PRINCIPAL COMPONENT REGRESSION WITH ARTIFICIAL NEURAL NETWORK TO IMPROVE PREDICTION OF IN ELECTRICITY DEMAND

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Abstract: *Planning for electricity demand is a key factor for the success in the development of any countries. Such success can only be achieved if the demand for electricity is predicted correctly and accurately. This study introduces a new hybrid approach that combines Principle Component Regression (PCR) and Back-Propagation Neural Networks (BPNN) techniques in order to improve the accuracy of the electricity demand prediction rates. The study includes 13 factors that related to electricity demand, and data for these factors have been collected in Malaysia. The new combination (PCR-BPNN) starts to solve the problem of collinearity among the input dataset, and hence, the reliability of the results. The work focuses also on the errors that recoded at that output stage of the electricity prediction models due to changes in the patterns of the input dataset. The accuracy and reliability of the results have been improved through the new proposed model. Validations have been achieved for the proposed model through comparing the value of three performance indicators of the PCR-BPNN with the performance rates of three major prediction models. Results show the outperformance of the PCR-BPNN over the other types of the electricity prediction models.*

Keywords:*electricity demand; accuracy and reliability, principle component analysis; multiple linear regressions; Back-Propagation Neural Network.*

1. Introduction

Energy demand prediction models play a vital role for policy makers in developing and developed countries[1]. To draw efficient and active plans, it is very important that result of such prediction models be accurate and reliable. Demand on electricity, which is a type of energy is very important in Malaysia as the growth of population and economic affects positively on the rate of electricity consumption during 1995-2013. Economist in Malaysia depends on accurate prediction for the reason that a single percentage of error may lead to gain or loss of great budget (millions of Ringgit) [2]. The overestimation of demand for electricity will create unnecessary idle capacity resulting in wasted financial resources while the underestimation of demand would lead to possible power failures devastating to the country's economy and life styles. Therefore, it will be advisable to use a model with high accuracy for predicting electricity demand so as to avoid costly mistakes [3].

There are many reasons behind the weak accuracy and reliability of the electricity prediction models. One of them is the properties of the input dataset, such multicollinearity among independent variables and pattern changes of the input variables [4]. Researchers employed different linear, nonlinear, and hybrid systems to get electricity prediction rate for different countries. One of the most important and widely employed methods is the expression of several independent parameters in response to the dependence parameter. This method is nominated as Multiple Linear Regression model (MLR) [5]. A big advantage of the MLR model is simplicity of computation to make predictions within a short time frame, involves lower costs and easy to use in explaining the relationship between input and output parameters [6]. According to [7], [8], [9], [10] and [11] multiple linear regression models were utilized to predict electricity demands in various countries. However, when independent variables are strongly correlated, MLR based models face serious difficulties (prediction rates considered as unreliable) [5]. One of the statistical approach for removing the multicollinearity problem and to reduce the complexity of independent variables is Principle Component Analysis (PCA) [12]. PCA is able to convert high correlated input data set to uncorrelated ones [13]. Therefore, various literature refer to using the PCA technique to select the optimal number of input features (independent variables) for any prediction models [5]. According to[14], [15] and [16], the PCA technique was used with linear model to improve the accuracy prediction model for electricity demand. This combined approach is called the Principle Component Regression (PCR) model. However, PCA cannot overcome the inability of linear models to analyze nonlinear patterns of input dataset [17]. Therefore, researchers have been attempting to develop another model to capture nonlinear datasets because there are several nonlinear variables that affect electricity demand rates.

The Back-Propagation Neural Network (BPNN) model is a suitable method for handling nonlinear independent variables and provides a good accuracy prediction model [18]. According to [19], Artificial Neural Network (ANN) method can be applied for knowledge extraction without considering the nature of non-linearity. According to [20], [21], [22] and [23], the ANN based model were used as a tool to predict electricity demand in various countries. The results indicated that the ANN model is better than other linear and nonlinear based models. Therefore, the advantage of a nonlinear tool, particularly the ANN model is to provide better accuracy for prediction of electricity demand than other linear models including the ones that prefixed with PCA statistic technique [24]. On the other hand, the ANN will not give accurate predictions when there are both linear and nonlinear variables in the same dataset [18], [25]. It is clear that prediction models which depend on single technique are not an appropriate solution for getting accurate demand rates. At output stage of any single based prediction models high rates of residual errors will be obtained, which have great impact on accuracy rate.

