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INDIA'S ELECTRICITY DEMAND FORECAST USING REGRESSION ANALYSIS AND ARTIFICIAL NEURAL NETWORKS BASED ON PRINCIPAL COMPONENTS

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Abstract
Power System planning starts with Electric load (demand) forecasting. Accurate electricity load forecasting is one of the most important challenges in managing supply and demand of the electricity, since the electricity demand is volatile in nature; it cannot be stored and has to be consumed instantly. The aim of this study deals with electricity consumption in India, to forecast future projection of demand for a period of 19 years from 2012 to 2030. The eleven input variables used are Amount of CO_2 emission, Population, Per capita GDP, Per capita gross national income, Gross Domestic savings, Industry, Consumer price index, Wholesale price index, Imports, Exports and Per capita power consumption. A new methodology based on Artificial Neural Networks (ANNs) using principal components is also used. Data of 29 years used for training and data of 10 years used for testing the ANNs. Comparison made with multiple linear regression (based on original data and the principal components) and ANNs with original data as input variables. The results show that the use of ANNs with principal components (PC) is more effective.

Keywords:
Artificial Neural Networks, Electricity Load Forecasting, Regression Analysis, Principal Components

1. INTRODUCTION

Power system development starts with the forecast of future demand. The consumption of electricity in India has increased around 10% annually from 2000 to 2009. It is the primary prerequisite for achieving the goal of optimal planning and operation of power systems. Electrical Energy is one of the most important sources for social and economic development of all nations. The growth in energy consumption is essentially linked with the growth in economy. Electricity demand increases due to the population growth, higher per capita consumption, and rapid development of industrial & commercial sectors, higher Gross Domestic Product (GDP) growth and structural changes in the economy of India with other countries. Further more government policies concerning the energy sector development in world energy markets will play key roles in the future patterns of energy production and consumption [1]. Load forecasting is very important for the reliable and economical operation of the power system. Modeling and prediction of electricity consumption play a vital role in developed and developing countries for policy makers and related organizations. The underestimation of the demand would lead to potential outages that are devastating to life and economy, whereas the overestimation would lead to unnecessary idle capacity which means wasted financial resources. Therefore, it would be better to model electricity demand with good accuracy in order to avoid costly mischievous [2].

The long term forecasting (more than a year ahead) is used to determine the capacity of generation, transmission or distribution system additions and the type of facilities required in transmission expansion planning, annual hydro thermal maintenance scheduling, etc. So, the time lines and accuracy of long term forecasting have significant effects on power system planning to construct new power generation plants and transmission facilities to meet the power demand in the future [3].

Several methods have been developed to perform accurate long term load forecasting. These methods are normally classified into two categories: conventional approaches and technique based on artificial intelligence. Load forecasting approaches based on conventional methods forecast current value of a variable based on the mathematical combination of the previous values of that variables and current values of other variables [4]. Traditionally Regression models have been the most popular in load forecasting and used to model the relationship between the load and external factors. A further advantage is that the relationships between input and output variables are easy to comprehend [5]. Chavez et al. (1999) used Auto Regressive Integrated Moving Average (ARIMA) time-series analysis models based on Box-Jenkins method to formulate the forecasting model for the prediction of energy production and consumption in Asturias, Northern Spain [6]. Hor et al. developed a multiple regression model for the prediction of load demand in England and Wales [7]. Their aim was to provide an accurate model for a long-term prediction for the monthly demand and the evaluation of the model was done by using Mean Absolute Percentage Error (MAPE). Asber et al. dealt with the development of a reliable and efficient Kernel regression model to forecast the load in the Hydro Québec distribution network [8]. Li Yingying et al. used principal component regression in power load forecasting for medium and long term [9].

