Baseline Energy Modeling Using Artificial Neural Network - Cross Validation Technique.

Wan Nazirah Wan Md Adnan, Nofri Yenita Dahlan, and Ismail Musirin

***Abstract*— This paper presents a baseline energy model development using artificial neural networks (ANN) with Cross-Validation (CV) technique for a small dataset. The CV technique is used to examine generalization abilities and model reliability of a small data. This CV-ANN model is simulated with thirty different structures using two CV techniques, Random Sampling Cross Validation (RSCV) and K-Fold Cross Validation (KFCV). Working days, class days and Cooling Degree Days (CDD) are used as ANN input meanwhile the ANN output is monthly electricity consumption. The coefficient of correlation (R) is used as performance function to check the model accuracy. The results are compared and best CV-ANN structure with the highest value of R is selected to develop the baseline energy model. The comparison reveals that most of the average R values are above 0.8 and it shows that the CV-ANN is capable to train the network even with small set of data. ANN-KFCV model with 6 neurons in hidden layer is chosen as the best model with average R is 0.91.**

***Index Terms*—Artificial Neural Network, Coefficient of Correlation, Cross Validation, Energy**

I. Introduction

MALAYSIA is one of the developing countries in Asia. The electricity consumption in Malaysia is increasing parallel with the economic growth. It is stated that the number of electricity consumption in Peninsular Malaysia increased by 7.5% from 2012 to 2014 [1]. Due to that, there is a need to reduce the electricity consumption while maintaining productivity. This situation has prompted Malaysian government to introduce energy efficiency (EE) of energy conservation measures (ECM) projects to manage these problems. ECM projects have been implemented with the aim to reduce electricity consumption in the building.

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. Developing the M&V baseline energy model is one of the important factors in predicting the energy consumption hence determine the saving. The International Performance Measurement & Verification Protocol (IPMVP) is adopted as the guideline in M&V. In IPMVP, four options are introduced in achieving M&V process which are Option A, B, C and D. For this study, only IPMVP Option C- Whole facility energy use is chosen. In this option, energy data of whole facility baseline and reporting period are often derived from utility bills [2].

The most widely used method for developing baseline energy model is regression analysis [3], [4]. However, this method is less accurate, especially for the non-linear characteristic. Therefore, Artificial Neural Networks (ANN) has been applied in several works to replace the traditional method [5], [6]. ANN is one of the popular techniques for forecasting that imitates the operation of human brain. It has been used to solve various engineering problems [7], [8]. To get the best result, large training data is needed as ANN learns from examples. Insufficient or small data sets normally creates inaccurate results and produce a large error during training stage.

As previously mentioned, the data for Option C is derived from utility bills which are available once a month. Therefore, only a small data set is available for this study hence may reduce the ANN accuracy. Several sampling techniques have been studied and integrated with ANN to increase the accuracy of small data set, and the most common techniques used in ANN is cross-validation (CV) [9]–[11]. There are several types of CV but this study only focuses on the integration of ANN with Random Sampling Cross Validation (ANN-RSCV) and K-Fold Cross Validation (ANN-KFCV).

The structure of this paper is organized as follows: Section 2 briefly explains the methodology including data collection, baseline model development, and performance evaluation. Section 3 discusses the result of the proposed methods and Section 5 provides the conclusion.

II. Methodology

The proposed method for the development of ANN-CV Baseline Energy Model is illustrated in Fig. 1. Development of CV-ANN Baseline Energy Model involves several steps including data collection, baseline model development using ANN with CV method, and model evaluation and selection.

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A. Data Collections

In this study, 23 months baseline data are obtained from the Facility Management Office, Universiti Teknologi Mara (UiTM), Shah Alam, Selangor, Malaysia. The dataset of Faculty of Electrical Engineering, UiTM is presented as in TABLE 1. Three input variables are measured in developing the baseline energy model i.e 1) UiTM working days, 2) UiTM class days, and 3) Cooling Degree Days (CDD). These parameters are assigned as ANN input and the targeted output for the baseline is the monthly electricity consumption.

When only 23 data available for ANN development, the performance of an ANN may depend heavily on the splitting of the data set [12]. Therefore, cross-validation technique is applied to the ANN to develop an accurate ANN model. Further details on cross-validation will be explained in the next section.

