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Model development to monitor and control energy consumption in South Africa

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***Abstract*—Energy presents unique challenges to present and future generations. The objective of this study is to develop a forecast model to assist in the control and monitoring of energy consumption in South Africa. The study employs artificial neural network (ANN) model, with the energy consumption representing the output whereas the input variables are technology transfers (domestic and foreign) and Research & Development (R&D). The developed ANN model was trained, tested and validated with data from 2005/06 to 2011/12. Predictions from the ANN was compared to regression analysis to validate its good accuracy.**

Keywords—Artificial Neural Network; technology transfers; Research & Development

I. INTRODUCTION

Energy is a vital element due to the interdependence of energy and economic development [1]. For sustainable development, the availability of energy would be required in adequate amount at a realistic cost [2]. Energy consumption for sustainable development can be influenced by the amount of Research & Development on energy together with technology transfers (both foreign and domestic). Energy consumption has continued to increase as it has always been leading to a continuous growth in oil imports and air pollution [3]. Technological improvements in the various sectors could drastically reduce the trend of energy consumption [3, 4]. Energy Research & Development would lead to the improvement of technology, whereas technology improvements would lead invariably to technology transfers [3].

Prediction provides assistance to monitor and control energy consumption with reference to input factors such as activity – Gross Domestic Product, Population, Research & Development, foreign technology transfer and domestic technology transfer, etc. Established methods for conducting energy prediction studies include regression analysis, modelling/simulation and short-term metering. Few studies have compared these methods in South Africa's energy consumption prediction. Those studies include [5] and [6]. Form [5], Olanrewaju et al., have utilized ANN model for predicting the energy usage in the industrial sector of South Africa between 1993 and 2000. The study looked at energy consumption under economic activity, GDP. Their results signified intense conformity between ANN model and observed values compared to regression analysis. The other study looked at GDP and population in predicting South Africa's energy consumption from 2002 to 2009. The study compared ANN and regression results. In comparison, ANN was discovered to be a better modelling technique [6]. The study of Sozen and Arcaklioglu [7] was to obtain equations based on economic indicators (gross national product – GNP and gross domestic product – GDP) and population increase to predict the net energy consumption of Turkey using ANNs in order to determine future level of the energy consumption and make true investments in Turkey. Based on the outputs of the study, the ANN model can be used to estimate the net energy consumption from the country's population and economic indicators with high confidence for planning future projections.

Energy is a basic need for different purposes in industrial facilities around the world. One of the major concerns for facility managers nowadays is how energy demands can be evaluated and predicted [8]. This present study compares artificial neural network – a modelling system with regression analysis to predict the energy consumed in South Africa considering the foreign and domestic technology transfer and the Research & Development as input factors.

The remainder of this paper is organized as follows: section 2 presents the data for this study. In section 3, the method employed is developed that is studied on the South African data. Section 4 presents the results and finally, conclusion is presented in section 5.

II. DATA

Table 1 shows the data gathered from 2005/06 to 2011/12 for this study. The missing data were calculated based on the trend and relationships of the gathered data. The following regression equations were used to calculate the missing data for energy from 2010/11 to 2011/12, for domestic technology transfer from 2007/08 to 2011/12 and foreign technology transfer from 2005/06 to 2009/10, where DTT represents domestic technology transfer and FTT represents foreign technology transfer, t in the equations below represents the coded years:

$$Energy = 9032914855 - 28597494t \tag{1}$$

$$DTT = 14342145 + 16316119t \tag{2}$$

$$FTT = 17222857143 + 3479642857t \tag{3}$$

TABLE I. ACQUIRED AND CALCULATED VALUES OF VARIABLES

Year	Energy (Joules)	DTT (Rands)	FTT (Rands)	R&D (Rands)
2005/06	7949201	119672000	33042857	712712000
2006/07	7742673	124677000	67839286	922202000
2007/08	7538066	148279286	102635714	1074767000
2008/09	6874635	164595405	137432143	1700671000
2009/10	6683347	180911524	172228571	947554000
2010/11	6459140	197227643	196300000	898173000
2011/12	6173165	213543762	285000000	949880000