Since the 1980s, Artificial Neural Network (ANNs) methods have received a great deal of attention and were proposed as powerful computational tools to solve the load forecasting problem [11]. AI-Saba and EI-Amin described the application of ANNs to long-term load forecasting, they produced results were close to the actual data while using the ANNs [12]. Ghanhari et al proposed the application of ANNs and Regression Analysis (RA) for Iran's annual electricity load, using GDP and Population variables [13]. Forecasting accuracy of each approach is evaluated by calculating Mean Absolute Error (MAE), the MAPE and Root Mean Square Error (RMSE). Bohman Kermanshahi et al. used multilayer Perceptron and recurrent neural networks for prediction of peak electric loads in Japan up to the year 2020, using variables such as gross national product, GDP, population, number of households, number of air-conditioners, amount of CO2 pollution, index of industrial production, oil price, amount of energy consumption, electricity price, average temperature and maximum electric power of the previous year [14]. Kadir Kavaklioglu modeled Turkey's electricity consumption using the support vector regression based on population, GDP, imports and Exports [15]. Sackdara et al. used the RA and ANNs approaches for electricity demand forecasting, using GDP, number of population, number of household and electricity price variables and compared the two methods using MAPE [16]. Azadeh and Ghaderi reported the application of ANNs, time series and ANOVA to forecast electricity consumption. They found that ANN has better predicted values for total energy consumption [17]. Back propagation neural network used to predict the electricity consumption in which the load data and economic data can be acquired. However, the generalization performance of the network is reduced due to high dimension and serious relevance of the network, resulting in decreased prediction accuracy. The characteristics of principal component analysis method that can eliminate correlation between variables are used to analyze the principal component relations of observational data [18]. The uncorrelated new variable, designed by principal component, account for the majority of the original variance. In recent years combining multiple linear regression with PCA and ANN with PCA, are being used to predict ozone concentration and load forecasting [20, 18].

In this paper, electricity demand of India is forecasted by using RA, ANNs, combining RA with PC and combining ANNs with PC, which consider five input variables: Population, Per capita GDP, Imports, Exports and Per capita power consumption. This work reports, the use of a new technique using ANNs based on principal components, therefore combining statistical and artificial intelligence technique. This paper is organized as follows: section 2 describes selection of proper economic factors, section 3 describes proposed models, section 4 provides Simulation results and evaluation, finally section 5 concludes.

2. SELECTION OF PROPER ECONOMIC FACTORS

The input variables are selected based on the correlation between the electricity demand and related parameters such as economic factors for long term load forecasting. After a careful investigation the following variables are selected as the input variables:

1. Amount of CO_2 emission: Emission means the release of greenhouse gases and/or their precursors into the atmosphere over a specified area and period of time. The statistical coefficient of multiple determinations (R^2 value) for electricity demand vs. CO_2 emission is 0.998.
2. Population: It is generally believed that a large population growth rate will bring a huge increase in total energy consumption. In India, with continuous improvement in the public revenue and living standards, energy consumption will increase with the steady growth of population and industrialization. R^2 value = 0.996
3. Per capita GDP: Generally, Economic growth measured by per capita GDP is an important factor in energy consumption. Mainly economic growth shows the effect on energy demand. R^2 value = 0.986
4. Per capita gross national income: Gross national income comprises the total value of goods and services produced within a country together with income received from other countries. R^2 value = 0.987
5. Gross Domestic savings. R^2 value = 0.919
6. Industry: R^2 value = 0.945
7. Consumer price index: It examines the weighted average of prices of a basket of consumer goods and services, such as transportation, food and medical care. R^2 value = 0.993
8. Whole sale price index: R^2 value = 0.995
9. Imports: It consists of transactions in goods and services from non residents to residents: R^2 value = 0.876
10. Exports: It consists of transaction in goods and services from residents to non-residents. R^2 value = 0.891
11. Per capita power consumption: R^2 value = 0.995

3. MODELS

Multiple linear regression (MLR) and ANNs are used to predict the long-term electricity consumption in India using above selected economic factors. These same models, but based on principal component analysis (PCA), are also used. The MLR method with PCA is referred as PCR and ANN with PCA is referred as PC-ANN.

PCA was first proposed by Hotelling in 1933. PCA is a multivariate statistical method widely used in data analysis in diverge fields, because it is simple, nonparametric method. PCA is a variable reduction procedure. It involves a mathematical procedure that transform number of (possibility) correlated variables into a smallest number of uncorrelated variables called principle components (PC). The mathematical technique in PCA is called Eigen analysis: solve for the Eigen values and Eigen vectors of a square symmetric matrix with sums of squares and cross products. The Eigen vectors associated with the largest Eigen values have the same direction as the first PC. The Eigen vectors associated with the second largest Eigen values determines the direction of the second principle component. The sum of the Eigen values equals the trace of square matrix and the maximum number of Eigen vectors equals the number of rows (or columns) of this matrix.

MLR is a technique used for modeling and analysis of numerical data. It is an analysis of values of a dependent variable based on the values of one or more independent variables [4]. Linear regression is a form of RA in which observational data are modeled by a least squares function, which is a linear combination of the model parameters. In simple linear regression, the model function represents a straight line or parabola. The data model, which represents simple linear regression, can be written as,

$$Y = aX_1 + bX_2 + e$$

where, Y is the dependent variable (Electricity consumption), X_1 and X_2 are the independent variables (example: Population and

Per capita GDP), 'a' and 'b' are the regression coefficients and 'e' is the error term. The error term represents unexplained variation in the dependent variable and treated as a random variable. The parameters Population and Per capita GDP are estimated to give a best fit of the data. Typically, the best fit is evaluated by using the least squares method. Although these models are simply a linear and additive association of explanatory variables, they have been extensively used with satisfactory results [19].