TABLE 1
UITM BASELINE DATA

Month	Ann Inputs			ANN Output
	Working days	Class Days	CDD	
1	21	20	602	159226
2	22	10	561	149040
3	19	0	575	109642
4	19	14	540	131503
5	22	19	562	143285
6	20	18	535	143633
7	19	19	522	139339
8	21	14	556	135623
9	18	0	468	122145
10	21	20	598	149997
11	22	17	581	147059
12	21	16	615	143215
13	20	20	614	143712
14	22	10	547	132817
15	20	0	563	117130
16	20	15	521	141788
17	22	18	543	157661
18	20	20	511	154709
19	22	17	551	142173
20	20	15	584	147437
21	21	21	628	141978
22	20	9	616	114970
23	20	0	561	117576

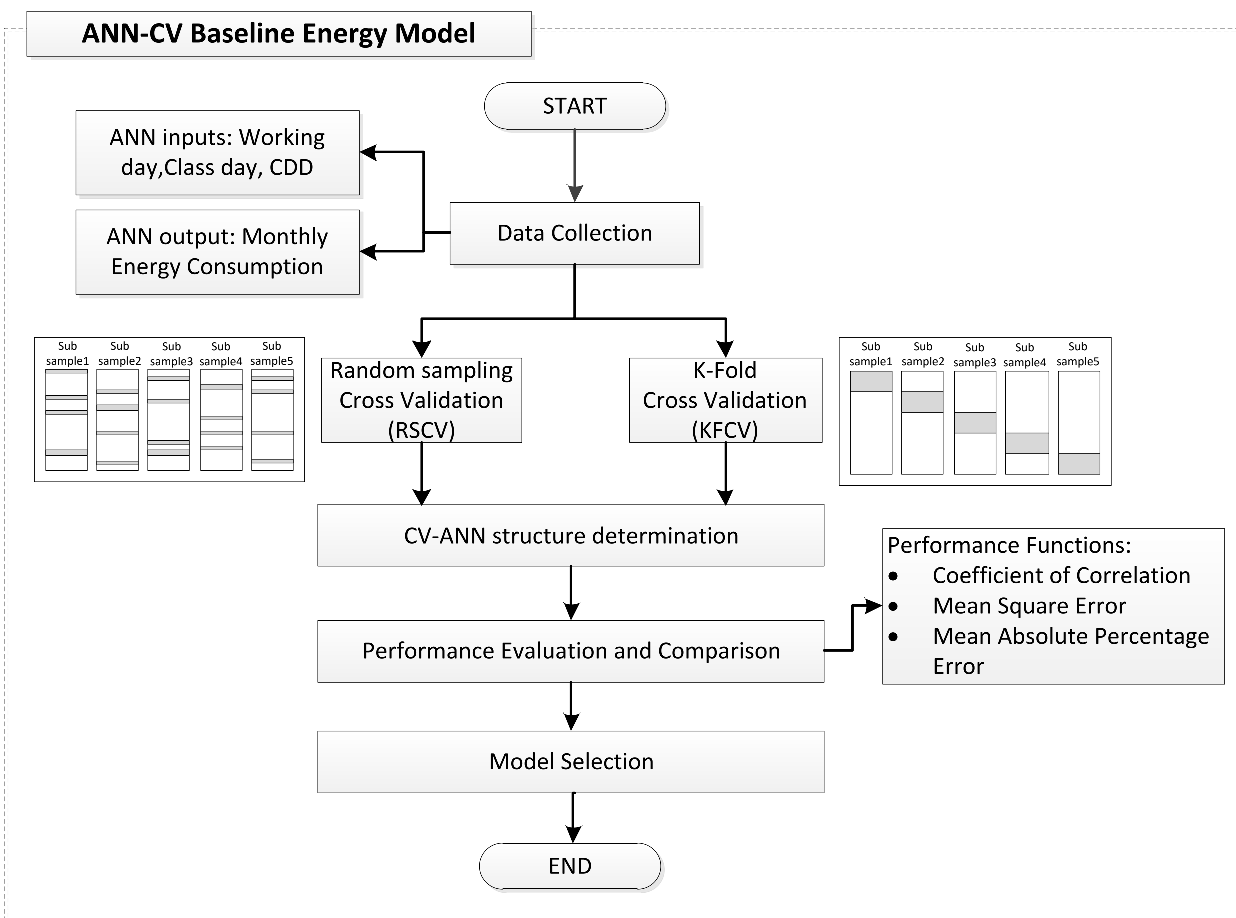

Fig. 1. Proposed method ANN-CV Baseline Energy Model

B. ANN-CV Baseline Model Development

Since the limited data available to train the network, the CV technique is most commonly used in ANN [13]–[15]. The idea of CV is to split the data set into training set, validation set, and testing set. The combination of training and validation set is divided into k subsample (k=5 for this study). In the first iteration, k-1 subsamples are used to train the data meanwhile the remaining subsample is used as validating the data. This process is repeated for k iterations.

The training set is used to adjust the ANN weights and biases The ANN training process is terminated when the validation set begins to increase. The validation set is used to validate the training process and to minimize the overfitting. The validation will stop the process when the overfitting starts to occur. Overfitting creates the ANN memorizes training patterns in such way that they cannot generalize well to new data and generates poor accuracy [16]. The testing data, which are not involved in the training process is used to evaluate the performance of the trained model. CV method is not only to evaluate how accurately the model is but also how the model generalizes on new data [17].

Two types of cross-validation techniques are applied in this study, RSCV and KFCV. In RSCV, each data split randomly into k subsamples meanwhile in KFCV, the data is partitioned into k-samples as illustrated in Fig. 1. The advantage of KFCV is that at the end of the iterations, each of the subsamples is used exactly once as a validation set.

