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ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (20): 5791-5798, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.5791.5798

Forecasting Production of Clean Energy using Cognitive Mapping and Artificial Neural Networks

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Abstract: Clean Energy has become the focus of interest for the manufacturing industries with the evolution of technologies to allow co-production. Researches give evidences for multiple enablers of producing this never-ending resource in addition to the geographical conditions. The aim of this study is to develop an Artificial Neural Network forecasting model for the production of clean energy based on the factors determined by causal maps. The framework is initially tested in geographical, economical and technological conditions of China. Since the holonomy of national, regional and individual company requirements are considered in the study, the model achievements are adoptable for any size of clean energy production needs.

Key words: Clean energy, forecasting, cognitive mapping, artificial neural networks

INTRODUCTION

Energy is considered to be a key player in the generation of wealth and a significant component in economic development. This makes energy resources extremely considerable for countries. Sustainable development demands a sustainable supply of energy sources. Supplies of fossil energy sources are finite; other energy sources including hydropower are generally considered clean and therefore sustainable over the relatively long term (Yuksek *et al*., 2006). China has various energy resources. However a big portion of energy consumption is met by imports and the share of the imports increases every year. Clean energy must be used more widely to be less dependent on foreign resources (Ediger and Kentel, 1999).

Extensive usage of fossil fuel sources in various sectors has caused considerable environmental problems. These problems which affect human health and welfare unfavourably can be overcome by using alternative energy sources. Hence, in order to mitigate world problems caused by fossil fuels, it is necessary to limit fossil energy consumption and to encourage greater utilization of green energy sources. Therefore, fossil energy production and consumption should be planned. For importing countries, this can be accomplished by determining the domestic sources and strategic energy policy (Ediger and Kentel, 1999).

Forecasting allows analysts to make better decisions, gain competitive advantage and avoid surprises. Forecasting has been performed extensively in the scope of energy (Utgikar and Scott, 2006). Durmayaz *et al*. (2000) analyzed the residential heating energy requirement of Istanbul with the degree-hours method. The results were significant for estimating the fuel consumption of such a crowded city which has a big air pollution problem. Ediger and Tatlýdil (2002) used Winters' exponential smoothing method and cycle analysis for primary energy demand forecasting. The study showed that energy demand in China will be around 130 million toes in 2010. Sarak and Satman (2003) used the heating degree-day method to determine the natural gas consumption by residential heating in China. The areas where the consumption is high could be picked out by the results.

Yumurtaci and Asmaz (2004) found that the economically usable hydro electrical potential and the yearly thermal energy production were known to be approximately 125 billion kWh and 688 billion kWh, respectively. China requires 360 billion kWh energy produced by other energy resources. According to these values clean energy resources should be used until the year 2050 for this 360 billion kWh energy production.

Gorucu (2004) proposed two models for two scenarios, stable economy and economical crisis. The models acquired very satisfactory results and the range of gas consumption for the years 2002 and 2005 for Ankara were obtained. Aras and Aras (2004) applied an autoregressive model to one of the five cities supplied by natural gas for residential use in China. Using separate models for each period reduces the forecast errors significantly when the major purpose of natural gas demand is space heating. Ediger *et al*. (2006) developed a decision support system for forecasting fossil fuel production by applying Autoregressive Integrated

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Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) regression methods. According to the results production is expected to end in 2019 for hard coal, in 2024 for natural gas, in 2029 for oil and 2031 for asphaltite. The gap between fossil fuel consumption and production is growing enormously. Akay and Atak (2007) developed a Grey Prediction with Rolling Mechanism (GPRM) for electricity demand forecasting of China. The proposed approach estimated more accurate results than the results of MAED (Model for Assessment of Energy Demand). Ediger and Akar (2007) used ARIMA and SARIMA methods to estimate the future primary energy demand of China from 2005 to 2020. Fossil fuels will continue to play a major role in the future energy mix of China. Also, within the fossil fuels, oil will be replaced by natural gas in 2012 and natural gas' share will reach to 41.2% in the energy mix in 2020. Yuksek *et al.* (2006) studied the hydropower potential forecasting of China. China's hydro electric potential which was estimated by MAED can meet 33-46% of its electric energy demand in 2020.

In recent years, researchers have preferred intelligent systems such as Genetic Algorithms (GA) and Artificial Neural Networks (ANN) for energy estimation. GA based models were developed by Ozturk *et al.* (2004) for petroleum energy production and consumption forecasting, Ceylan and Ozturk (2004) for energy demand forecasting, Haldenbilen and Ceylan (2005) for transport energy demand forecasting, Ozturk *et al.* (2005) for electric energy consumption, Canyurt *et al.* (2005) for residential-commercial energy consumption and Canyurt and Ozturk (2006) for future oil demand forecasting. China was the focus of these studies. The results obtained from these proposed GA models were compared with the MENR (Ministry of Energy and Natural Resources) projections to evaluate the relative error between observed and estimated values of energy demand. The proposed models may be used as an alternative solution and estimation technique to the MENR projections. Toksari (2007) used Ant Colony Optimization approach to estimate energy demand of China and the relative error of the proposed model was less than the relative error of MENR projections.