To overcome the problems come from mixed pattern datasets, hybrid approach can be utilized, which is a combination of linear and nonlinear approaches. The best use of the combined approach is in capturing different patterns (linear and nonlinear) in the input dataset. There are many ways for achieving this combination. One of them, which followed by this work, is getting the preliminary prediction rate using linear approach. Then, recording the residual errors at the output stage of the linear part and analyze them using nonlinear approach. Finally, the preliminary results from the linear part and the output of the error analysis from the nonlinear part will be combined. The output of this combination gives the final rate of electricity prediction demand. The part of this work is also to find out the best combination (hybrid) approach in prediction of electricity demand for Malaysia. The main purpose for determining this hybrid approach is to improve the accuracy of electricity demand prediction rate. This work uses PCR, which is a combination of PCA and MLR, to get the preliminary prediction, and utilizes ANN to analyses the residual errors. The final combination approach that proposes by this work is PCR-BPNN.

2. Features and Data collection

In this study thirteen parameters have been involved. These parameters are reflecting the long term based demand rate of electricity. The factors are population, GDP, GNP, Income per capita, employment, exports, imports, tourist arrivals, carbon emissions, Consumer Price Index, mean climate, industrial electricity and residential electricity. Factors can be grouped as below:

1- Some of the factors have economic reflect such as GDP, GNP, Income per capita, export, and import. It is clear that growth of economic has great impact on energy consumption, such as electricity usage. The mentioned factors can be represented as main corners to estimate the level of economic growth for any country. Any growth of these factors means growth of economic, and in turn increases the consumption rate of electricity.

2- The second factor is reflecting the number of people in an area. It covers the population, the employment number, are tourist arrivals. It is clear that electricity consumption has direct relationship with number of usages. More population in an area means usage of more cooling systems, heating systems, more lightning, and more using electrical devices.

3- Some factors related to the environmental issues, such as carbon emissions and mean climate. Usage behavior of electricity is changing with the climate and environmental impacts. Increasing temperatures or humidity, which are climate related, changes the type of the cooling or heating system usage in an area. Based on these factors, the consumption rates will increase or sometimes will decrease.

4- Some factors affect the consumer behavior such as consumer price index. This factor always affects negatively on electricity consumption rare. Increasing the price mostly decreasing the rate of consumption of an area.

5- Finally, there are some factors have direct impact on increasing the rate of consumption, which are industrial electricity consumption rate and residential consumption rate. Expanding the area or the number of these factors has direct impact on increasing the rate of electricity consumption.

There are also many factors, such as end use rate of consumption, have not involved in this study as they have short term impact of the consumption and demand rate of electricity. The end use behaviour is changeable from day to day based on the daily requirements. This leads that their impact could not be considered in datasets that their time span is about 20-25 years.

Records for these factors are collected from Malaysian Statistical Department. Historical data for these factors are coming in the time span of 1995 to 2013, as shown in the Figure 1.