ANNs are able to give better performance in dealing with the nonlinear relationships among their input variables [20]. It is proved that the multilayer perceptron with error back propagation is an appropriate model for long-term load forecasting [13] also one hidden layer is enough to approximate any function [19], if presenting enough hidden nodes. Therefore, multilayer perceptron has been chosen in this paper and the input variables are selected based on the correlation technique. The multilayer perceptron consists of (i) input layer (ii) output layer (iii) one or more hidden layers containing nodes which help to capture the nonlinearity in the data. A Neural Network can be trained to perform particular function by adjusting the values of weights between elements so that a particular input leads to a specified target output. Therefore, the network is adopted, based on a comparison of the output and the target. Using supervised learning, these networks can learn the mapping between one data spaces to others.

Normalization of data within a uniform range is essential (i) to prevent larger numbers from overriding smaller ones, and (ii) to prevent premature saturation of hidden nodes, which impedes the learning process [16].

In most cases, the ANNs are obtained using two distinct data sets: training and validation. The training data set is used to determine the network topology and the associated weights by solving a non-linear optimization problem with the objective function being dictated by the mean squared error (MSE). The validation data set is used to compute the ANN performance. Cross-validation is usually used to avoid the over fitting problem that often appears when applying ANN [19]. The best network topology corresponds to an ANN, which presents a minimum value of MAPE for the validation data set.

The application of PC in ANN model aims to reduce the collinearity of the data sets, which can lead to worst predictions and to determine the relevant independent variables for the prediction of electricity consumption. The difference between PC-ANN approach and the ANN method is that the input variables are used in ANNs method and PC are used in PC-ANN method. Consequently, the network architecture will be less complex due to the decrease of input variables.

4. SIMULATION RESULTS & EVALUATION

The input variables are selected based on the correlation coefficients between the electricity consumption and corresponding economic factors. These correlation coefficients provide the measure of the relation between the two variables. High correlation coefficient was found between these input variables and predicted output variables. Therefore these variables were used to provide the future electricity consumption in India. The statistical package for social studies (SPSS) are used for applying RA and ANNs and XLPro are used for applying PCA on a desktop PC with system configuration Intel Core2duo CPU, 2.67 GHZ with 1 GB RAM.

RA and ANNs are used to predict the electricity consumption. These models are based on the original data (RA and ANNs) and on the PC (PCR and PC-ANNs). Table.1 shows the total variance of the original variables. The seven largest Eigen values in eleven characteristics roots exist in variable correlation matrix, respectively 10.072, 0.555, 0.341, 0.016, 0.010, 0.003, 0.002 and their cumulative contribution to the total explained variance is 99.99%. The first seven principal components provide the most information of original data and extracted.

Table.2 shows the components score coefficient matrix table reveals the system information of principal components with the original variables, which demonstrate the relative importance of each standardized predictors in the PC calculations.

The prediction of electricity consumption based on the eleven input variables such as Amount of CO2 emission, Population, Per capita GDP, Per capita gross national income, Gross Domestic savings, industry, Consumer price index, Whole sale price index , Imports, Exports and per capita power consumption. To apply the ANN model several network structure were tested to find most opt topology. The best architecture consisted of a three layer network with eleven neurons in the input and eight neurons in the hidden layer and one neuron in the output layer. Sigmoid and hyperbolic function were used as activation function in the neurons of hidden layer and output neurons. To evaluate the performance of the ANNs with back propagation algorithm (original variables as inputs) results are compared with the RA. Considering seven PC inputs, and applied for the above models. The best architecture consisted of a three layer network with eleven neurons in the input and eight neurons in the hidden layer and one neuron in the output layer.

