A predictive approach for effective management and planning within the energy sector of South Africa

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Abstract

Being able to predict the future demand of electricity constitutes part of the issues utilities companies, policy makers and private investors willing to invest in developing countries are facing. The use of efficient, reliable electricity demand predictor would improve significantly the infrastructure planning and the expansion of power transmission. In this paper, the national demand for electricity at a macro level, based on data relating to macro level economic and demographic indicators was predicted using Artificial Neural Network (ANN). Forecasted values for five electricity sectors namely agricultural, transport, mining, domestic and commerce/manufacturing sectors were obtained using ANN. Four growth scenarios have been considered for the forecasting namely low, moderate, high (less energy intensive) and high (same sectors) scenarios. These inputs values for the period of 2014 to 2050, from the Council for Scientific and Industrial Research (CSIR), were used to test data and validate the use of this new approach for the prediction of electricity demand. The deviations between the predicted values using ANN and the recommended values by CSIR were well within an acceptable range. This study demonstrates that the use of ANN would improve significantly the decision making within the energy sector.

Keywords
Artificial Neural Network, Particle swarm optimization, energy, predictor, decision making

1. Introduction

The understanding of future patterns of electricity usage is crucial in various planning context, especially in developing countries such as South Africa. Electricity providers are interested in future national demand in order to plan and secure electricity supply (Imtiaz et al., 2006). Any plan to invest in electricity generation depends largely on the anticipation of the long-term need for electricity (Doriana et al., 2006). The growing population of country such as South Africa would have to take into account the implications on future electricity needs. This is necessary in order to ascertain that the electricity supply capacity is sufficient to support future plans.

In order to forecast future electricity demands, several factors external to the energy policies are generally considered. These factors includes the growth of the population, the performance of the economy, the advancement of the technology and the prevailing weather conditions. This could be a source of uncertainties because of the lack of reliable data in most developing countries due to the macroeconomic and political instability (Steinbuks, 2017). Hence, in order to illustrate the predictive approach proposed in this study, potential "drivers" of electricity, historical data were obtained from the South African Reserve Bank, Chamber of Mines and Statistics SA as documented in the Council for Scientific and Industrial Research report (CSIR) (2016). The Gross Domestic Product (GDP), the Final Consumption Expenditure of Households (FCEH), the Index for Manufacturing production volumes, the Index for Mining production volumes, the population, the number of households and average household size and the gold ore milled and gold ore treated, related to South Africa, are the drivers data considered in this study. Table 1 provides the details of the sources of the details used for the forecasting results reported in this paper.

Table 1. Sources of data

"Driver" data	**Source**
Gross Domestic Product (GDP)	Reserve Bank of South Africa
Final Consumption Expenditure of Households (FCEH)	Reserve Bank of South Africa
Index for Manufacturing production volumes	Statistics South Africa
Index for Mining production volumes	Statistics South Africa
Population	Statistics South Africa
Number of households and average household size	Statistics South Africa
Gold ore milled and gold ore treated	Chamber of Mines

The modelling of energy is receiving a widespread interest among engineers and scientists with a specific focus on energy production and consumption. Reasonable knowledge of past, present and likely future demands would make useful contributions to planning and policy formulation. A few approaches have been developed for the planning and prediction of future demands. The use of a fuzzy time series was suggested by Ismail et al. (2015). Better forecasted values and increased forecasting accuracy are reported in comparison to some selected approaches. Different regression models, based on co-integrated data, have been used by Bianco et al. (2009). Acceptable deviations, in comparison to the official projections have been observed. A fuzzy linear regression model for load forecasting has been developed by Al-Kandari et al. (2004). The results obtained strongly support the use of fuzzy model for reliable operation of electric power systems. Erdogdu (2007) proposed the use of ARIMA (AutoRegressive Integrated Moving Average) for the forecast of the electricity demand. This study was able to provide guidance on a better estimation of electricity demand in Turkey. Soares and Souza (2006) used the generalized long memory for the forecasting electricity demand that outperformed a benchmark model considered in their investigation. Artificial Neural Network (ANN) was used by Park et al. (1991) for the prediction of electric load. The results shows that ANN was very useful in order to interpolate and provide future load pattern, making this approach more flexible in comparison to other regression methods. The forecasting of monthly electrical energy consumption was done by Azadeh and Tarverdian (2007) based on Genetic Algorithm (GA). Apart from being flexible, the GA was able to identify best model for future electricity consumption forecasting as reported in this study. The feasibility of using Support vector machines to forecast electricity load was done by Pai and Hong (2005). This study reveals that the proposed model outperformed ARIMA model. The feasibility of applying chaotic particle swarm optimization algorithm was done successively by Hong (2009). It appears that this model outperformed the GA and the support vector machines for the forecasting of electric load as per the results reported. This is by no means all the existing forecasting models but it presents a good overview of the possibility to predict future electricity demands and plan accordingly. Table 2 summarizes some of the existing forecasting models in tabulated format.