Population (X_1)	Employment Number (X_2)	Tourist Arrival (X_3)	GDP (X_4)	GNP (X_5)	Income per Capita (X_6)	Export (X_7)	Import (X_8)	Carbon Emission (X_9)	Mean Climate (X_{10})	Price index of consumption (X_{11})	Industrial consumption (X_{12})	Residential consumption (X_{13})
204.77	20.22	19.26	3.79	75.10	144.59	129.09	69.02	12.57	0.79	0.28	16.52	7.38
206.12	20.90	19.91	3.76	75.55	151.12	139.26	64.24	12.75	0.80	0.28	16.97	7.52
207.47	21.57	20.56	3.84	76.00	153.63	147.43	69.47	12.03	0.95	0.27	18.61	7.77
208.82	22.25	21.21	3.91	77.45	154.16	148.60	74.69	12.10	0.93	0.32	18.86	7.79
209.17	23.03	21.96	3.96	78.34	156.66	152.00	73.86	12.21	0.95	0.27	18.97	7.83
210.52	23.81	22.70	4.01	81.22	159.17	155.40	73.04	12.32	0.96	0.31	19.28	7.85
211.87	24.59	23.45	4.16	82.11	161.68	158.80	72.21	12.42	0.98	0.29	19.78	7.86
212.23	25.37	24.19	4.31	83.99	164.19	162.20	71.38	12.53	0.96	0.33	20.29	7.90
213.59	26.07	24.81	4.43	84.42	169.16	162.07	69.06	12.51	0.89	0.30	21.27	7.91
214.96	26.78	25.43	4.54	84.84	174.13	161.95	66.74	12.50	0.90	0.29	22.26	7.92
216.33	27.48	26.05	4.66	85.27	179.10	161.82	64.42	12.49	0.96	0.29	23.24	7.92
217.69	28.18	26.67	4.77	85.69	184.07	161.70	62.10	12.47	0.91	0.27	24.22	7.94
219.10	28.22	26.70	4.74	85.77	197.76	170.42	60.48	12.21	0.92	0.26	24.19	7.96
220.51	28.25	26.73	4.70	85.84	211.44	189.15	58.85	11.94	0.93	0.27	24.17	8.22
221.92	28.29	26.76	4.66	85.92	225.12	187.87	57.23	11.68	1.13	0.29	24.14	8.48
223.34	28.32	26.79	4.62	86.00	238.80	196.59	55.60	11.41	1.20	0.27	24.11	8.74
224.78	28.76	27.09	4.28	86.59	246.09	193.25	61.53	11.25	1.20	0.26	24.56	8.77
204.77	20.22	19.26	3.79	75.10	144.59	129.09	69.02	12.57	0.79	0.28	16.52	7.38
206.12	20.90	19.91	3.76	75.55	151.12	139.26	64.24	12.75	0.80	0.28	16.97	7.52
207.47	21.57	20.56	3.84	76.00	153.64	147.43	69.47	12.03	0.95	0.27	18.61	7.77
208.82	22.25	21.21	3.91	77.45	1541.56	148.60	74.69	12.10	0.93	0.32	18.86	7.79
209.17	23.03	21.96	3.96	78.34	1566.66	152.00	73.86	12.21	0.95	0.27	18.97	7.83

Figure 1. Part of the Historical dataset 1995 – 2013

3. Work Methodology

The methodology of this work is going on through analyzing data in the following ways:

1. Finding out the reduction of features without losing information comes in all thirteen variables. Through this process two important things (reliability and complexity) can be analyzed.
2. Finding out a model that can predict electricity demand rate at higher accuracy.

To achieve that, this work utilizes the following techniques:

a) Principle Component Analysis (PCA) as feature reduction.

b) As prediction models; combination between Multiple Linear Regression (MLR) and Back Propagation Neural Network (BPNN) with PCA

The data analysis was conducted three methodologies based on principal components such as PCR as a linear model, PCANN as a nonlinear model and PCR-BPANN as a Hybrid approach

3.1. Dataset preparation

Data that used for electricity prediction model have to meet the following:

1. It should cover all information and independent variables that related to electricity demand, and
2. It should be as small dimensionality as possible to reduce the complexity and speed up the execution of the proposed model.

Meeting these two requirements is a tradeoff. Involving as much variables as possible makes the model more reliable as variables that have impact on electricity will be included all in the calculation. Only in that case results of prediction models can be considered by decision makers. However, increasing number of independent variables leads to finding more correlated variables in the dataset. This will affect the reliability of the results, and increase the complexity and execution time of the proposed models. For that, at this stage the work involves all variables that have impact on electricity demand. At the same time, the work utilizes PCA technique to minimize the dimensionality size of the dataset in a condition of keeping the information that provided by the original dataset in the reduced one.

At this step, this work involves all thirteen variables that have been considered in most works and studies that conducted during 2000-2013. The work covers most variables that have impact on demand rate. The work checks the impact of this increase of variable number on the possibility of finding more correlated variables inside the dataset. Figure 2 shows the correlation among the variables.

Variables	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}
X_1	1.00												
X_2	0.97	1.00											
X_3	0.96	0.98	1.00										
X_4	0.86	0.93	0.95	1.00									
X_5	0.97	0.95	0.98	0.88	1.00								
X_6	0.98	0.98	0.95	0.86	0.94	1.00							
X_7	0.97	0.97	0.97	0.88	0.96	0.98	1.00						
X_8	0.96	0.97	0.99	0.92	0.97	0.95	0.97	1.00					
X_9	0.78	0.79	0.69	0.65	0.65	0.81	0.75	0.70	1.00				
X_{10}	0.86	0.87	0.79	0.73	0.79	0.86	0.80	0.81	0.71	1.00			
X_{11}	0.55	0.60	0.62	0.61	0.58	0.54	0.56	0.62	0.39	0.53	1.00		
X_{12}	0.88	0.85	0.94	0.84	0.96	0.85	0.91	0.92	0.48	0.64	0.56	1.00	
X_{13}	0.97	0.96	0.99	0.90	0.99	0.95	0.97	0.98	0.69	0.78	0.60	0.95	1.00

