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Predicting energy consumption using artificial neural networks: a case study of the UAE

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Predicting energy consumption is very important for improving resource planning and for more efficient production. This study uses artificial neural network (ANN) models to predict energy consumption in the United Arab Emirates (UAE). The multilayer perceptron model (MLP) and Radial Basis Function (RBF) were used for this purpose. Historical input and output data related to the long-term energy consumption in the UAE were used for training, validation, and testing. The developed neural network models were compared to find the most suitable model with high accuracy.

keywords: energy, artificial neural networks, multilayer perceptron model, radial basis function, United Arab Emirates.

1. Introduction

Energy plays a vital role in the social and economic development of nations, and energy consumption levels are a sign of economic prosperity (Ahmad et al., 2014; Lee and Tong, 2011; Ekonomou, 2010). Energy supports factors of production output and thus stimulates economic development (Dalei, 2016; Omri and Kahouli, 2014). Energy is fundamental in transforming, transporting, and manufacturing all goods, and it is vital to the development of any economy. Sustaining efficient-energy management requires developing and utilizing an energy agenda to ensure a balance between supply and

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demand (Maliki et al., 2011). However, the rate of energy consumption is increasing concerns about supply difficulties, exhaustion of energy resources, and environmental impacts, such as ozone depletion, global warming, and climate change (Pérez-Lombard et al., 2008).

Energy forecasting has attracted interest from many researchers (Kaytez et al., 2015; Perwez and Sohail, 2014; Neto and Fiorelli, 2008; Swan and Ugursal, 2009; González and Zamarreno, 2005; Kalogirou and Bojic, 2000). Predicting energy consumption requires good accuracy, which is very important for energy planning in developing countries (Kaytez et al., 2015; Kankal et al., 2011). In addition, predicting energy consumption in the long term is necessary for studies on capacity expansion, energy supply strategy, capital investment, revenue analysis, and market research management (Ekonomou, 2010). Numerous models have been used to model energy consumption. Traditional techniques include regression, time series, and econometric models. Soft computing tools can also be used, such as artificial intelligence, fuzzy logic, genetic algorithms, ant colony optimization, particle swarm optimization, and support vector machines (Kaytez et al., 2015; Omri, 2013; Kankal et al., 2011; Shahbaz and Feridun, 2012; Ekonomou, 2010).

This study developed a model for predicting energy consumption in the UAE. This was accomplished using an artificial neural network (ANN) along with historical energy consumption data from the UAE. The relationships with demographic, economic, and climate variables were investigated to predict energy consumption. This is the first study in UAE to use ANN with this set of variables to predict energy consumption. ANNs are multivariate nonparametric methods that are capable of modeling complex, nonlinear relationships, and they usually perform better than traditional linear models (Pao, 2009). ANN methods are useful for determining relationships from complex data (Marvuglia and Messineo, 2012), and they can provide powerful nonlinear predictions for energy consumption that overcome traditional techniques and econometric models due to their limitations or linear assumptions (Wang et al., 2011). Predicting energy consumption with good accuracy will help to avoid underestimation or overestimation of consumption costs.

2. Literature Review

Various studies have investigated the relationships between energy consumption and a number of macroeconomic variables, such as economic growth, employment, imports, exports, and foreign direct investment (FDI) (Dalei, 2016; Matar and Bekhet, 2015; Omri and Kahouli, 2014; Lee and Tong, 2011; Bekhet and Othman, 2011; Kankal et al., 2011; Sadorsky, 2010; Goldemberg, 2000). Dalei (2016) examined the effect of gross domestic product (GDP), trade openness, clean energy production, net inflow of FDI, and carbon emission on energy consumption in the top three open economies in Asia (China, Japan, and India). The results revealed that that GDP, trade openness, and carbon emission have a positive impact on energy consumption. Energy consumption initially rises at an increasing rate until a certain threshold point, and then it rises but at diminishing rate via technological effects with increases in per capita income.

Sbia et al. (2014) explored the relationships between FDI, clean energy, trade openness, carbon emissions, and economic growth in the UAE for the period of 1975–2011. The empirical findings confirmed that FDI, trade openness, and carbon emissions correlate with declines in energy demand. Also, economic growth and clean energy have positive impacts on energy consumption.

Salahuddin and Gow (2014) investigated the relationships between economic growth, energy consumption, and carbon dioxide emissions in Gulf Cooperation Council (GCC) countries. The empirical results show a positive and significant association between energy consumption and CO_2 emissions and between economic growth and energy consumption in both the short term and the long term. In addition, energy consumption and CO_2 emissions affect each other, and there is unidirectional causal relationship between economic growth and energy consumption.

Salahuddin et al. (2015) examined the relationship between carbon dioxide emissions, economic growth, electricity consumption, and financial development in the GCC using panel data for the period of 1980–2012. The results revealed no significant short-term relationships. Additionally, a positive long-term relationship was found for both electricity consumption and economic growth with carbon dioxide (CO_2) emissions. However, while the relationship between CO_2 emissions and financial development was negative and significant. Their findings imply that electricity consumption and economic growth stimulate CO_2 emissions in GCC countries, whereas financial development reduces it.