Table 2. Forecasting models for electricity demands forecasting

Forecasting models	**Literature references**
Time series models	Ismail et al. (2015)
Regression models	Bianco et al. (2009)
Fuzzy linear regression	Al-Kandari et al. (2004)
ARIMA models	Erdogdu (2007)
Generalized long memory	Soares and Souza (2006)
Artificial Neural Network (ANN)	Park et al. (1991)
Genetic Algorithm (GA)	Azadeh and Tarverdian (2007)
Simulated annealing	Pai and Hong (2005)
Particle swarm optimization	Hong (2009)

The objective of this work was to explore the use of Artificial Neural Network (ANN) in creating a model of electricity forecast. This approach is based on: (a) the formulation of an ANN considering the GDP, the FCEH, the index for manufacturing and mining, the population growth, the number of household and the forecast for gold ore as inputs and the CSIR recommended annual electricity demands as outputs; (b) training the ANN with these CSIR recommended data; (c) verification (testing) of the ANN behavior with the CSIR data in order to ensure that the

proposed model is able to forecast successfully the electricity demand with data not used in the training and testing stage.
Singh et al. (2017) studied hourly short-term electricity load forecast using artificial neural network (ANN). Good prediction with less error in forecasting is reported. ANN has been used as a solution for short-term load forecasting in microgrids. The model has produced low errors compared to other simple models (Hernández et al., 2014). Chae et al. (2016) propose a short-term building energy usage forecasting model based on an Artificial Neural Network (ANN) model with Bayesian regularization algorithm. Their results demonstrate that the proposed model with adaptive training methods is capable to predict the electricity consumption. This is by no means all existing studies where ANN was used for the prediction within the energy sector. It provides a good overview of the possibility to implement this approach within the energy sector in South Africa. While this modelling technique is advantageous with regards to developing accurate mathematical model even when the phenomenon occurring during the process is not fully known, ANNs are incapable to extrapolate with accuracy (Arce-Medina and Paz-Paredes, 2009).

2. System model

System model for the proposed forecast of electricity demands in this paper is a multilayer ANN, where the network is trained for optimized value using Particle Swarm Optimization (PSO). System model for the proposed forecast of electricity demands consists of an ANN where all its neurons trained with PSO. This approach offers the possibility to alter the inputs data and analyze different scenarios as evidenced by the results reported in this study. Particle Swarm Optimization (PSO) has been implemented in many area of computational intelligence and optimization problems. PSO has proven to be successful in training ANNs as well. In this section, a brief description of ANN and PSO is provided in order to improve the readability of this work.

2.1 Artificial Neural Network (ANN)

ANN has neurons as fundamental elements. These neurons accepts inputs and produce outputs by performing a weighted sum while going through a transfer function. ANNs are organized into three different layers namely input layers, hidden layers and output layers (Figure 1). The actual computation takes place within the hidden layers, described as the root of the ANN.