Figure 2. Correlation coefficient among the independent variables

As the correlation among the independent variables shows high records, results of any prediction models with such input dataset will not be considered as reliable, even, if it has high accuracy rates. Therefore, this work is proposing the PCA technique for two reasons; the first is removing the correlation among the independent variables. The second is reducing the number of features to as minimum as possible in a condition that information in original dataset should be kept in the reduced dataset with a percentage of at least 80% [26]. Only with the present of these two conditions, the optimum number of PCA that can be fed to the prediction models instead of original features can be determined. The satisfaction of these two conditions could be measured through cumulative percent variance (CPV). From Figure 3, the change of the CPV will be straight line at 97.52%, and accordingly, as shown in the figure, only four PCs can be considered for next stage as a less dimensional and uncorrelated input dataset.

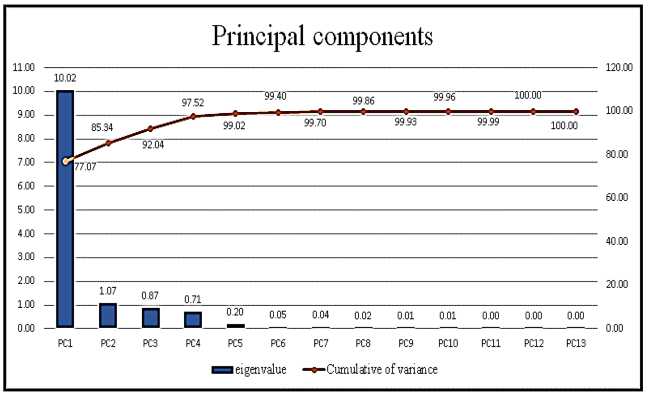

Figure 3. Explained Eigenvalue and accumulative of variance

Another test is to check the eigenvalues that will be obtained through the process of PCA calculation, and compare them with CPV values. Table 1 shows the result of PCA calculation for finding the eigenvalues. The table provides the variance of the total original parameters. The four largest eigenvalues in thirteen characteristic roots exist in a variable correlation matrix comparison of 10.02, 1.73, 0.87 and 0.71 respectively with the cumulative contribution to the total explained variance as %99.2. The first four PCs explain the most information from the original dataset and is extracted and therefore, the study can fed just five PC complements instead of all 13 independent variables. This process reduces the dimensionality of the independent variables, and keeps the original information up to 97.52%. The four selected PCs will be fed to three proposed electricity demand prediction models to find out the best accuracy. The aim of the use of three different techniques is to check the impact of linearity and nonlinearity patterns of input dataset on the accuracy rate of prediction models.

Table 1: Total of Variance

components	Eigenvalue	Variance %	Cumulative %
PC1	10.02	77.070	77.07
PC2	1.07	8.267	85.34
PC3	0.87	6.703	92.04
PC4	0.71	5.478	97.52
PC5	0.20	1.507	99.02
PC6	0.05	.380	99.40
PC7	0.04	.296	99.70
PC8	0.02	.156	99.86
PC9	0.01	.069	99.93
PC10	0.01	.039	99.96
PC11	0.00	.021	99.99
PC12	0.00	.010	100.00
PC13	0.00	.004	100.00

Finally, this work checks whether the reduced dataset has information from all or not. Table 2 shows each PC with reference to the independent variables. Each component related some original independent variables such as PC_{1i} that more related to the population (POP), GDP, GNP, Income per capita, exports, imports, tourist arrivals, industrial electricity and residential electricity factors and PC_{2i} that more related to climate. While, PC_{3i} more related to Consumer Price Index (CPI) factor. The last component PC_{4i} related to carbon emissions (CO_2) factor.