A reliable evaluation of the ANN prediction accuracy is important in selecting an appropriate architecture. For this paper, feed-forward multi-layer perceptron (MLP) architecture is employed, which is the most popular used for prediction [19], [20]. There are three layers involved, an input layer, a hidden layer and an output layer as in Fig. 2. The input neurons are equal in number to the ANN's inputs and because of ANN only has a single output, therefore only a single output neuron is selected. 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. Total weights and biases is calculated based on number of neurons in hidden layer (H), number of input (I) and also number of output (O) as shown in Equation 1.

$$\mathit{Total\ weights\ and\ biases} = [(I+1)*H] + [(H+1)*O] \qquad (1)$$

To obtain an optimum structure, different neurons in hidden layer are assigned to the network. Too few neurons in hidden layer cannot train the network properly and too many neurons in hidden layer may overfitting the network and poor network generalization [18]. Therefore, selection of neurons in the hidden layer is one of the important parts in the study of neural network. For this work, the number of hidden neurons is set between 6 and 20 neurons to maximize the network's reliability. This means that 15 structures for each CV and total of 30 structures are evaluated. Structures with one hidden layer are chosen as several authors found that simpler networks are better due to less memory [21], [22]. These ANN structures are trained with the parameter setting as in TABLE 2. For all structures, random weight and biases initialization is employed to the randomness of CV procedures.

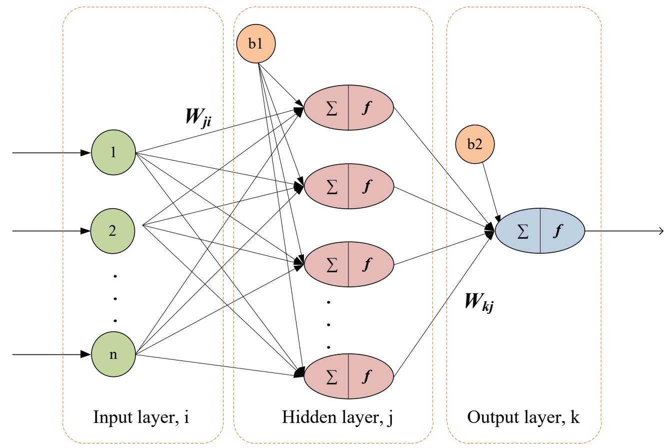

Fig. 2. ANN structure with three layers: input, hidden and output layer.

In this study, all structures are trained using CV technique and after each training, the average prediction error of each structure is calculated and recorded. Finally, the lowest model prediction error is selected as the best model.