III. METHODOLOGY

ANN is a powerful tool which is widely used to model a system just with sample data series [9]. It consists of a group of interconnected artificial neurons processing information in parallel [10]. In contrary to programmed traditional mathematical models, ANN learns the relations between selected inputs and outputs by training. Once the inputs are presented to the networks, they will be multiplied by their adjustable weights and then they are summed and transferred in the processing elements in order to produce an output [11]. The inputs to the ANN for this study are domestic technology transfer, foreign technology transfer and Research & Development, whereas the output is the consumed energy.The multilayer perceptron (MLP) with backpropagation trained algorithm was employed for this study. The computational procedure of the network is described below [12]:

$$Y_j = f(\sum_i w_{ij} X_{ij}), \tag{1}$$

where Y_j is the output of node j, $f(.)$ the transfer function, w_{ij} the connection weight between node j and node i in the lower layer and X_i the input signal from the node i in the lower layer. The backpropagation is a gradient descent algorithm. It tries to improve the performance of the neural network by reducing the total error by changing the weights along its gradient.

The backpropagation is based on a steepest descent technique with a momentum weight (bias function) which calculates the weight change for a given neuron. It is expressed as follows [12, 13]: let $\Delta w_{ij}^{p}(n)$ denote the synaptic weight connecting the output of neuron i to the input of neuron j in the pth layer at iteration. The adjustment $\Delta w_{ij}^{p}(n)$ to $w_{ij}^{p}(n)$ be given by

$$\Delta w_{ij}^{p}(n) = -\eta(n) \frac{\partial E(n)}{\partial w_{ij}^{p}}, \tag{2}$$

where η(n) is the learning rate parameter. By using the chain rule of differentiation, the weight of the network with the backpropagation learning rule is updated using the following formulae:

$$\Delta w_{ij}^{p}(n) = \eta(n)\, \partial_j^{p}(n)\, X_i^{p-1}(n) m(n) \Delta w_{ij}^{p}(n-1), \tag{3}$$

$$\Delta w_{ij}^{p}(n+1) = w_{ij}^{p}(n) + \Delta w_{ij}^{p}(n), \quad (4)$$

where $\partial_j^p(n)$ is the nth error signal at the jth neuron in the pth layer, $X_i^{p-1}(n)$ is the output signal of neuron i at the layer below and m is the momentum factor.

IV. RESULTS

Linear regression analysis

The regression equation for this study takes the form $y = a_0 + a_1x_1 + a_2x_2 + a_3x_3$, and error e_i is equal to $y - \hat{y}$, the variation between the actual and predicted values. Where a_0, a_1, a_2 and a_3 are the regression coefficients whereas x_1, x_2 and x_3 are the R&D, DTT and FTT variables. The regression equation solves for the coefficients by minimizing the sum of the squares of the deviations of the data from the model (least-square fit). The least-square fit of the model is:

$y = 1.0336e^{7} - 0.0186x_1 - 4.9247e^{-5}x_2 - 2.0646e^{-4}x_3$ with maximum error of 1.903 e^5 and R^2 is 0.9819.

ANN analysis

MATLAB R2014a (8.3.0.532) was used to carry out the neural network analyses. Comparison of the performance of different cross-validated networks, from 1 to 10 hidden neurons, the best network performance was established and selected. The predicted energy consumption is very close to the actual energy consumption with minimal error as observed by visual inspection. It was a network creation of three input neurons (R&D activity, foreign technology transfer and domestic technology transfer), five hidden neurons and a single output neuron (energy consumption). In the analysis, network parameters of learning rate and momentum were set to 0.3 and 0.2, accordingly. Variable learning rate with momentum (trainlm) as network's training function, sigmoid and linear activation functions for the layers were employed. For the prediction, 2005/06, 2007/08, 2009/10 and 2011/12 were used for training, 2006/07 and 2009/10 for testing, whereas 2008/09 is used for validation. Figure 2 shows the comparison of the errors between the ANN and regression analysis. R^2 of this analysis is 0.9859 and the maximum error is 1.6195e5. Figure 2 compares statistically the results of ANN and regression analysis.