Table 2: Relation between PCs and included Variables

	Component			
	PC1	PC2	PC3	PC4
POP	**0.985**	-0.076	0.008	0.033
GDP	**0.988**	-0.006	0.032	0.087
GNP	**0.991**	0.086	-0.031	-0.070
income per capita	**0.916**	0.141	-0.034	-0.031
Employment	**0.979**	0.038	-0.027	-0.148
export	**0.981**	-0.093	0.039	0.097
import	**0.986**	-0.006	-0.033	0.013
Tourist	**0.986**	0.087	-0.032	-0.032
CO2	0.661	-0.215	-0.075	**0.708**
CPI	0.365	-0.432	**0.817**	-0.106
climate	-0.087	**0.873**	0.424	0.217
Industrial electricity	**0.915**	0.144	-0.093	-0.316

Residential electricity	**0.986**	0.085	-0.051	-0.076

3.2. Linear Model

Principle component regression (PCR) is selected as a linear model to check the respond of such type models to different pattern types of input dataset. PCR is resulted from the combination of Multiple Linear Regression (MLR) and PCA. Fist, PCA will convert a *P* number of features to *K* number of PCs (*K* should always be less than *P*). Then, the output of PCA will be fed to MLR to get the prediction rate. The general equation for a PCR model can be formulated as shown in the equation1.

$$Y_i = \beta_1 PC_{1i} + \beta_2 PC_{2i} + \cdots \ldots\ldots + \beta_k PC_{ki} + \varepsilon_i \quad \textit{Equation}.1$$

Where:
Yi,is the dependent variable (gives the prediction rate of electricity demand in *Kote*),
PCi,is the new uncorrelated independent variables,
$\boldsymbol{\beta_k}$,is the regression coefficient of $\boldsymbol{PC_i}$and***εi***is the random error.

According to Table1 and Table2, the value of *K* is equal to four. Therefore, the final equation of the MLR based prediction model will be as shown in the equation2:

$$Y_i(\mathrm{Ktoe}) = 0.959 \times PC_1 + 0.151 \times PC_2 - 0.070 \times PC_3 - 0.196 \times PC_4 \quad \textit{Equation 2}$$

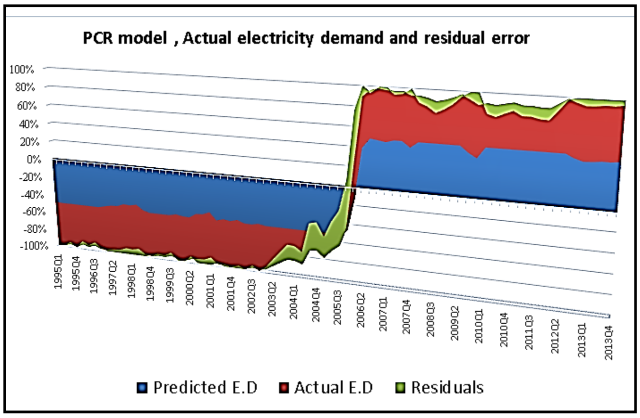

Figure 4. Predicted rate with PCR and actual rate of demand

Figure-4 shows the comparison between the regression model (PCR) and electricity consumption rate (Ktoe) in the actual dataset with the residual errors. This work utilizes MSE, RMSE, and MAPE as performance indicators to evaluate the errors. The indicators show 0.014, 0.121 and 41% respectively. The figure shows that not all parts for the both curves are fit. It means that PCR can fit and map input and output up to high accuracy. However, some nonlinear parts of the target still not fit in the picture.

3.3. Nonlinear Model

To test the input dataset patterns with nonlinear model, this work proposes the PCBPNN. The architecture is consisting of PCA and BPNN. Any BPNN, typically, has three layers as shown in the Figure5. Input layer, hidden layer, and output layer. At each layer there are nodes called neurons. The number of each node at each layer changes with the change of the problem. The nodes at input layer are four, which is the number of the selected PCs. The output layer has only one node, which gives the predicted rate of electricity demand.

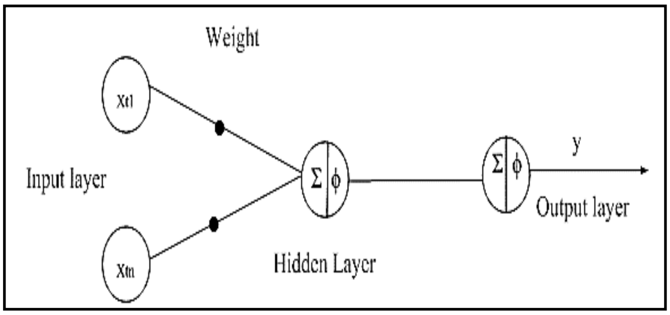

Figure 5. Architecture of a PCANN

$$y_i = f\left(\sum_{i=0}^{n} w_{ij}\, x_{ij}\right) \qquad \textit{Equation 3}$$

Where
Y_j is the output of node *j*,
f (.) is the transfer function,
w_{ij} the connection weight between node *j* and node i in the lower layer and
X_{ij} is the input signal from the node i in the lower layer to node *j*.
Equation 3. Presented the neural network was a biased weighted sum of the inputs and passed the activation level through a transfer function to achieve the output. The units of a network were ordered in the form of layered feed forward structure.

