial and error technique.

Nowadays, the major usage of electricity in commercial and residential sectors comes from the chiller plant where it produces chilled water for the cooling system to the building. Heating, Ventilation and Cooling (HVAC) contributes more than 24% of the energy use in the commercial building [13]. It is essential to implement energy efficiency and energy saving in the building to reduce the electricity cost of the chiller plant. Therefore, predicting the energy consumption based on input variables affecting factor is needed and this is one of the major analyses and focuses in this paper. Any changes in the input variables may vary the energy consumption.

Although the ANN has been studied in many applications, as far as the authors are aware, there are few works reported on M&V modeling of chiller system using ANN. The aim of this paper is to develop an accurate M&V baseline energy model using Hybrid Artificial Neural Network (HANN) for chiller system. Hybridization of ANN with Evolutionary Programming (EP) is implemented to optimize the neural network training process and to select the optimal values of ANN parameters, which are initial weights and biases. This baseline model using a test data of chiller system in a commercial building in Kuala Lumpur and this model used to calculate the adjusted baseline energy hence to quantify energy saving.

The overall structure of this paper is organized as follows: Section II explained the methodology including baseline energy development and saving calculation. Meanwhile, section III described the results, analyses and discussion. Finally, section IV concludes the paper.

2. M&V Model Development

The development of M&V HANN Model is divided into two phases, 1) M&V Baseline Energy Development phase and 2) Post-retrofit Saving Calculation phase as in Figure 2.

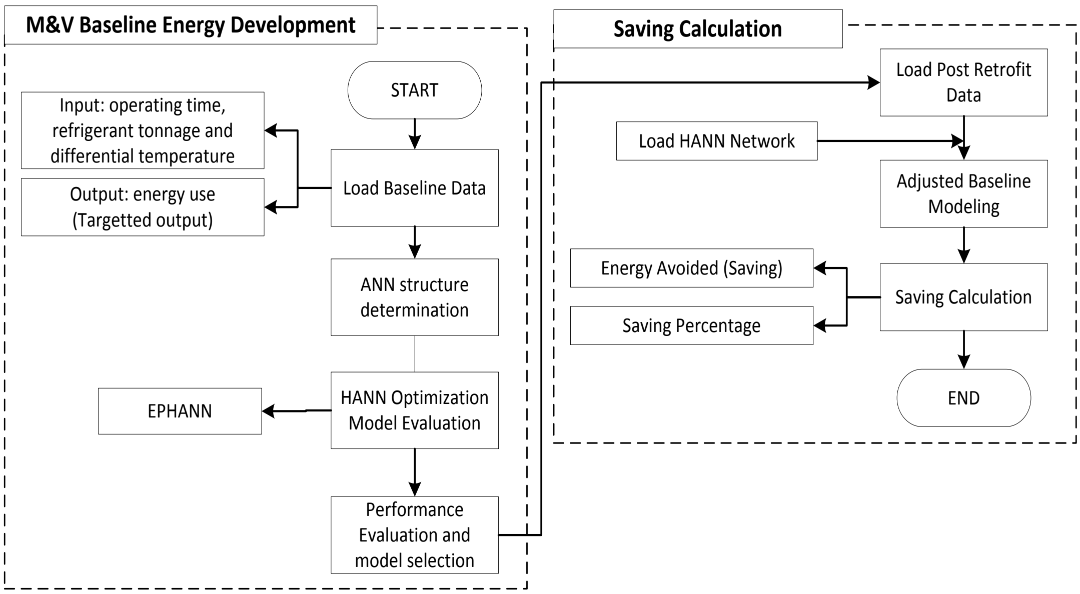

Figure 2. M&V HANN flowchart

In this study, M&V data are collected from an automated centralized control of building's air-conditioning system, Building Automation System (BAS) that is in one of the commercial buildings in Kuala Lumpur, Malaysia. There are two types of data: 1) 2,928 baseline data from September 2015 – December 2015 and 2) 2,184 post-retrofit data from September 2016 – November 2016. Three input variables are measured in developing the M&V HANN Model i.e. 1) operating time: hour of the day, from 1 to 24, 2) refrigerant tonnage: the cooling capacity or heat removal capacity to indicate the capacity or size of the refrigeration plant, and 3) differential temperature: the difference in temperature between inlet temperature (temperature of cooling water from cooling tower into condenser) and outlet temperature (temperature of cooling water from condenser to cooling tower). These parameters are assigned as ANN input and the targeted output for the baseline is the hourly electrical energy consumption (baseline measured energy), kWh. For the post-retrofit, hourly electrical energy consumption (post-retrofit measured energy) is used to calculate the saving. Figure 3 and Figure 4 show the hourly electrical energy consumption for baseline and post-retrofit respectively.