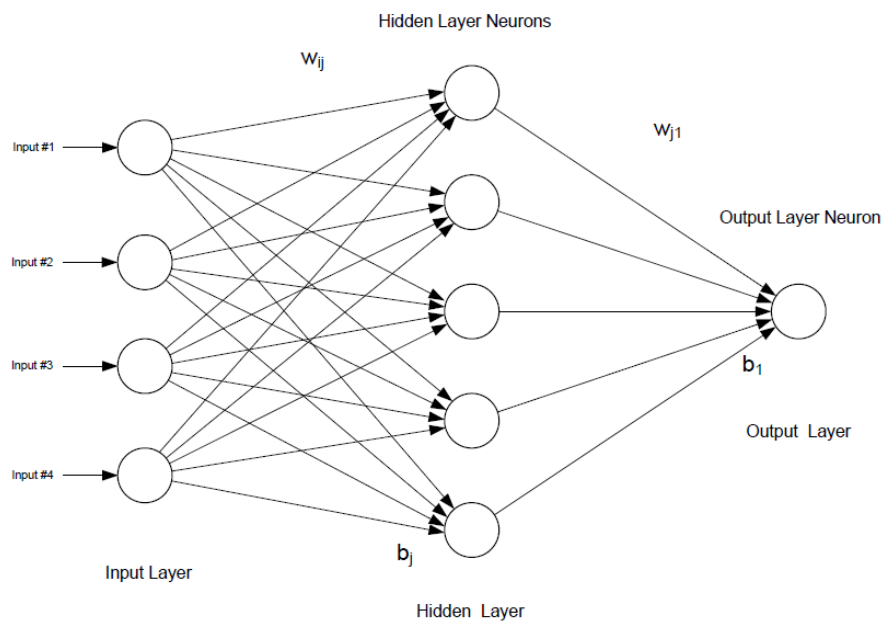


Figure 1. Typical ANN architecture

In order to train ANNs, back-propagation is the most common method (Rumelhart et al., 1986). A set of data that consist of inputs and desired output are normally used for the training of ANN. The following steps are adopted for the training (Das et al., 2014):

a. Reading of the inputs and desired outputs;
b. Computation of the result by weighted sum of inputs and passing through the transfer functions;
c. Comparison of the result with expected result;
d. Computation and updating of fitness value based on comparison;
e. Repetition of steps 2 and 3 until all training points are completed;
f. Adjustment of weights in the appropriate direction in order to optimize fitness;
g. Repetition of steps 1–6 until acceptable fitness value is obtained.

2.2 Particle Swarm Optimization

PSO exploits the cooperation between a population of individuals, where, each one influences the neighbours, and implement it in engineering optimization problems. A predefined set of rules are being followed by the particles. Based on the fitness function, PSO computes and identify a particle with a good solution. The particle having the best fitness is selected as teacher from who the other particles will learn from. With no identical particles, each particles learn from each other in order to improve their fitness.

PSO is able to train a network of networks. A number of ANN will be formed while all weights are being initialized to random values. A comparison between fitness of each network is done. The network with the best fitness is described as the teacher network (the global best). This network conducts the training of the others in order for them to update themselves. Each neuron is characterized by a position and velocity. The former corresponds to the weights of a neuron while the former is used to update and control the position. The position of the neuron from the global best is gradually adjusted in order for it to be closer to the global best. The training of swarm of neural networks is conducted as follows:

a. Examination of the training data and recording of the sum of the network errors, for each individual network;
b. In order to identify the best network in the problem space, all of the errors are compared;
c. If the desired minimum error is reach for any network, its weights will be recorded while exiting the program.
d. Else, PSO is run in order to update the position and velocity vectors of each network.
e. Repetition from step 1.

The minimal requirements for performance is linked to the statistical calculation also known as the multiple correlation coefficients given as follows (Das et al., 2014):

$$R^2 = 1 - \frac{\text{Fitness}}{\sum(\text{Recorded value} - \text{Mean recorded value})} \tag{1}$$

With the fitness given by:

$$\text{Fitness} = \sum(\text{Recorded value} - \text{network predicted value}) \tag{2}$$

The closer the multiple correlation is to one, the more accurate the network is. The MATLAB codes used to train the ANN using PSO is available in Alam study (2016).

3. Forecasted driver values used

The recommended demand forecasts for national consumption of electricity for the period 2014 – 2050, as recommended by CSIR, were used. In order to take into account the uncertainties regarding the future values of the drivers, considered in this study, into the electricity forecasts, four different scenarios have been specified (namely “low”, “moderate”, “high (less energy intensive or LI)” and “high (same sectors or SS)”). The range of all inputs and outputs parameters considered are given respectively in Table 3 and 4. Details of the data are available in the CSIR report (2016).