Matar and Bekhet (2015) explored the relationship among electricity consumption and economic growth, export, and financial development in Jordan for the period of 1976–2011. They used annual time series data and an autoregressive distributed lag model. The empirical results show that there is a long-term equilibrium relationship between electricity consumption and economic growth, and there is a unidirectional relationship where real GDP affects electricity consumption. Kankal et al. (2011) used an ANN and regression analyses to model energy consumption in Turkey using GDP, population, import and export levels, and employment. The proposed models show that the future energy consumption of Turkey would vary between 117.0 and 175.40.

Lately, ANNs have been used extensively to predict energy consumption. Kargar and Charsoghi (2014) used an ANN to predict annual electricity consumption in Iran based on population, gross national product (GNP), imports, and exports as input variables using data from 1983 to 2010. Marvuglia and Messineo (2012) proposed a model using an Elman ANN to predict electricity consumption one hour in advance in Palermo, Italy. The results of the ANN model show high prediction accuracy.

Ekonomou (2010) applied a multilayer perceptron model (MLP) to predict long-term energy consumption in Greece. The MLP was used by testing several possible architectures to select the one with the best generalizing capability. Actual recorded input and output data that influence long-term energy consumption were used for training, validation, and testing. The prediction results were accurate. Datta et al. (2000) proposed an ANN model to predict electricity consumption in a supermarket using different independent input variables. The performance of neural networks was compared with traditional multiple regression techniques.

The present study uses GDP as an indicator for economic growth, CO_2, population, electricity consumption, exports, and imports to predict energy consumption in the UAE using an ANN.

3. Energy Consumption Model

Recently, the UAE has witnessed substantial economic growth compared to other developing countries in the Gulf region. Over thirty years, the country has achieved a comparable income levels to industrialized nations. Large oil revenues have allowed the UAE to expedite the lengthy process of saving and capital investment without passing through the hypothetical development stages towards high mass consumption (Shihab, 2001). Oil and natural gas account for 40% of the country's exports and provides 38% of the country's GDP. However, the UAE government has established several diversification strategies to reduce future dependence on oil revenues, which are exhaustible. Attractive incentives for foreign investors have been developed, and economic sectors are opening up to FDI (Khan and Agha, 2015). After becoming an exporter of crude oil, the population has grown at a rate of 6.68% (Figure 1). The continuous population growth in UAE would certainly influence the UAE long term energy consumption.

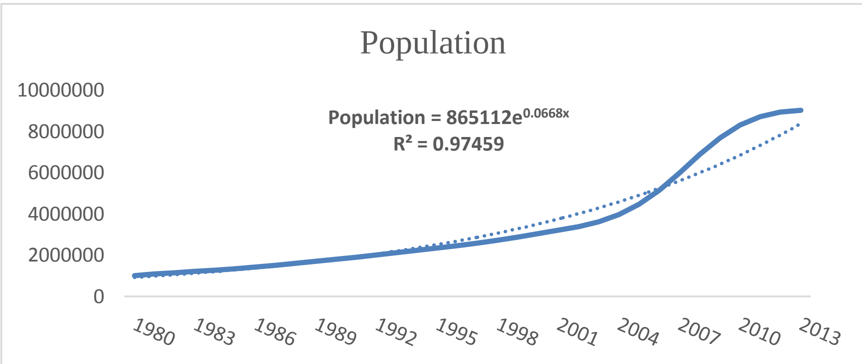

Figure 1: Population in the UAE during 1980–2012

The economy has grown tremendously at rate of 3.97% per year (Figure 2), and the GDP per capita is one of the highest worldwide. Based on Sbia et al. (2014) economic growth in UAE has a positive impact on energy consumption. Their study revealed that there is unidirectional relationship between GDP and energy consumption.

Figure 3 shows the UAE imports and exports during the period of 1980–2012. Although, imports and exports have increased, imports have been higher than exports during this period.

Over the last three decades, energy demand and annual electricity use have grown substantially. The rise in economic growth (indicated by GDP), the high rate of population growth, and a moderately low energy cost are among the factors that have increased the demand for energy. The energy consumption (Figure 4) in the UAE has increased

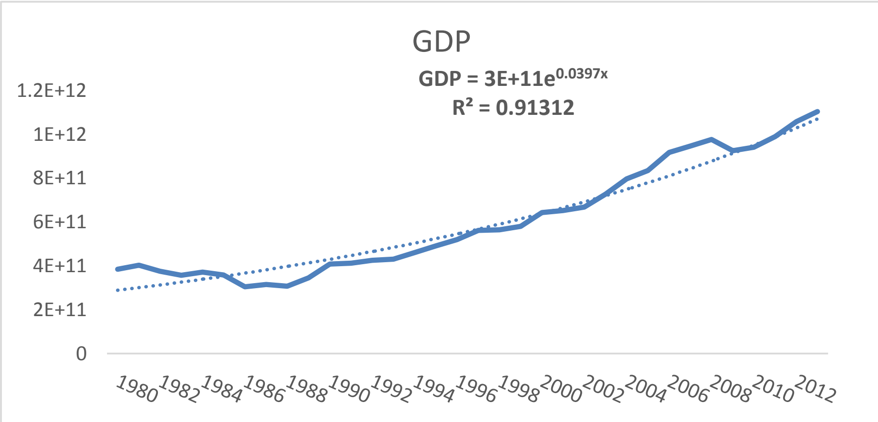

Figure 2: Gross domestic product in the UAE (1980–2012)