TABLE 2
ANN PARAMETER SETTING

Training Algorithm	Levenberg-Marquardt(LM)
Data division function	Cross Validation technique
Transfer function – hidden layer	logsig
Transfer function – output layer	purelin

C. Performance Evaluation

To evaluate the model performance and accuracy, ANN predicted output will be compared with the targeted output. Several performance functions or prediction error calculations are evaluated to determine the model accuracy.

The Coefficient of Correlation, R is measured the strength of association and the direction of a linear relationship between two variables. R_all is the Coefficient of Correlation performance on the entire dataset, R_train is the Coefficient of Correlation for training set, R_valid is the Coefficient of Correlation for validation and R_test is the Coefficient of Correlation for testing set. The closer Coefficient of Correlation to 1, the higher similarities between the targeted and the predicted output [23]. The coefficient of correlation is defined by:

$$R = \frac{\sum_{i=1}^{n}(t_n - \overline{t_n})(p_n - \overline{p_n})}{\sqrt{\sum_{i=1}^{n}(t_n - \overline{t_n})^2 \sum_{i=1}^{n}(p_n - \overline{p_n})^2}} \qquad (2)$$

Other performance criteria are also used to validate the model accuracy, which are Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE). Smaller values of MSE and MAPE indicate that the results are more accurate. The mathematical equations of *MSE* and *MAPE* are shown below:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}|t_n - p_n|^2 \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{t_n - p_n}{t_n}\right| \tag{4}$$

where t_n is the targeted output data, p_n is the predicted output data from the ANN, n is the number of samples in the data set and $\overline{t_n}$ and $\overline{p_n}$ are the mean values for the targeted and predicted output respectively.

III. Results And Discussion

In developing the baseline energy model, initial weights and biases are randomly initialized and thirty neural network structures are developed and trained with the different combinations of neurons in hidden layers. Predicted output and performance functions are recorded and evaluated for each training phase. CV is performed to evaluate the robustness and to examine the sampling variation performance of neural network model. In the CV method, data is divided into 5 subsamples and randomly runs for several times.

The overall results for the effect of hidden neurons for both average *R_test* and *R_all* across 5 subsamples are summarized in TABLE 3 and TABLE 4. In both tables, the average of *R_test* and *R_all* measured in terms of predicted and targeted outputs are presented. In general, most of the *R_test* and *R_all* are above 0.8 and it shows that the neural network is capable to train and approximate functions. The capability of the neural network to learn is based on the acceptability of the testing model and overall model [14].

The comparison between ANN-RSCV and ANN-KFCV for average 5 subsamples of *R_all* , MSE and MAPE are presented in Fig. 3, Fig. 4 and Fig. 5. Fig. 3 clearly shows that average *R_all* 5 subsamples of CV for both methods are above 0.835. The lowest average *R_all* for ANN- RSCV is 0.83918 (14 neurons in hidden layer) meanwhile the highest average *R_all* for ANN-RSCV is 0.87641 (19 neurons in hidden layer). For ANN-KFCV, lowest average *R_all* is 0.84493 (20 neurons in hidden layer) meanwhile the highest average *R_all* is 0.87248 (6 neurons in hidden layer). From the graph in Fig. 4, the lowest average MSE for ANN-RSCV is 54893428 (20 neurons in hidden layer) and the highest is 85850717 (15 neurons in hidden layer). Meanwhile for ANN-KFCV, the lowest average MSE is 51853558 (6 neurons in hidden layer) and the highest average MSE is 83923777 (20 neurons in hidden layer). As can be seen in Fig. 5, the average MAPE for both methods are less than 5.4%. The lowest average MAPE is 0.041616 for ANN-RSCV (20 neurons in hidden layer) and 0.042412 (6 neurons in hidden layer) for ANN-KFCV.

In general, CV in neural network is used to estimate the prediction error, model robustness, and generalization abilities by averaging the subsamples results. These 30 models for both ANN-RSCV and ANN-KFCV are compared to each other and the model with the smallest prediction error or in other words, the highest *R_all* is chosen for prediction purposes.