Table 3. Input parameters range

Parameters	**Range**
Population (in millions)	2014: 53.48
	2050: 67.19
Loss percentage across all scenarios	2014: 9.00
	2050: 11.50
Percentage GDP growth forecasts per scenario	2014: 1.57 (low); 1.57 (moderate); 1.57 (high LI); 1.57 (high SS)
	2050: 1.80 (low); 2.50 (moderate); 3.00 (high LI); 3.00 (high SS)
FCEH % growth forecasts per scenario	2014: 1.16 (low); 1.16 (moderate); 1.16 (high LI); 1.16 (high SS)
	2050: 2.40 (low); 2.98 (moderate); 3.19 (high LI); 3.55 (high SS)
Manufacturing index forecasts per scenario	2014: 106.4(low);106.4(moderate);106.4 (high LI);106.4(high SS)
	2050: 165.1(low); 299.7(moderate);241.5(high LI);400.1(high SS)
Forecasts for mining production index	2014: 102.7(low);102.7(moderate);102.7 (high LI);102.7(high SS)
	2050: 197.2(low); 231.1(moderate);207.8(high LI);339.9(high SS)
Forecasts for gold ore treated (million metric tons)	2014: 41.6 (low); 41.6 (moderate); 41.6 (high LI); 41.6 (high SS)
	2050: 33.5 (low); 38.6 (moderate); 27.0 (high LI); 39.8 (high SS)

Table 4. Output parameters range

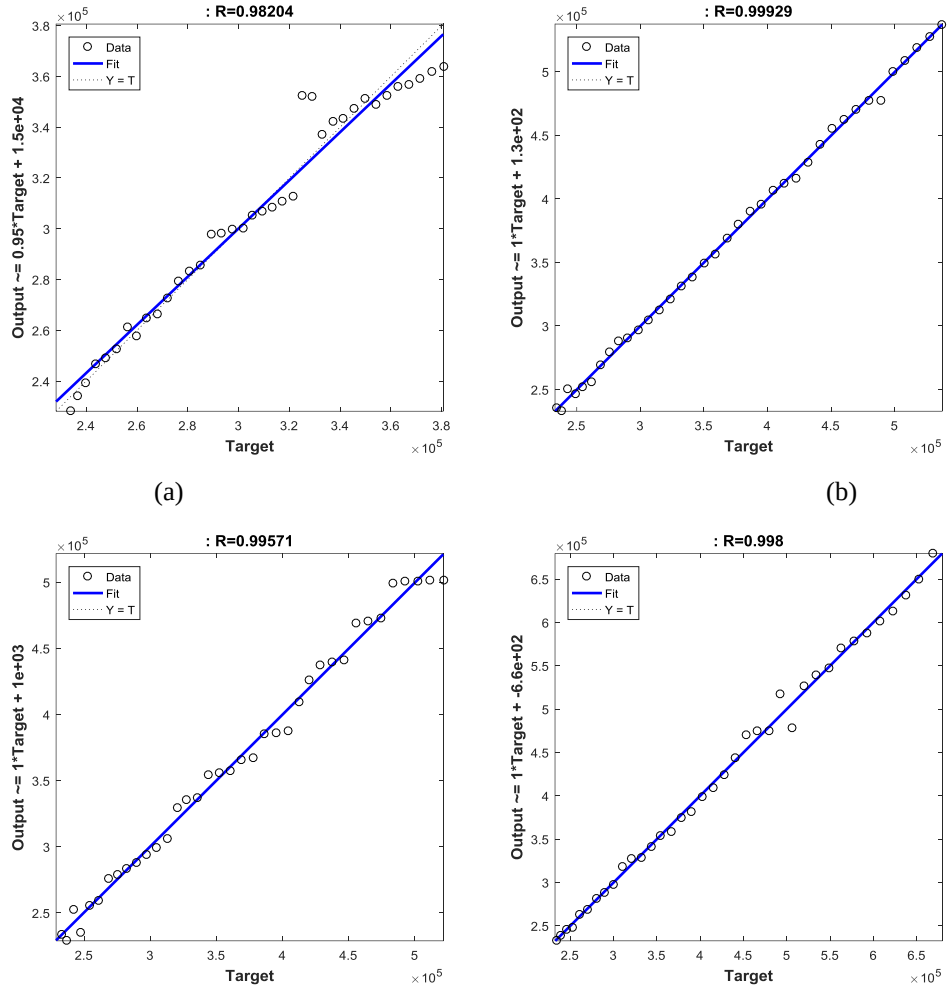
Parameters	Range
National electricity demand (GWh): CSIR recommended forecasts	2014: 233758 (low); 233758 (moderate); 232960 (high LI); 233758 (high SS)
	2050: 380591 (low); 537379 (moderate); 521559 (high LI); 668272 (high SS)