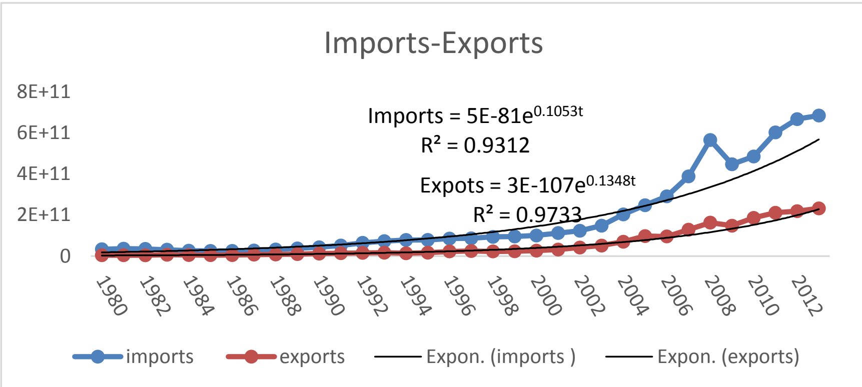

Figure 3: Time trend for Imports and Exports in the UAE for the period of 1980–2012

at an annual rate of 6.26%. Since then, energy consumption from oil and natural gas has increased dramatically in 44 years, from 3677.7 kg of oil equivalent per capita in 1971 to 7691.0 kg in 2013. The per capita energy consumption has become the highest in the world.

Simultaneously, the country has witnessed an increase for demand on electricity (Figure 5). Carbon emissions per capita was at least twice that in developed countries and 10 times higher than the annual average emissions worldwide (Kazim, 2007). Figure 6 shows the carbon emissions during the period of 1980–2012. Hamdi and Sbia (2013) examined the causal relationship between carbon dioxide emissions, energy consumption and real output for a panel of Gulf Cooperation Council (GCC) countries namely Bahrain, Kuwait, Saudi Arabia, Qatar and United Arab Emirates over the period 1980–

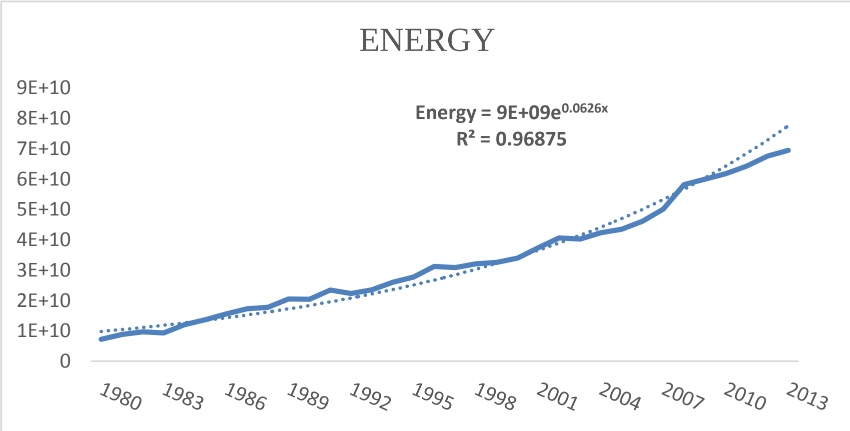

Figure 4: Changes in energy consumption over time in the UAE

2009. Their empirical exercise supported the presence of Environmental Kuznets Curve (EKC) hypothesis for these countries only in the long-run. They also found bidirectional causality between carbon emissions and energy usage in the short-run.

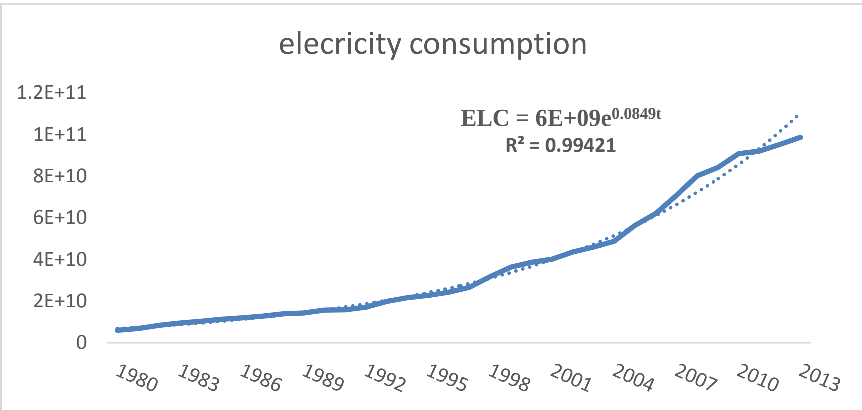

Figure 5: UAE electricity consumption during 1980–2012

It is obvious that more electricity will be consumed as population increases which will lead to more energy consumption. Additionally, energy consumption is related to the manufacturing process which is affected by the amount of export oriented industries as well as imports. GDP is a major macroeconomic indicator to reflect economic growth, and therefore as GDP increases it also results in high energy consumption. Finally, this overall change in energy consumption patterns lead to high CO_2emissions. Following the empirical literature in EC in Table 1, the following model is proposed to