Table.1. Total variance table

Components	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Eigen value	10.072	0.555	0.341	0.016	0.010	0.003	0.002	0.001	0.000	0.000	0.000
% variance	91.563	5.044	3.101	0.145	0.092	0.026	0.019	0.007	0.002	0.001	0.000
Cumulative %	91.563	96.607	99.708	99.853	99.945	99.971	99.990	99.997	99.999	100.000	100.000

Table.2. Principal Components score coefficient matrix

Variables	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
CO_2 emission	0.308	0.152	-0.291	0.174	0.025	-0.396	-0.175	0.695	0.102	-0.294	0.008
Population	0.237	0.732	0.637	-0.037	-0.037	-0.013	-0.005	0.002	0.000	-0.006	0.001
Per capita GDP	0.314	-0.025	-0.086	-0.144	0.173	-0.307	0.451	-0.138	0.075	0.158	-0.704
Per Capita GNI	0.314	-0.019	-0.093	-0.117	0.189	-0.305	0.456	-0.158	-0.028	0.133	0.706
GD saving	0.306	-0.259	0.199	-0.393	0.607	0.284	-0.267	0.221	-0.275	0.013	-0.014
Industry	0.311	-0.207	0.108	-0.146	-0.040	0.031	-0.256	-0.284	0.777	-0.267	0.053
CPI	0.309	0.107	-0.292	-0.384	-0.418	-0.177	-0.394	-0.342	-0.420	-0.076	-0.025
WPI	0.308	0.153	-0.301	-0.157	-0.321	0.630	0.220	0.281	0.175	0.328	0.026
Imports	0.297	-0.364	0.315	0.369	-0.250	-0.196	-0.254	0.083	-0.040	0.608	0.009
Exports	0.300	-0.339	0.275	0.225	-0.309	0.205	0.359	0.024	-0.294	-0.561	-0.030
Per capita Consumption	0.304	0.220	-0.304	0.632	0.356	0.256	-0.155	-0.374	-0.091	-0.034	-0.031

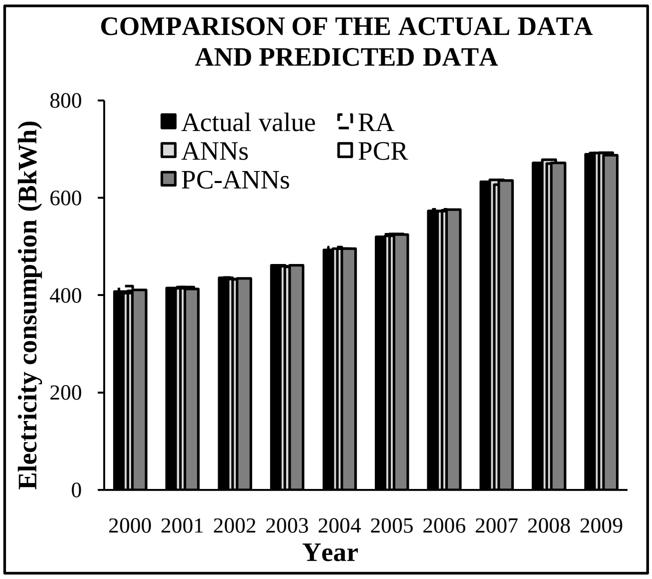

Fig.1. Comparison of Actual and Predicted data

Table.3. Comparison of Actual and predicted data

Year	Actual output (BkWh*)	Output (BkWh*)			
		RA	ANNs	PCR	PC-ANNs
2000	407.477	418.496	404.370	409.042	410.4932
2001	415.035	416.728	414.226	416.739	412.5651
2002	435.756	436.457	433.072	432.341	434.2804
2003	461.692	453.619	459.705	457.825	461.4266
2004	492.806	498.661	495.834	495.516	495.8465
2005	519.697	525.358	521.715	525.544	524.2425
2006	572.943	576.780	572.498	574.200	575.5584
2007	633.329	629.730	637.252	626.90	635.655
2008	671.878	666.569	678.328	670.726	671.9613
2009	689.537	692.052	692.360	692.806	687.9017

Note: * Billion Kilowatt hour

Sigmoid and Hyperbolic tangent function were used as activation function in the neurons of hidden layer and output neurons. The results obtained from the ANNs and RA approaches (both original variables and PC as inputs) are as follows as well as the bar chart of the results is shown in Fig.1 and Table.3.

For the purpose of evaluating forecasting capability, we examine forecasted accuracy by calculating the following statistical parameters in both training and validation stage. The statistical parameters are the root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Bias Error (MBE) is given by the Eq.(1 - 3).

$$\text{RMSE}=\sqrt{\frac{\sum_{i=0}^{n}(A_i - P_i)}{n}} \tag{1}$$

$$\text{MAPE}=\left(\frac{1}{n}\sum_{i=0}^{n}\left|\frac{(P_i - A_i)}{A_i}\right|\right)X100 \tag{2}$$

$$\text{MBE}=\frac{1}{n}\sum_{i=0}^{n} P_i - A_i \tag{3}$$

where, Pi, Ai are the predicted and actual values, and 'n' is the total number of predictions.