4. Results and discussions

The performance of the proposed ANN in predicting the electricity demands resulting for the period 2014-2050 for the four scenarios considered was satisfactory based on the higher values of regression between the predicted and target (National electricity demand) outputs during training, testing and validation phases as shown in Figure 2(a), (b), (c) and (d). The statistical coefficients of multiple determinations (R2-value) are equal to 0.98204, 0.99929, 0.99571 and 0.998 corresponding to the low, moderate, high less intensive and high same sector scenarios respectively. These R2-value are basic measures of the quality of fit. In this case, values of 0.98204, 0.99929, 0.99571 and 0.998 indicate respectively that 98.204%, 99.929%, 99.571% and 99.8% of the electricity demands variability are explained by linear regression. These regression plots suggests that the responses obtained from ANN for any new inputs data within the range considered are relatively acceptable.

The ANN and the CSIR recommended forecasts obtained for all four of the scenarios are shown graphically in Figure 3(a) and (b). The electricity forecasts are presented for the four different scenarios specified in this study. Similar trends were observed when comparing the results predicted with ANN and recommended by CSIR. In order to measure the ability of ANN to predict the electricity demands, the comparison between the results recommended by CSIR and the results predicted using ANN has been done per scenario. Figure 4(a), (b), (c) and (d) show respectively the annual electricity demand forecast corresponding to low, moderate, high (less intensive) and high (same sectors) scenario. The average prediction error between ANN and CSIR outputs was calculated for each scenario. The deviations observed are reported as secondary axis on the same graphs. It appears that the maximum deviation correspond to ±9% for the low scenario. A deviation below 3% and 6% were observed for the moderate and high scenario respectively.

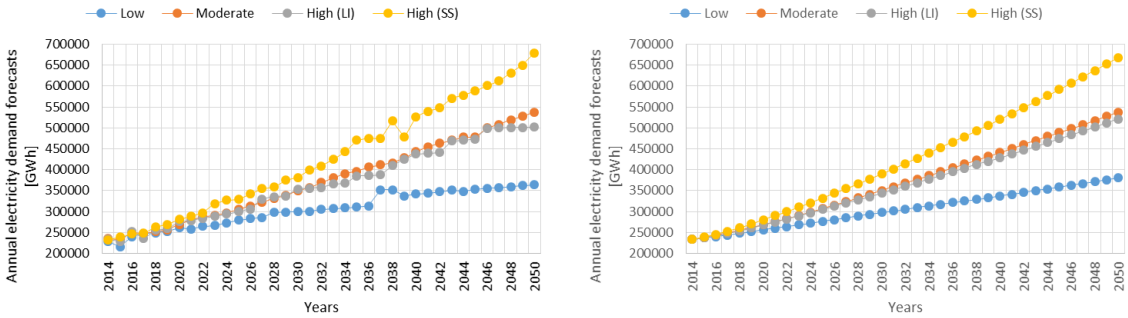
These results suggest that ANN offers the possibility to understand future patterns of electricity usage in various planning context. Although the case study considered in this work is related to South Africa, a similar approach could be adopted for many developing countries provided that reliable data are available. The flexibility shown by ANN means that it is possible to make reasonable judgement while planning or formulating policy in the energy sector.