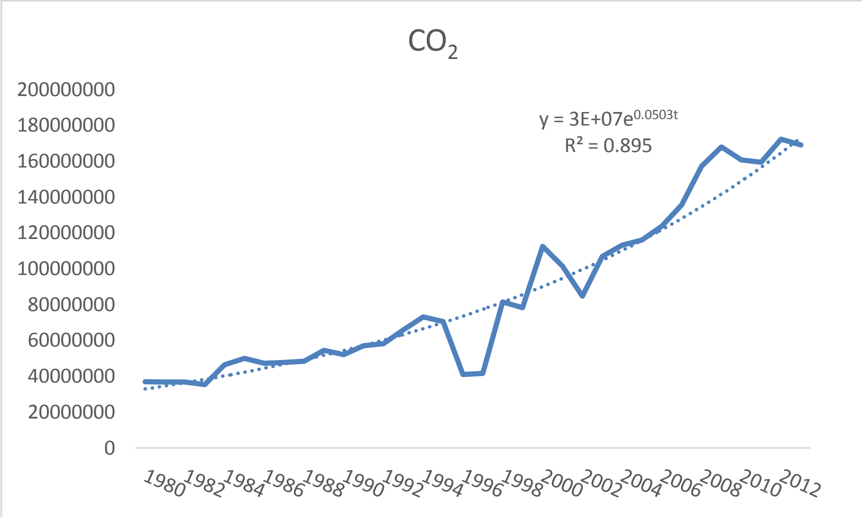

Figure 6: UAE carbon emissions from 1980 to 2012

Table 1: Some Studies on Energy Forecasting for Various Countries

Study	Countries	Periods	Variables	Method	Causality relationship
Sözen et al. (2005)	Turkey	1975–2003	P, GG, IC, GDP, OES	ANN	ANN predicted net energy consumption
Sözen and Arcaklioglu (2007)	Turkey	1968–2005	GDP, GNP, P, IC, GG, M, X	ANN	ANN predicted net energy consumption
Toksarı (2007)	Turkey	1970–2005	GDP, P, M, X	ACO	ACO predicted EC
Geem and Roper (2009)	South Korea	1980–2007	GDP, P, M, X	ANN, LR,EXP	ANN achieved the best results in predicting EC
Kavaklioglu et al. (2009)	Turkey	1975–2006	P, GNP, M, X	ANN	ANN predicted ELC
Ekonomou (2010)	Greek	1992–2008	AT, IPC, ELC, GDP	ANN , LR , SVM	ANN outperformed the other methods
Kankal et al. (2011)	Turkey	1980–2007	GDP, P, M, X, EMP	ANN, LR, PR	ANN achieved best results
Arouri et al. (2012)	12 Mena countries	1981–2005	CO2, GDP, EC	Panel unit root tests and co-integration	EC $\leftrightarrow$ C (in the long-run)
Dagher and Yacoubian (2012)	Lebanon	1980–2009	EC, GDP	ECM , Granger Causality	EC $\leftrightarrow$ GDP
Hamdi and Sbia (2013)	GCC) countries	1980–2009	GDP, OR	Co-integration analysis , ECM	EC $\leftrightarrow$ C (in the short-run)
Sbia et al. (2014)	UAE	1975–2011	CO_2, TO, FDI, CLE, GDP	ARDL	GDP $\rightarrow$ EC

$\rightarrow$, $\leftrightarrow$, Denotes, unidirectional causality, bidirectional causality, bidirectional causality, *ELC*: Electricity consumption, *EC*: Energy consumption, *GDP*: Gross domestic product
CPI: Consumer price index, *FDI*: Foreign direct investment, *TO*: Trade openness, *P*: Population, *X*: Exports, *EMP*: Employment, *AT*: Ambient temperature, *OR*: Oil Revenues
M: Imports, *IPC*: Installed power capacity, *CLE*: Clean energy, *GG*: gross generation, *OES*: other energy sources, *ARDL*: Autoregressive distributed lags, *SVM*; Support Vector Machine
VAR: Vector autoregressive, *VECM*: Vector error correction model, *ACO*: Ant colony optimization, *ANN*: Artificial neural networks, *EXP*: Exponential model, *PR*: Power Regression
ECM: Error-correction model

predict energy consumption in UAE in equation (1):

$$EC = f(ELC, GDP, C, X, M, P) \tag{1}$$

where, EC represent the energy consumption in metric tons, ELC represents electricity consumption in KW/h, ELC was used to predict EC in the study of (Ekonomou, 2010), real gross domestic product shows as GDP (constant US$), GDP was used to predict EC in the study of (Kankal et al., 2011; Ekonomou, 2010; Geem and Roper, 2009; Sözen and Arcaklioglu, 2007; Toksarı, 2007), C displays as CO_2 emissions as in metric tons C was used to predict EC in the study of (Arouri et al., 2012), X stands for overall exports of goods and services (constant US$), whereas M depicts the imports of goods and services (constant US$), X and M were used to predict EC in the study of (Kankal et al., 2011; Geem and Roper, 2009; Sözen and Arcaklioglu, 2007; Toksarı, 2007), and lastly P is the total population in UAE measured as people per sq. Km of land area, P was used to predict EC in the study of (Kankal et al., 2011; Geem and Roper, 2009; Sözen and Arcaklioglu, 2007; Toksarı, 2007).