TABLE 3
THE EFFECT OF HIDDEN NEURONS ON ANN-RSCV FOR SMALL DATA SET

Number of hidden neurons	Subsample1		Subsample2		Subsample3		Subsample4		Subsample5	
	R_test	R_all	R_test	R_all	R_test	R_all	R_test	R_all	R_test	R_all
6	0.79138	0.87969	0.88953	0.86973	0.84461	0.84154	0.88764	0.89252	0.86280	0.87942
7	0.88233	0.88858	0.85754	0.88116	0.84253	0.86917	0.87625	0.86581	0.89663	0.87428
8	0.87406	0.84999	0.88108	0.84655	0.77356	0.86602	0.82795	0.89180	0.95150	0.91928
9	0.80678	0.85872	0.95491	0.90434	0.84359	0.87925	0.88349	0.86033	0.87099	0.86301
10	0.90924	0.90170	0.62271	0.85065	0.74727	0.84442	0.88820	0.85014	0.80674	0.82083
11	0.76343	0.87270	0.87400	0.88873	0.92473	0.88001	0.79075	0.81492	0.87353	0.87642
12	0.77739	0.86054	0.88474	0.86224	0.92765	0.90144	0.73427	0.87045	0.79263	0.80633
13	0.92509	0.90433	0.91003	0.89832	0.84094	0.84346	0.88787	0.86317	0.73617	0.85793
14	0.93811	0.88759	0.95582	0.89868	0.20873	0.70708	0.82643	0.82405	0.82387	0.87849
15	0.72600	0.81143	0.84769	0.83945	0.89267	0.87367	0.87785	0.88896	0.81100	0.85371
16	0.82502	0.87902	0.89103	0.85690	0.63060	0.85494	0.68468	0.85197	0.82594	0.85264
17	0.84125	0.85047	0.83045	0.83174	0.82602	0.86236	0.78465	0.86332	0.93903	0.89926
18	0.86860	0.87138	0.85294	0.84494	0.81643	0.85404	0.87261	0.88392	0.90951	0.88274
19	0.81718	0.86036	0.84798	0.86285	0.82084	0.87968	0.94462	0.89397	0.79476	0.88519
20	0.75724	0.88051	0.79885	0.79461	0.71657	0.85906	0.81788	0.88046	0.96531	0.89861

TABLE 4
THE EFFECT OF HIDDEN NEURONS ON ANN-KFCV FOR SMALL DATA SET

Number of hidden neurons	Sub sample 1		Sub sample 2		Sub sample 3		Sub sample 4		Sub sample 5	
	R_test	R_all	R_test	R_all	R_test	R_all	R_test	R_all	R_test	R_all
6	0.88605	0.88646	0.87564	0.89123	0.81087	0.83324	0.82416	0.88185	0.89363	0.86962
7	0.88245	0.88726	0.84492	0.88839	0.82037	0.84191	0.81112	0.88004	0.89164	0.85512
8	0.90841	0.89293	0.82175	0.88279	0.83020	0.83023	0.76598	0.86809	0.88028	0.82130
9	0.79942	0.86888	0.84025	0.87967	0.82663	0.84078	0.78597	0.87385	0.89467	0.85771
10	0.89574	0.88887	0.82736	0.87173	0.83631	0.83009	0.75722	0.86663	0.87809	0.84834
11	0.85787	0.88241	0.87856	0.89380	0.81518	0.83730	0.80293	0.87809	0.87732	0.84456
12	0.83796	0.88182	0.83138	0.88077	0.81952	0.83614	0.82418	0.85133	0.88254	0.85344
13	0.86097	0.88200	0.84817	0.88564	0.82740	0.83409	0.79164	0.87708	0.88258	0.84284
14	0.86533	0.88061	0.83557	0.88137	0.81721	0.83058	0.81882	0.87100	0.87001	0.84177
15	0.85973	0.87947	0.87164	0.89623	0.82326	0.80625	0.80550	0.87769	0.88023	0.85024
16	0.88050	0.88581	0.86731	0.88973	0.81296	0.82467	0.79555	0.86568	0.86960	0.82729
17	0.85401	0.87445	0.88773	0.87902	0.80564	0.81928	0.83116	0.87901	0.88300	0.84970
18	0.85274	0.87670	0.84888	0.87491	0.81563	0.83461	0.80196	0.87446	0.88435	0.86184
19	0.84000	0.87633	0.82470	0.88154	0.82675	0.82227	0.79195	0.87038	0.87388	0.83303
20	0.83638	0.88008	0.83061	0.87130	0.81439	0.83372	0.75499	0.84413	0.86394	0.79539