2.1 M&V Baseline Energy Development Phase

In this phase, ANN structure and parameters need to be determined. For this paper, the number of neurons in the hidden layer is set between 5 and 20 neurons only. This means that a total 16 structures are evaluated. Structures with one hidden layer are chosen as several authors found that simpler networks are better due to less memory [14], [15] These ANN structures are trained with the parameter setting as in Table 1. The training algorithm used and recommended by the MATLAB and mostly used to determine the error is trainlm (Levenberg-Marquardt) for most condition and default algorithm [16].

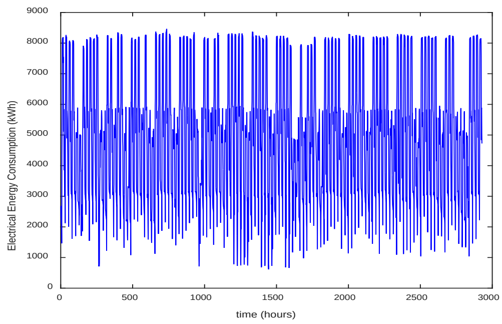

Figure 3. Baseline Electrical Energy Consumption

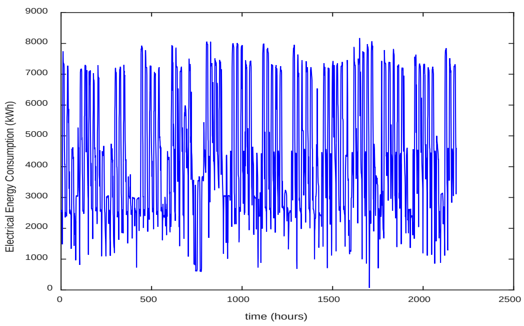

Figure 4. Post-Retrofit Electrical Energy Consumption

For this baseline model, 70% of the data is allocated for training, 15% for validation and 15% for testing. The selected transfer functions are logsig for hidden layer and purelin for the output layer. The input variables are normalized in the range of -1 to 1 so that all the inputs are at a comparable range and to ensure that all the data is equally distributed between the input variables and the outputs [17]. Then, the ANN outputs are de-normalized to get the predicted electrical energy consumption.

In the training process, ANN tries to find the correlation between input and predicted output according to the given set of input and targeted output. ANN creates the input-output mapping by adjusting the weights and biases at each iteration to minimize the error between the targeted and predicted output.

Table 1. ANN Parameter Setting

Training Algorithm	Levenberg-Marquardt(LM)
Data division function	Divide block (70/15/15)
Transfer function – hidden layer	logsig
Transfer function – output layer	purelin

In order to obtain the optimum initial weights and biases parameters, the ANN need to be trained and optimized using Evolutionary Programming (EP) with the objective function to maximize Coefficient of Correlation (R). This hybrid method is called Evolutionary Programming Hybrid with Artificial Neural Network (EPHANN). In the other words, this EPHANN is trained to minimize the error during the training process.

EP is one of the Evolutionary Algorithm stochastic optimizations techniques, originated from the research of Lawrence J.Fogel in 1960. It is inspired by the theory of natural selection and evolution [18]. Who is fit enough to copy themselves will survive and who are unfit eventually go extinct.

EPHANN flowchart is illustrated as in Figure 5. EPHANN starts with the random number initialization of initial weights and biases based on the number of neurons in the hidden layers. Secondly, the fitness function is evaluated where ANN is trained to find the maximum value of R. The maximum and minimum values of R, weights and biases are determined in order to calculate the next process.

Then, the mutation process started where each parent replicates into a new population (offspring). Each of offspring is mutated according to Gaussian mutation. The ANN is trained for the second time to determine the new R. Next, parents are combined with offsprings before the selection process. During the selection process, parents and offspring compete to survive and the best solutions with the selected parameters are retained to be parents of the next generation. Before starts the next evolution process, a convergence test is executed to check whether to continue or stop the evolution process.