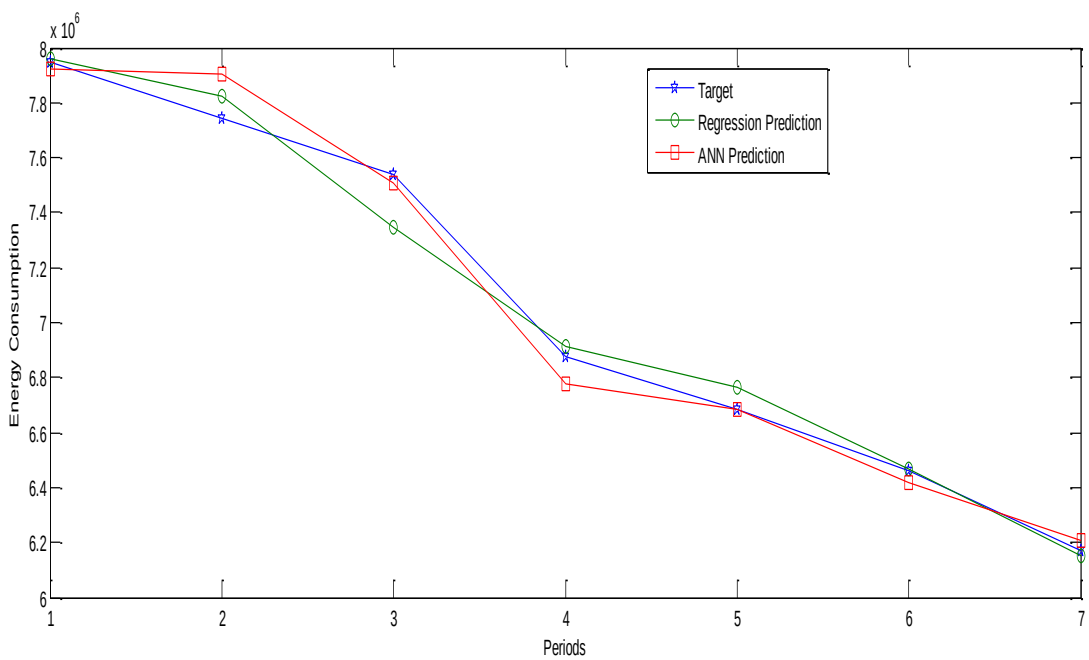

Fig. 1. Predicted and target values of energy consumption

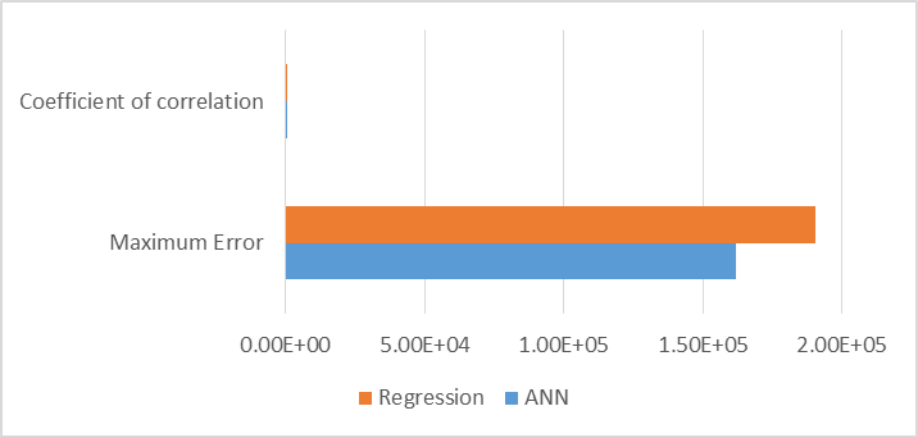

Fig. 2. Comparison with statistical measures

V. CONCLUSIONS

This paper investigated two models, namely regression analysis and artificial neural network, as tools to establish accurately the relationship between South Africa's energy consumption, foreign and domestic technology transfers including Research and Development. In comparison, the results of ANN and regression analysis were measured statistically through maximum error and coefficient of correlation R^2 (Figure 2). From the visual inspection and Figure 2, ANN is seen to give a better prediction even though regression analysis also predicted well. The prediction model established would enable proper energy management in the monitoring and control of energy usage.

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BIOGRAPHY

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