4. Methodology

ANNs are biologically inspired and modeled to imitate the capabilities of the human brain. A neural network model is composed of a number of fully connected units called neurons, which are comparable to the biological neurons in the brain (Kankal et al., 2011; Eletter et al., 2010; Eletter and Yaseen, 2010). A neuron is the basic processing unit of the network. Neurons cooperate across different layers through several weighted connections (Eletter and Yaseen, 2017; Bekhet and Eletter, 2014; Memarian et al., 2012). Similar to biological neurons, these connections basically determine the function of the ANN, and the weights represent long-term memory (Ekonomou, 2010).

A neuron receives information from other neurons or sometimes from an external stimulus. It then generates an output that is transferred to destination neurons for further processing. The network learns by adjusting the connection weights repeatedly such that the sum of squared error is minimized (Ekonomou et al., 2016). After training, the ANN uses the acquired knowledge to respond to new inputs and make accurate predictions, but the input–output relationship remains unknown (Ekonomou et al., 2016; Li et al., 2014; Kankal et al., 2011).

This study uses a feed-forward ANN that comprises a number of neurons organized in a layered architecture. A typical feed-forward neural network model has three layers: input, hidden, and output layers (see Figure 7). The input layer feeds input signals into the network without processing any information. Information flows from the input to the output in one direction. The number of neurons in this layer is equivalent to the number of independent variables. The hidden layer is an intermediate layer between the input and output. The hidden layer provides the network with its ability to generalize. Each hidden neuron combines all weighted inputs fed from the previous layer. The weighted sum is subjected to nonlinear transformation using an activation or transfer function. Usually, the transfer function is a nonlinear function, such as a sigmoid, identity, Gaussian, or hyperbolic tangent function, among others (Bekhet and Eletter, 2014; Kankal et al., 2011; Eletter and Yaseen, 2010; Eletter et al., 2010).

Additionally, a radial basis function (RBF) is also commonly used as a transfer function (Li et al., 2014). Finally, the output layer transmits the outcome of the output neuron $\hat{y}$ (the predicted value of the dependent variable) or a solution to the problem outside the net. The number of neurons in this layer should be equal to the number of dependent variables.

A representative training set containing pairs of independent variables and dependent variable is used to train the neural network. The ANN accumulates knowledge from

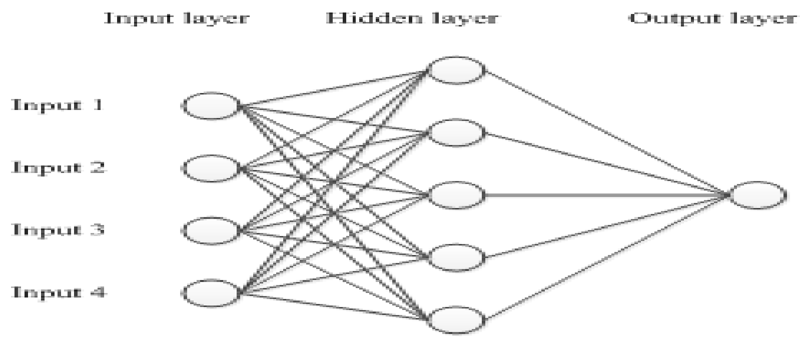

Figure 7: A typical artificial neural network

mapping between inputs and outputs. After that, the network is able to generalize when given examples. A learning algorithm is used to adjust connection weights and biases for the network so that it can work out a specific computational task. The aim of learning algorithms such as back-propagation is to determine the best set of connection weights that minimizes the error. However, back-propagation has some draw backs since it depends on the learning rate and momentum used (Kaytez et al., 2015; Kankal et al., 2011). The ANN performance highly depends on its topology (the numbers of hidden layers and hidden neurons in each layer), as well as the activation function and the learning algorithm.

During model building, the training set passes through the net more than once. Each time that data is introduced to the net is called an epoch. During each epoch, the learning algorithm uses the error signal to adjust the synaptic weights. The algorithm continues to update the synaptic weights in proportion to the error in an iterative process until one of the stopping criteria is met (no decrease in the error or the total number of epochs is reached).

4.1. ANN model building and training

The proposed ANN model uses six variable inputs, and the output variable is energy consumption. Annual data collected from the World Bank (2014) are used for energy consumption (EC), electricity (ELC) in KW/h, real GDP (Y), CO_2 emissions (C) in metric tons, export of goods and services (X), imports of goods and services (M), and population (P) for the period of 1980–2014. Although there are other variables that significantly affect energy consumption (such as use of renewable energy, FDI, ambient temperature, etc.), the available data for these variables does not cover the whole period.

According to equation (1), ELC, Y, C, X, M, and P are the inputs for the neural network because they play a significant role in energy consumption in the long term. EC is the output variable. The ANN learns from the given examples by mapping between input–output in order to make estimation (Kaytez et al., 2015). After training, ANN will be able to predict the output with good accuracy while the input-output relationship remains unknown because of its black box nature (Li et al., 2014). All variables were normalized the option for rescaling of covariates in SPSS to improve the network training. Data normalization was necessary to make sure that all inputs have the same weight and that the range of values is limited for the neuron's transfer function, which will make the network converge and generate meaningful output after training. Both ANN models use input and output historical data for 1980–2002, 2009, and 2013 for training, while data from 2003–2008 and 2010–2012 are used for testing. The analysis was performed using SPSS software (version 24).