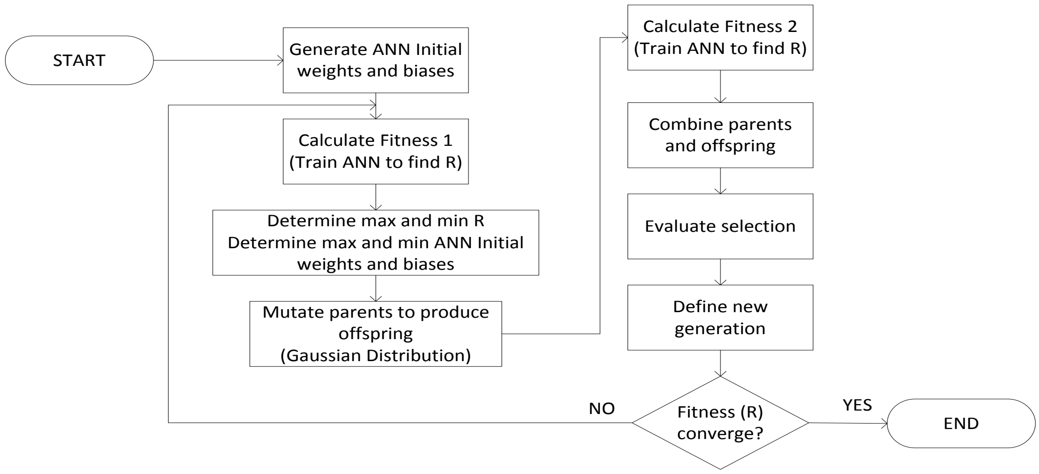

Figure 5. EPHANN flowchart

To evaluate the model performance and accuracy, ANN predicted output will be compared with the targeted output using several performance functions. For this study, R is selected as the objective function to optimize the performance of these two models. R measures the strength of association and the direction of a linear relationship between two variables. The higher value of R (the closer R to 1) indicates the strong linear correlation or in other words, the higher similarities between the targeted and the predicted output [19]. Out of 16 EPHANN structures, only one is selected as the baseline model based on the highest value of R.

Other than that, other performance criteria are also used to validate the model accuracy, which are Mean Square Error (MSE), Standard Error (SE) and Mean Absolute Percentage Error (MAPE) between the measured and predicted values. The lower values of MSE, SE and MAPE indicate that the more accurate the results.

The mathematical representation of R, MSE, SE and MAPE are shown in the Equation (1) - Equation (4).

$$\boldsymbol{R} = \frac{N(\sum Y_t Y_p)-(\sum Y_t)(\sum Y_p)}{\sqrt{[N\sum {Y_t}^2-(Y_t)^2][N\sum {Y_p}^2-(Y_i)^2]}} \tag{1}$$

$$\boldsymbol{SE} = \sqrt{\frac{\sum_{i=1}^{N}(Y_p-Y_t)^2}{n-p-1}} \tag{2}$$

$$\boldsymbol{MSE} = \frac{\sum_{i=1}^{N}(Y_p-Y_t)^2}{N} \tag{3}$$

$$\boldsymbol{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_p-Y_t}{Y_t}\right| \boldsymbol{x\ 100} \tag{4}$$

where N is the number of observation in the data set, Y_t is the targeted output data, Y_p is the predicted output data from the ANN, and n is the number of input variable.

2.2 Post-Retrofit Saving Calculation Phase

In this phase, the post-retrofit input data is used to determine the adjusted baseline energy hence to quantify saving. The post-retrofit input data is loaded as an input into the selected EPHANN baseline model to predict the output. This predicted output is known as adjusted baseline energy. According to IPMVP, saving or avoided energy use is obtained from the difference between the adjusted baseline energy and post-retrofit measured energy as stated in Equation (5).

$$\begin{aligned}&\boldsymbol{Avoided\ energy\ use} = \\ &\boldsymbol{adjusted\ baseline\ energy - post - retrofit\ measured\ energy}\end{aligned} \quad (5)$$

3. Results and Discussion

This result part is divided into two sections, the baseline energy development result and post-retrofit saving calculation result.

In the baseline energy development, EPHANN is developed with the objective function to maximize the value of R. Random numbers of initial weights and biases are initialized and network structures are trained and optimized with the different combinations of neurons in hidden layer. As previously mentioned, 5 - 20 numbers are neurons are considered for this optimization. Predicted output and performance functions are measured and recorded for each training phase. In selecting the best network structure, the value of R is evaluated and the number of neurons, as well as the initial weights and biases, are documented. The selection of the best structure is based on the maximum value of R as an objective function, as well as MAPE, SE and MSE as additional criteria. Later, in the post-retrofit saving calculation, the selected structure is applied to obtain the adjusted baseline energy hence to calculate saving.