(a) (b)

(c) (d)

Figure 2. Regression plots for training, testing and validation (a) low, (b) moderate, (c) high (LI) and (d) high (SS)



(a) (b)

Figure 3. Results trends per scenerio using (a) ANN and (b) CSIR forecasts

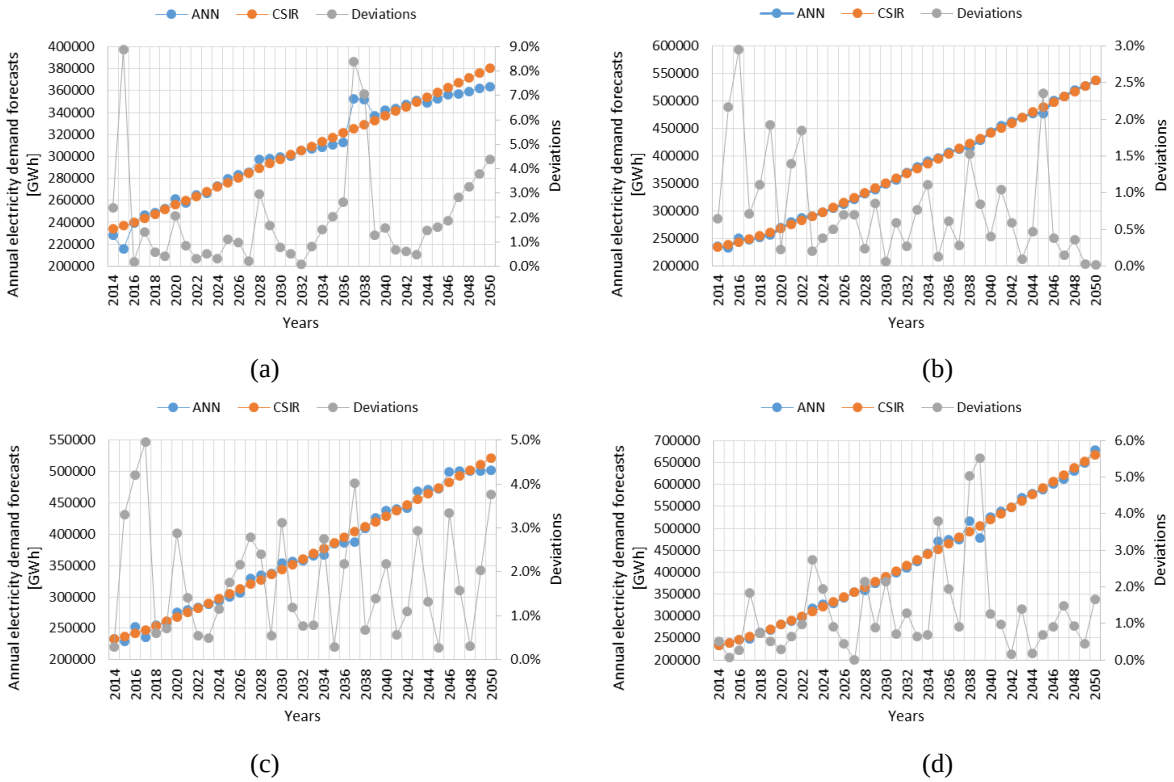


Figure 4. Comparison between ANN and CSIR prediction for (a) low, (b) moderate, (c) high (less intensive) and (d) high (same sectors) scenarios

Conclusion

Reasonable knowledge of past, present and likely future demands would make useful contributions to planning and policy formulation. This work explores the use of Artificial Neural Network (ANN) in creating a model of electricity forecast. The system model for the proposed forecast of electricity demands is a multilayer ANN, where the network is trained for optimized value using Particle Swarm Optimization (PSO). The minimum R2-value, which measures of the quality of fit, was 0.98204. This means that more than 98.204% of the electricity demands variability are explained by linear regression. In addition, the responses obtained from ANN for any new inputs data within the range considered are relatively acceptable. In order to measure the ability of ANN to predict the electricity demands, the comparison between the results recommended by CSIR and the results predicted using ANN has been done per scenario. A maximum deviation of ±9% have been observed. Although the results reported in this paper are restricted to the year 2014 to 2050, based on the available data, this study demonstrate the possibility to understand future patterns of electricity usage in various planning context.

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Biography

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