The most popular neural network training algorithm is back-propagation neural network (BPNN). This type of NN is used for the regression purpose. It is proven that the architecture of back propagation neural net is a proper model for a long term based prediction models [20]. Therefore, this work uses BPNN, which also can capture more nonlinearity dataset. The hidden layer part of NN supports such approach to learn nonlinear pattern. This study used only one hidden layer

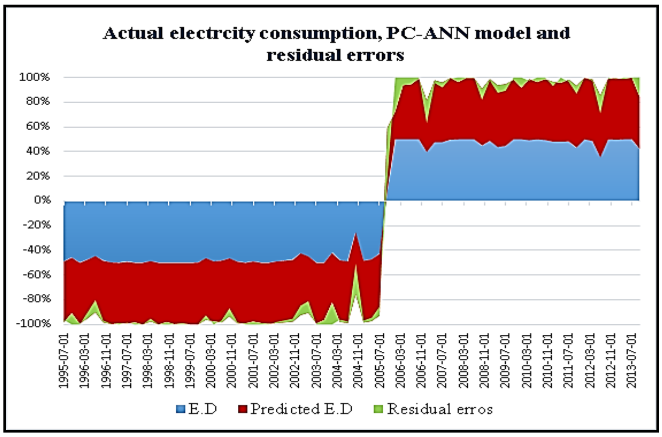

Figure 6. PC-ANN model and actual data on electricity demand

Figure 6 provides the results of applying the PC-BPANN nonlinear model. The model can provide more accurate than the linear model. The MSE, RMSE and MAPE for PC-BPNN model are 0.010, 0.1039 and 12%.

3.4. Hybrid Approach

The combination of two sub-models (PCR and BPNN) formed PCR-BPNN, which stands for (Principle Component Regression – Back Propagation Neural Network). Each sub model has its own output, and the idea of PCR-BPNN is combining these two outputs together in order covering both linear and nonlinear patterns of input dataset in the prediction process.

The methodology of this hybrid approach is built on computing the direct relation between the demand rate with changes of linear and nonlinear parts of input dataset. This concept is illustrated in equation4.

$$y_t = L_t + N_t \qquad Equation\ 4$$

Where,

L_t is the linear component analysis and

N_t is the nonlinear component analysis.

To estimate both components the following techniques are implemented:

PCR is applied to provide a preliminary prediction electricity demand model. Moreover, the work also obtains residual errors from the PCR using equation 5.

$$e_t = y_t - \hat{L}_t \text{Equation 5}$$

Where

e_t is the error (residual) from PCR model at the time t,

y_t is dependent variable of electricity demand and

$\hat{L}_t$ is the preliminary predicted value for the time t.

Finally, BPNN is utilized for the resulting error (residual) from a linear model (PCR) employing equation 6.

$$\boldsymbol{e_t = f(e_{t-1}, e_{t-2}, e_{t-3}, \ldots, e_{t-n}) + \varepsilon_t \quad \text{Equation 6}}$$

Where f nonlinear function is determined by BPNN model and ε_t is the random of error. Then the output is a prediction of residual from the BPNN is denoted $\hat{J}$ and the combined predict will be shown the by this equation 7.

$$\boldsymbol{\hat{y} = \hat{L}_t + \hat{J}_t \text{Equation 7}}$$

Therefore, we arrive at the preliminary prediction via the PCR linear model then improve the total prediction for the nonlinear model using BPNN. The idea of this hybrid system can be found in [27]. Figure 7 shows the framework for this combination method.