4.1.1. MLP model development

A typical MLP neural network was used to predict energy consumption in the UAE. The MLP model consists of input, hidden, and output layers. Several MLP architectures with different transfer functions, and learning algorithms were examined, and the best model was determined in terms of the minimum prediction error. Historical data for the input and output variables are used to train the developed models. Three types of training were examined: batch, online, and mini batch. After performing a number of trails using each type, mini batch training was chosen because it provided better results. Mini batch training divides the training set into subsets of equal size and then uses each subset to adjust the synaptic weights. The training then continues until the stopping criteria are reached. Mini batch training is also recommended for medium size training sets.

The gradient descent was used to optimize the synaptic weights, and this method is recommended for use with mini batch. The different trails (Table 2) used different levels of learning rate and momentum. The learning rate indicates how fast the network learns, while momentum is used to prevent instabilities when a high learning rate is used. Training continues until there is one consecutive step with no decrease in error based on the testing set. Extensive simulations have been carried out by excluding one of the input variables at a time and comparing the output obtained. The best output was obtained by using the six variables analyzed earlier in previous section.

Table 2: MLP output

No	Architecture	Backpropagation	Learning rate	Momentum	Training error	Testing error	Activation function hidden	Activation output
1	6/5/2001	Gradient descent	0.4	0.9	0.648	0.232	Hyperbolic tangent	Identity
2	6/2/2001	Gradient descent	0.3	0.9	0.776	0.845	Hyperbolic tangent	Identity
3	6/4/2001	Gradient descent	0.2	0.9	0.196	0.82	Hyperbolic tangent	Identity
4	6/3/2001	Gradient descent	0.2	0.9	0.023	0.035	Sigmoid	Sigmoid
5	6/3/2/1	Gradient descent	0.2	0.9	0.029	0.084	Sigmoid	Sigmoid
6	6/3/2001	Gradient descent	0.2	0.9	0.111	0.159	Hyperbolic tangent	Hyperbolic tangent
7	6/3/2001	Gradient descent	0.2	0.7	0.04	0.056	Sigmoid	Sigmoid
8	6/3/2001	Gradient descent	0.2	0.95	0.05	0.046	Sigmoid	Sigmoid
9	6/3/2001	Gradient descent	0.2	0.85	0.024	0.109	Sigmoid	Sigmoid
10	6/3/2001	Gradient descent	0.25	0.85	0.03	0.118	Sigmoid	Sigmoid

The best model results with minimum error in the testing set were achieved with the fourth trial. Figure 8 presents the best MLP model has six neurons as inputs, three hidden neurons, one output neuron, a learning rate of 0.2, and momentum of 0.9. It also uses the gradient descent back-propagation learning algorithm and sigmoid activation function in the hidden and output layers. The error was 0.035 in the testing set.

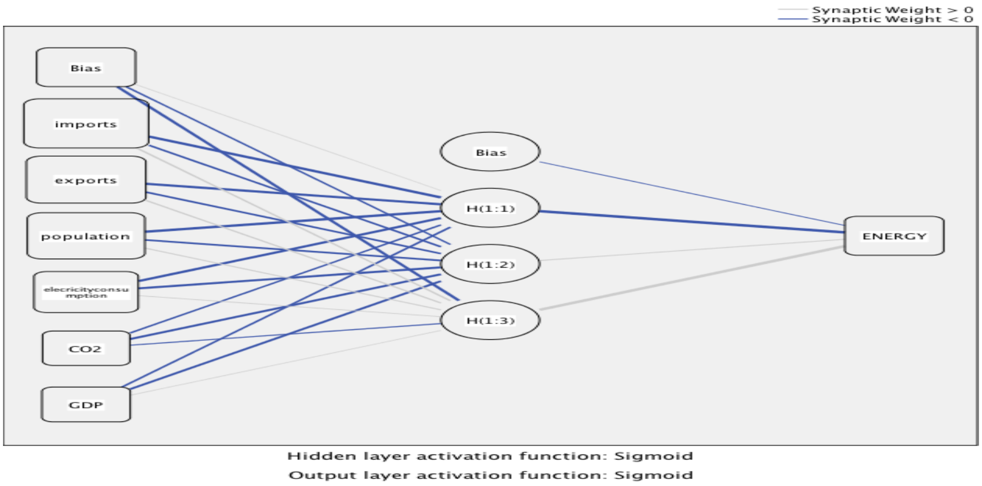

Figure 8: The proposed MLP model

4.1.2. Radial basis model

The six input variables were also used as inputs for the RBF model, and EC was again the output variable in this case. Many trials were carried out to find the best RBF model to predict EC with minimum error. At the beginning of the model development, the number of hidden units was set to automatic selection, where the number of hidden neurons is selected if it yields the smallest error. However, the results were not satisfactory. Thus, a new strategy was used where the number of hidden units was set to 1 unit as a first step, and then each new trial increased by 1 unit while monitoring the mean square error. In each trial, the network uses the training data for training. Training continues while the mean square error decreases for each increase in the number of hidden neurons until reaching 10 neurons in the hidden layer. In each trial after the tenth one, the error starts increasing again. Table 3 shows the trial results.