3.1 Baseline Energy Development Results

Figure 6 presents the average R of 16 structures for EPHANN. From the graph, the lowest average R of 0.97778578 is obtained from the combination of 5 neurons in hidden layer meanwhile the highest value of average R is 0.9814089, attained from the combination of 19 neurons. Therefore, hidden layer with 19 neurons with the training R is 0.97938, validation R is 0.9863 and testing R is 0.98635 as illustrated in Figure 7 is selected as the best performance based on the maximum value of R objective function. The ideal R is one and as can be seen, the average R for all structures is above 0.977. The R for all selected values are high and close to unity which can be considered good and acceptable [19]. Apart from that, other performance criteria such as MAPE, MSE and SE are also evaluated. The value of MAPE is 8.7250%, MSE is 170800.35 and SE is 413.56 for selected structure, 19 neurons in the hidden layer as in Table 2. It can be concluded that there is no direct correlation between number of neurons and R.

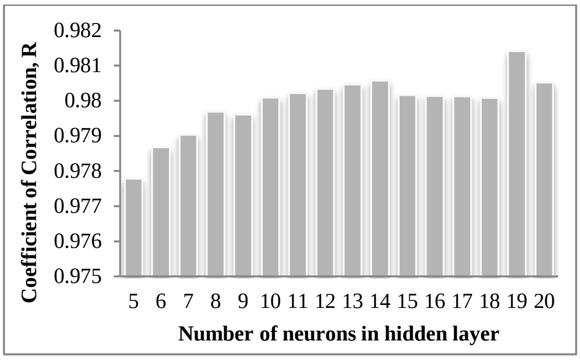

Figure 6. Average Coefficient of Correlation, R for 16 EPHANN structures.

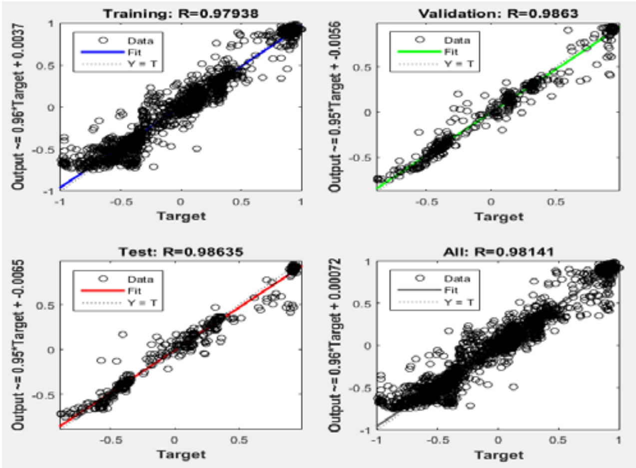

Figure 7. Training, validation and testing results for EPHANN

The results of optimal values for EPHANN is illustrated in Table 3. In Table 3, the EPHANN optimal value for neurons in the hidden layer is 19 with a set of 96 initial weights and biases. W_{ji} represents a set of weights between input and hidden layer and W_{kj} is a set of weights between hidden layer and output. Whereas, b_1 and b_2 are the biases for input-hidden layer and hidden layer – output respectively

This selected EPHANN structure with 19 number of neurons gives small error based on several performance criteria mentioned above and has been nominated as baseline energy model for the post-retrofit saving calculation stage.

Table 2. EPHANN Performance Evaluation For 19 Neurons In Hidden Layer.

Computation time	4355s
MAPE	8.725%
MSE	170800.35
SE	413.56

Table 3. Optimal Values Of EPHANN.