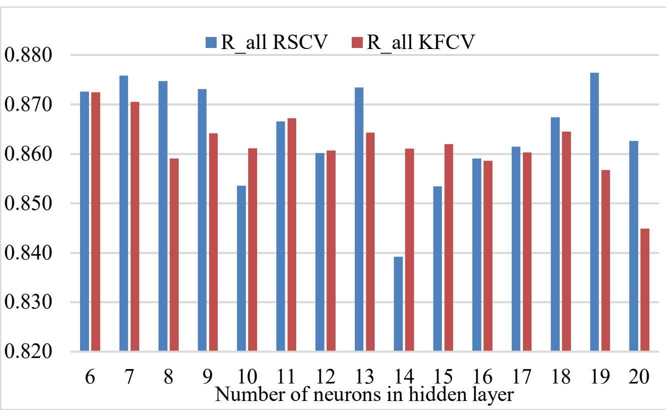

Fig. 3. The comparison between ANN-RSCV and ANN-KFCV for average 5 subsamples of R_all.

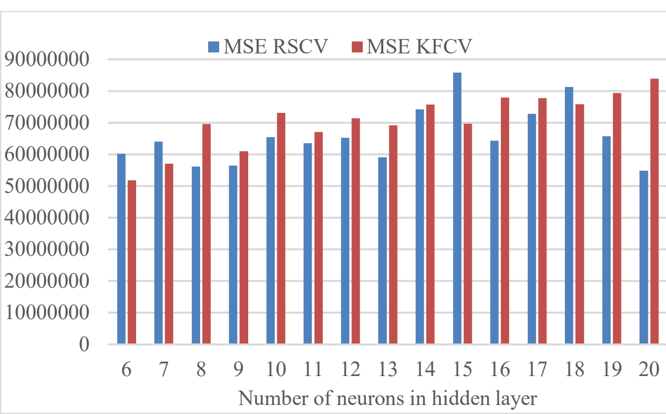

Fig. 4. The comparison between ANN-RSCV and ANN-KFCV for average 5 subsamples of MSE.

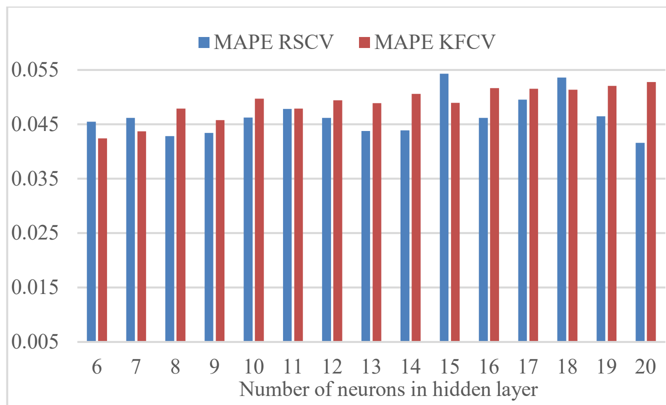

Fig. 5. The comparison between ANN-RSCV and ANN-KFCV for average 5 subsamples of MAPE.

From the analysis, ANN-KFCV model with 6 neurons in the hidden layer is chosen as the best model based on the the highest values of all coefficient of correlation results, *R_trn, R_vld, R_test* and *R_all* as shown in Fig. 6. This selected model achieved regression coefficients of *R_all* = 0.90761 and separately *R_train* = 0.93322, *R_valid* = 0.87192 and *R_test* = 0.96103. The values for all coefficient of correlation are greater than 0.87 which considered acceptable and compliance with IPMVP protocol. Apart from that, this model also gives the smallest error based on MSE and MAPE error criteria as in TABLE 5 .These results indicate that a very high prediction accuracy model is produced using cross-validation neural network even with the limited data available.