Since the error was decreases until reaching nine neurons in the hidden layer, the best RBF model is the one ninth trial. Figure 9 presents the best RBF model has six input neurons, nine hidden neurons, and one output neuron. It uses softmax activation function in the hidden layer and an identity activation function in the output layer, and the error is 0.775 in the testing sample.

Table 3: RBF output

No.	Architecture	Training error	Testing error	Activation function hidden	Activation output
1	6/1/2001	10.84	7.439	Softmax	Identity
2	6/2/2001	4.738	3.767	Softmax	Identity
3	6/3/2001	1.206	2.715	Softmax	Identity
4	6/4/2001	0.79	2.689	Softmax	Identity
5	6/5/2001	0.542	2.624	Softmax	Identity
6	6/6/2001	0.336	2.624	Softmax	Identity
7	6/7/2001	0.235	1.346	Softmax	Identity
8	6/8/2001	0.164	1.578	Softmax	Identity
9	6/9/2001	0.124	0.775	Softmax	Identity
10	6/10/2001	0.089	0.814	Softmax	Identity

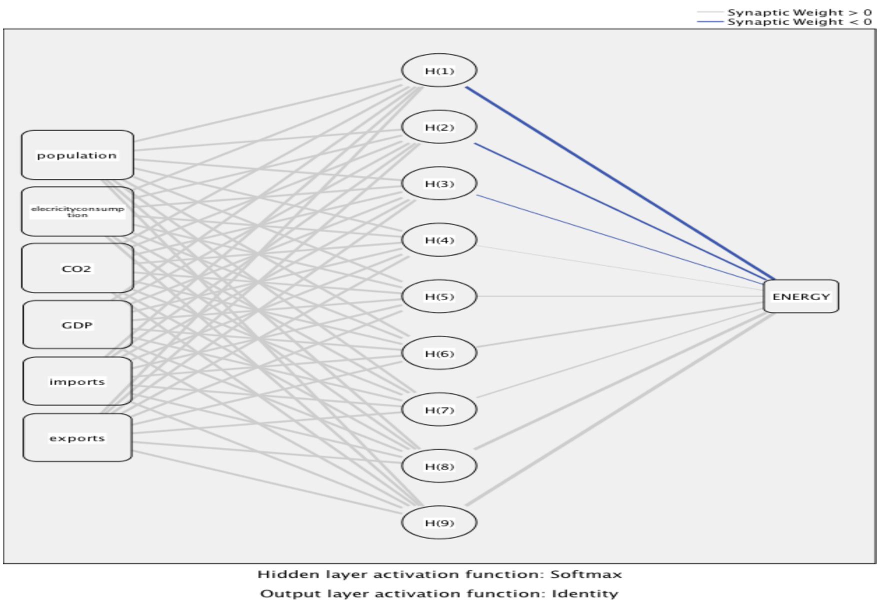

Figure 9: The proposed RBF model

5. Results and Discussion

After training, MLP and RBF neural networks were used to predict energy consumption in the UAE for the periods of 2003–2008 and 2010–2012. Figure 10 presents a plot of the predicted values of energy consumption by the proposed MLP model against the actual values. Points in the figure show training and testing data. The slope is almost 45 degrees, which indicates that the MLP model predicted the actual energy consumption with good accuracy.

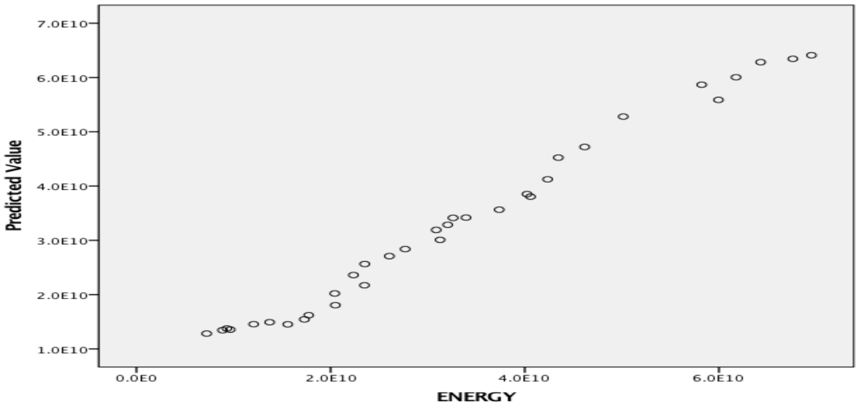

Figure 10: Predictions using MLP verses actual energy consumption

Figure 11 presents a plot of the predicted values of energy consumption by the RBF model against the actual values. The RBF model predicted the actual energy consumption relatively well, but the results are not as good as the MLP results.