Number of neurons	19
Initial weights	Initial biases
$W_{ji} = \begin{bmatrix} 0.471997 & 0.673694 & 0.625833 \\ 0.732280 & 0.427756 & 0.211772 \\ 0.980469 & 0.832662 & 0.915374 \\ 0.666675 & 0.171178 & 0.134094 \\ 0.682952 & 0.440510 & 0.967885 \\ 0.875178 & 0.752225 & 0.619705 \\ 0.507584 & 0.615329 & 0.640627 \\ 0.467764 & 0.254020 & 0.013343 \\ 0.244637 & 0.350275 & 0.789305 \\ 0.565827 & 0.612905 & 0.899419 \\ 0.760591 & 0.337590 & 0.002007 \\ 0.345030 & 0.635815 & 0.516199 \\ 0.447452 & 0.516489 & 0.624242 \\ 0.515656 & 0.519388 & 0.265077 \\ 0.157155 & 0.626287 & 0.398898 \\ 0.980685 & 0.949027 & 0.977488 \\ 0.298596 & 0.223302 & 0.303548 \\ 0.154410 & 0.994382 & 0.566608 \\ 0.935552 & 0.877242 & 0.215923 \end{bmatrix}$	$b1 = \begin{bmatrix} 0.598069 \\ 0.388718 \\ 0.935632 \\ 0.826833 \\ 0.051143 \\ 0.827538 \\ 0.387655 \\ 0.445624 \\ 0.009028 \\ 0.280017 \\ 0.291876 \\ 0.429787 \\ 0.701167 \\ 0.010150 \\ 0.236892 \\ 0.401307 \\ 0.087566 \\ 0.883407 \\ 0.436402 \end{bmatrix}$
$W_{kj} = [0.135211\ 0.978418\ 0.214167\ 0.135574\ 0.052467\ 0.264518\ 0.757128\ 0.435545\ 0.506531\ 0\ .494566\ 0.094069\ 0.970953\ 0.424779\ 0.270046\ 0.935122\ 0.220571\ 0.189398\ 0.280432\ 0.673909]$	$b2 = [0.308651]$

3.2 Post-Retrofit Saving Calculation Results

The selected EPHANN structure is applied to the post-retrofit data to calculate the adjusted baseline. The graph of the overall M&V process is represented in Figure 8. The graph shows the measured energy consumption for baseline and post-retrofit as well as the results of baseline energy model and adjusted baseline model from EPHANN. The range of data from 0 to 200 is illustrated for both baseline and port-retrofit out of 2,928 data for baseline and 2,184 for post-retrofit. The avoided energy is calculated from the difference between actual energy consumption for post-retrofit and adjusted baseline energy. As can be seen, the adjusted baseline energy is slightly higher than the measured energy consumption. This indicates that there is a saving in the post-retrofit phase. The avoided energy use calculated for this model is 132,944.59 kWh that contributes to 1.38% of saving percentage

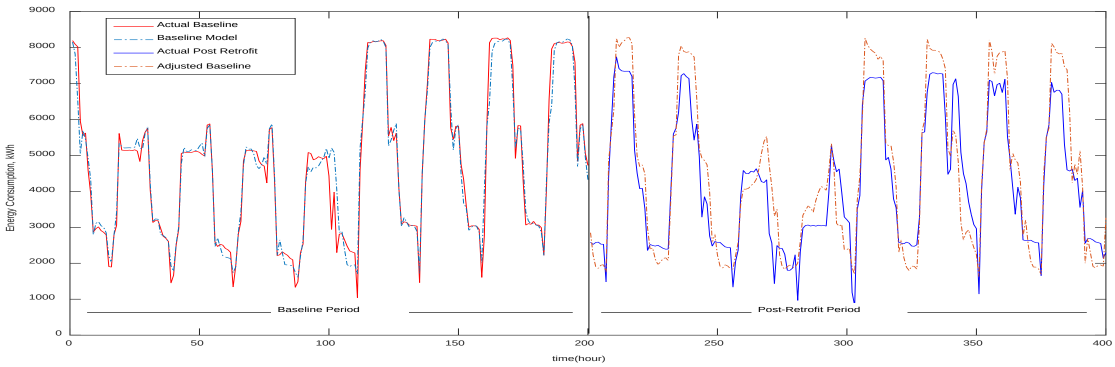

Figure 8. Measurement and Verification Framework

4. Conclusion

The main objective of this work was to develop an accurate baseline energy model for a chiller system hence to determine saving. In this work, M&V HANN baseline energy model with 16 combinations of neurons have been developed to assess the optimum value of the objective function, R. EP is used as an optimization technique to optimize the ANN initial weights and biases. For the effect of operating time, refrigerant tonnage and differential temperature on Coefficient of Correlation, the optimum condition suggested by the EPHANN is the combination of 19 neurons in a hidden layer. For future works, other optimization techniques such as Particle Swarm Optimization and Artificial Bee Colony are suggested to be considered to develop an accurate baseline energy model.

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