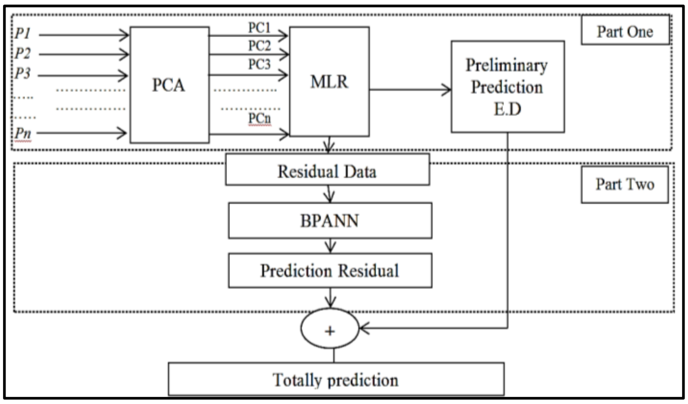

Figure 7.Framework of hybrid approach

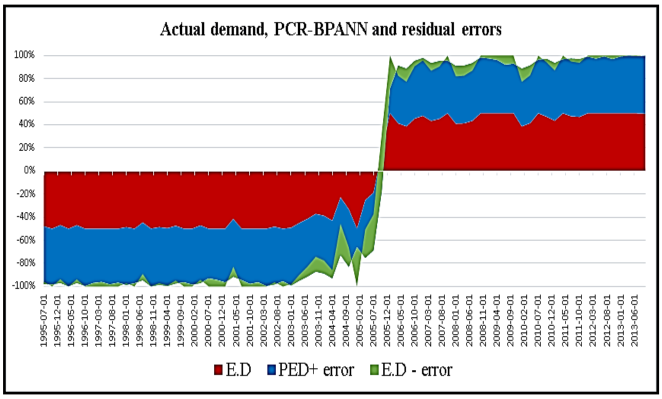

Figure 8.Hybrid approach (PCR-BPNN) and actual data on electricity demand

4. Results and Discussion

Table 3 gives the performance indicator values for linear model (PCR), nonlinear model (PC-BPNN) and hybrid approach (PCR-BPNN). Based on the mean square error (MSE), root mean square error (RMSE) and mean absolute percentage error (MAPE) those three different criterions to measure values of error.

The result showed that the PCR-BPNN model has better prediction accuracy than other two models.

Table 3 compression of performance indicators

Statistical parameters	PCR linear	PC-BPNN nonlinear	PCR-BPNN hybrid
MSE	0.014	0.010	0.0044
RMSE	0.121	0.1039	0.0665
MAPE%	41%	7%	5%

Table 4 Comparison of the real dataset with predicted dataset

Q.years	Actual output	PCR	PC-NN	PCR-BPNN
1995.3	3990.75	3963.54	3796.16	4030.53
1995.4	4106.00	3952.89	3816.96	4104.56
1996.1	4211.00	4056.32	4069.97	4098.76
1996.2	4316.00	4265.43	4399.80	4232.71
1996.3	4421.00	4244.36	4387.87	4402.47
1996.4	4526.00	4292.88	4438.78	4395.92
1997.1	4490.50	4305.43	4398.29	4345.18
1997.2	4455.00	4454.74	4471.32	4348.18
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2013.4	13256.00	12834.59	13528.81	12978.07

From the results in Table 4, the actual value of electricity demand 1995.3 was 3990.75 Ktoe and in the year 2013.4 is 13256.00 Ktoe. The electricity consumption computed using PCR-BPNN model is 4030.53 Kote at 1995.3, and 12978.07 at 2013.4 which are better estimated than other models.

To predict electricity demand for future (2014 to 2020), this study utilized PCR-BPNNs. Estimated rate of electricity prediction are shown in the table-7.

Table 5, Predicted electricity demand for 2014-2020 by PCR-BPNN model

Year	Predicted Output (Ktoe)
2014	13476.0485
2015	13994.8025
2016	14743.6516
2017	15052.4606
2018	15861.1627
2019	16270.0381
2020	16678.6722

5. Conclusion

The accuracy of predicting the electricity demand is quite important for effective implementation of energy policy. This paper has demonstrated that a more accurate prediction model for electricity demand is a hybrid approach that jointly combines with the PCR linear model and the BPNN nonlinear model. The goal of utilizing this combination was to capture different patterns of the independent variables. The PCR model is a suitable model to cover a linear dataset. However, the PCR model could not capture the nonlinear data part. Using BPNN model provides the work ability to accurately fit the nonlinearity part to the residual error that the PCR model could not capture. The BPNN model provided a better result than the PCR model based on the performance indicator measures. Hence, the significance of this combination method is improving the prediction electricity demand model. Additionally, the results of RMSE and MAPE show that this hybrid system is more accurate than any other model. Finally, this hybrid combination can be used in modelling applications in other areas.

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