MAPE and RMSE measure the residual errors, which gives a global idea of the difference between the predicted and actual values. MBE indicates if the predicted data are over/under estimated. Table.4 presents the values of the statistical parameter results using RA and ANNs (original and PC data) for both training and validation stage. From the result in Table.3 and Table.4, the actual electricity consumption in the year 2000 was 407.477BkWh, and in the year 2009 was 689.537 BkWh. The electricity consumption calculated, using RA with original variables as input. The results were 418.496 BkWh and 692.052 BkWh for the year 2000 and 2009. The MAPE is 0.969, RMSE is 7.189 and MBE is 6.218. The electricity consumption calculated using ANN with original variables as input. The results were 404.370 BkWh and 692.360 BkWh for the same year. The MAPE is 0.507, RMSE is 3.160 and MBE is 2.77. The electricity consumption calculated using RA with PC as input.

Table.4. Statistical parameters achieved using RA and ANN (both original variable and PC inputs) during training and validation stages

Statistical parameters	**Training**				**Validation**			
	RA	**ANNs**	**PCR**	**PC-ANNs**	**RA**	**ANNs**	**PCR**	**PC-ANNs**
MAPE	4.602	2.095	2.033	2.651	0.969	0.507	0.597	0.430
RMSE	7.189	3.225	2.692	3.621	5.643	3.160	3.583	2.496
MBE	6.281	2.683	2.174	4.025	4.8262	2.727	3.121	2.147

The results were 409.042 BkWh and 692.806 BkWh for the year 2000 and 2009. The MAPE is 0.597, RMSE is 3.583 and MBE is 3.121. The electricity consumption calculated using ANN with PC as input. The results were 410.492 BkWh and 689.901 BkWh for the same year respectively. The MAPE is 0.507, RMSE is 3.160 and MBE is 2.77. The results for the year 2001 to 2008 are also presented in Table.3. Based on the comparison of the above four methods, the PC-ANNs method was more accurate. Future electricity consumption for the year 2012 to 2030 was calculated for electricity consumption forecasting with estimated input variables.

ANN models used to predict the future input variables such as amount of CO_2 emission, Population, Per capita GDP, Per capita gross national income, Gross Domestic savings, industry, Consumer price index, Wholesale price index, Imports, Exports and per capita power consumption. So, future predictions of electricity consumption are evaluated by PC-ANNs from the year 2012 to 2030. The results are given in Table.5.

Table.5. Predicted Electricity Consumption

Year	**Predicted Output (BkWh)**	**Year**	**Predicted Output (BkWh)**
2012	855.66	2022	1625.89
2013	920.69	2023	1721.75
2014	974.1	2024	1843.69
2015	1036.96	2025	1950.34
2016	1090.12	2026	2118
2017	1186.08	2027	2274.02
2018	1258.83	2028	2445.12
2019	1333.9	2029	2639.16
2020	1414.82	2030	2755.45
2021	1506.69		

The forecasted models have enhanced accuracy due to applying PC-ANN. The reports on 17-th electric power survey of India predict the electricity consumption in the year 2016-2017 is 1190.1 BkWh. But the predicted electricity consumption calculated using PC-ANNs was 1186.086 BkWh.

5. CONCLUSION

Forecasts are quite important for effective implementation of energy policies. In this paper, the net electricity consumption of India is modeled as a function of economic factors: Amount of CO2 emission, Population, Per capita GDP, Per capita gross national income, Gross Domestic savings, industry, Consumer price index, Wholesale price index, Imports, Exports and per capita power consumption. These economic factors (input variables) were selected through calculation of correlation coefficient. This way of selecting these factors for India is one of contribution of our paper. Two different approaches were used: one is original data, as input variables and the other is PC data as inputs. The results showed that the use of ANNs led to more accurate results than linear models (MLR and PCR).The electricity consumption is complex with multiple influencing factors, so regular prediction models do not well for its prediction due to the account of nonlinearities. The application of PC in this model was considered better than using the original data, because it reduced the number of inputs and therefore decreased the model complexity. Considering MLR and PCR, the statistical parameters were lower in PCR. PC-ANNs are better than ANNs, the use of PC based models was considered more efficient, due to elimination of collinearity problems and reduction of the number of inputs. So far less number of papers is available in the literature considering of PCA input for ANN, it is one of the major contribution of our paper. It was also verified that the proposed models PC-ANNs approach is suitable and accurate for prediction. Based on the results, it was better than other three models. In addition, the ANN model is flexible and can provide the optimal solution to predict the future demand.

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