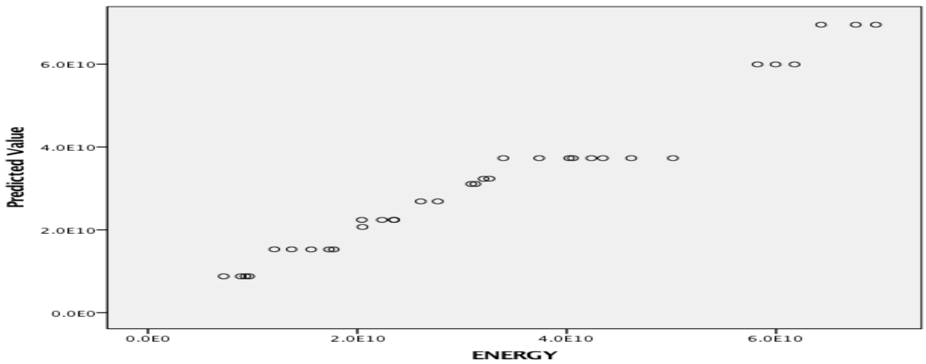

Figure 11: The predicted using RBF verses actual energy consumption

The error of the best MLP in the testing set was 0.035; on the other hand, the error of the best RBF model in the testing is 0.775. The results of the sum of squared error in the testing set reveal that the MLP outperforms the RBF model.

Table 4 compares the actual energy consumption and the predicted energy consumption produced using the MLP model and the RBF model for the testing set. Figure 12 also compares the actual UAE energy consumption and the predicted results. It is obvious that the MLP results are closer to the actual results (Ekonomou, 2010) and therefore outperforms the RBF model in predicting energy consumption in the UAE.

Table 4: Comparison between actual and predicted energy consumption in the UAE

Year	Actual	MLP predicted	RBF predicted
2003	40228120036	39360508406	37301037127
2004	42355503528	42511436466	37301037127
2005	43459390644	46262474821	37301037127
2006	46165810174	48703769170	37301037127
2007	50142925411	53432984466	37301037127
2008	58220776142	59158592916	59950964892
2010	61760061981	59993071834	59950964892
2011	64297598850	63767214106	69526561198
2012	67614252506	64974814591	69526561198

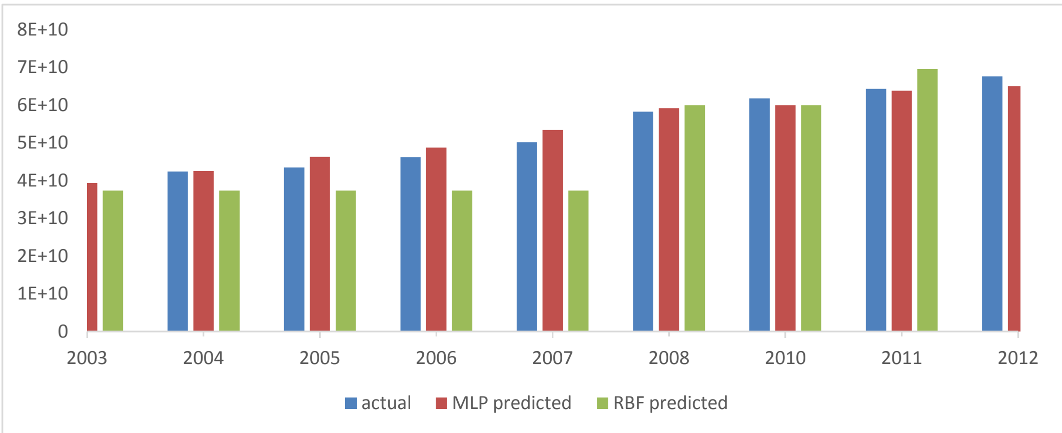

Figure 12: Comparison of actual and predicted energy consumption using MLP and RBF models

The results of our research are consistent with the findings with Ekonomou (2010) who used MLP to predict long-term energy consumption and his findings showed that MLP outperformed the linear regression (LR) model and the support vector machine (SVM) model. In addition, the results of Geem and Roper (2009) showed that MLP better estimated energy demand than linear regression and exponential model. Additionally, Kavaklioglu et al. (2009), Sözen and Arcaklioglu (2007), Sözen et al. (2005) used ANN to predict energy consumption in Turkey with good accuracy.

6. Conclusion

This study used two ANN models to predict energy consumption in the. Although the results of both ANNs were close to the actual results, the MLP model produced more accurate results than the RBF model. Thus, MLP is a promising tool for predicting energy consumption in the UAE. As a result, the MLP may be used to predict the future trends of energy consumption in UAE. Accurate predictions of energy consumption are vital in long-term planning strategies and energy-related policies. Therefore, policymakers need to pay more attention to the increasing rate of energy consumption, which highly impacts capital investment and environmental quality (Ekonomou, 2010). In addition, precise prediction of energy needs will enable policymakers to diversify UAE energy resources and utilize other potential sources such as renewable or clean energy to meet future energy demand, especially since oil resources are exhaustible. In addition, energy is related to other challenges, such as climate change and environmental impacts, which cannot be ignored. Policymakers should also put new energy plans into action and encourage the establishment of sustainable policies and investments in renewable energy and solar projects.

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A. Appendix

Table 5: Descriptive statistics

Variable	Mean	Standard deviation
Energy	32881291280.00	18366768370.00
Electricity consumption	37694675320.00	29662066500.00
CO2	86505103.40	45990702.20
GDP	605031803300.00	253322024100.00
Imports	179969378800.00	205853519500.00
Exports	56779801950.00	71544482200.00
Population	3503622.30	2542691.90