The predicted outputs of ANN-KFCV model is compared with targeted outputs as illustrated in Fig. 7. As can be seen, most of the measured and predicted data points matched, except for several data points. The final values of weights and biases of ANN-KFCV model with 6 neurons in the hidden layer are presented in TABLE 6 with a set of 26 initial weights and biases.

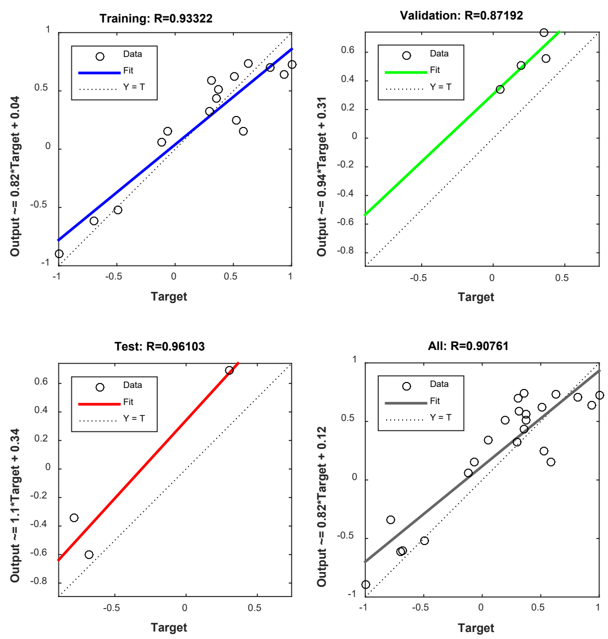

Fig. 6. The coefficient of correlation of ANN-KFCV selected model.

TABLE 5
ANN-KFCV PERFORMANCE EVALUATION

MSE	37094577
MAPE	0.0376

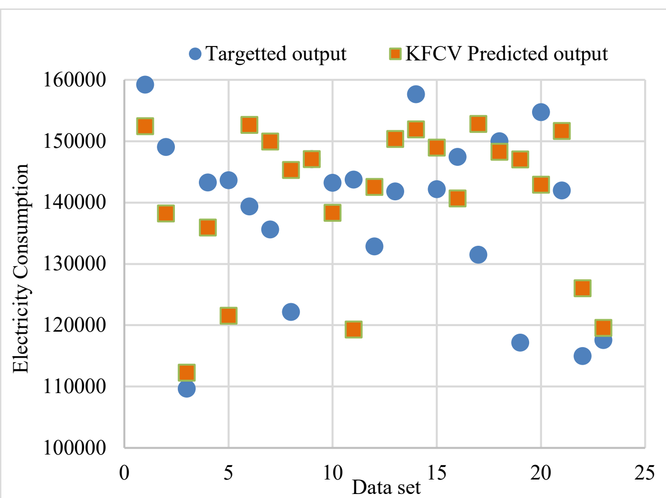

Fig. 7. Comparison of targetted (actual) output versus selected ANN-KFCV predicted output.

IV. CONCLUSION

In this work, baseline energy model is developed using CV-ANN to simulate the electrical energy consumption of a building. Thirty combinations of CV-ANN structures using two CV techniques, RSCV and KFCV have been constructed. Because of the small data available, CV technique is used in this paper to create model diversity and also to evaluate generalization abilities of various CV-ANN structures. The input data consisted of working days, class days and CDD meanwhile the output data is monthly electricity energy consumption. The ANN_KFCV structure with 6 neurons in hidden layer gives small error based on R and has been nominated as baseline energy model. It is believed that the research objective for this work has been met with the completion of this study. For future works, optimization techniques are needed to be embedded in CV-ANN to obtain the better ANN performance accuracy.

TABLE 6
FINAL VALUES OF WEIGHTS AND BIASES FOR SELECTED ANN-KFCV MODEL

Wji	0.15224	0.62789	0.51772			
	0.58001	0.16991	0.41790			
	0.60355	0.43964	0.10992			
	0.62418	0.99224	0.13981			
	0.05289	0.87913	0.63450			
	0.60720	0.64261	0.24633			
Wkj	0.84090	0.84223	0.92670	0.57733	0.68432	0.29256
b1	0.75215					
	0.68770					
	0.56387					
	0.67110					
	0.03833					
	0.32270					
b2	0.21087					

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