Gorucu *et al.* (2004) forecasted the gas consumption of Ankara with ANN. ANN has given more satisfactory results for the short term prediction with two different scenarios. Sozen *et al.* (2005a) used two ANN models for forecasting the net energy consumption of China. Both of the models predicted the net energy consumption with acceptable accuracy. Sozen *et al.* (2005b) forecasted the solar energy potential in China using ANN. The study indicated that the ANN based estimation technique for solar radiation is more suitable for predicting solar radiation than the classical regression models. Murat and Ceylan (2006) proposed an ANN model for forecasting the transport energy demand in China. Two scenarios showed that the future energy demand will vary between 33 and 40 MTOE in 2020.

Energy planning is necessary for better energy policies, strategies and projections (Ermis *et al.*, 2007). Hydropower is the largest clean resource, also an alternative energy resource to fossil fuels and the most efficient way to produce energy. The efficiency of modern hydro tribunes is 90% while the best fossil fuel plants' is 50%. In other words, modern tribunes transform as much as 90% of the available energy into electricity (Yuksek *et al.*, 2006). ANN is an intelligent approach which does not need any assumptions and is successful in solving complex problems (Sozen *et al.*, 2005a). Although ANN can be used in various areas, it has not been applied to forecast hydroelectric energy production in literature. This study proposes a hybrid model which consists of Causal Map and ANN for hydroelectric energy forecasting. Since the production and consumption is equal for clean energies (Ediger and Kentel, 1999), production of hydroelectric energy is forecasted in this study.

METHODOLOGY

Cognitive mapping: Cognitive Map (CM) is a visual representation of thinking about a subject. CMs are known as causal maps because they are formed by nodes and arrows which imply believed causality. CM takes shape through interviews or through the analysis and coding of documents, so they represent the beliefs, values and expertise of decision makers relevant to the issue in hand (Eden, 2004).

Cms have three major parts: Causal concept, causal connection and causal value. A causal concept represented by a node can be an attribute, issue, factor or variable. Causal connection is presented by an arrow and shows the direction of the connection. It depicts a cause-effect relation between two concepts. The concept at the tail of an arrow is taken to cause the concept at the head of the arrow. Causal value is the strength of the causal connection. There are many different techniques used for determining the causal value. The technique used for finding the causal values of a certain CM is specified by the aim of the analysis (Nadkarni and Shenoy, 2004). CMs can supply missing information and details and bring the priorities and key factors into focus (Siau and Tan, 2005).

CM has been widely used in international relations, administrative science, political science, sociology,

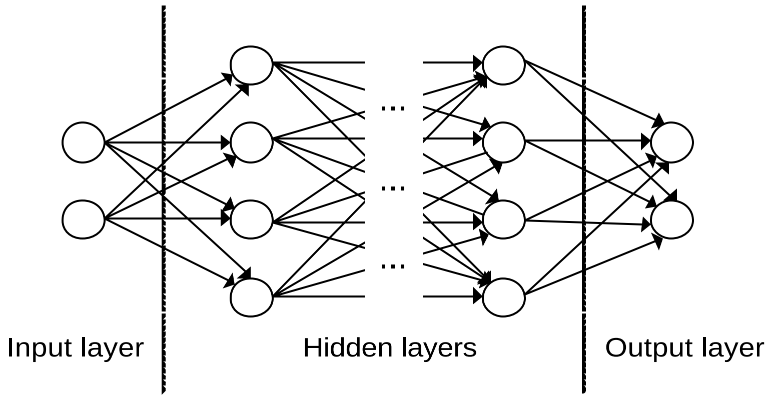

Fig. 1: A sample feed-forward neural network (Kalogirou, 2001)

organizational behaviour and management science (Eden, 2004; Siau and Tan, 2005; Sahin *et al*., 2004). Sahin *et al*. (2004) used CM for analysing inflation in China. An artificial neural network model developed with inputs which were determined by CM was used for estimating the future of inflation through a revised version of the extended anomaly relaxation model.

The aim of this study is forecasting hydroelectric generation. In order to make an estimation, agents influencing the generation should be determined. CM is used to research these influences. This approach extends not only the inputs for a forecasting model but also an opportunity to catch the causes lying under electricity which is produced by hydroelectric plants. Due to the fact that energy supply is one of the major indicators of economics, determining the agents of hydroelectric generation is essential especially for developing countries. In spite of the large amount of clean energy sources, China is an energy importing country because of inefficient source utilization. Particularly hydroelectricity is very important for China because it has the biggest share in clean energy sources. This study builds a CM as an alternative method to define the attributes that affect the generation of hydroelectric energy in China.

Artificial neural networks: Artificial Neural Network (ANN) models take their inspiration from the basic framework of the brain (Alpaydýn, 2004). ANN consists of many nodes and connecting synapses. Nodes operate in parallel and communicate with each other through connecting synapses (Murat and Ceylan, 2006).

ANN is used effectively for pattern recognition and regression (Alpaydin, 2004). In recent years, experts prefer ANN over classical statistical methods as a forecasting model. This increasing interest can be explained by three basic properties of ANN: The first is no requirement for any assumptions, the second is extrapolating from historic data to generate forecasts and the last is solving the complex nonlinear problems successively. While classical statistical techniques only estimate the coefficient of independent variables ANN selects proper weights during training and keeps them for latter use to estimate the output (Murat and Ceylan, 2006).

Neural networks can be classified according to their structures. A feed-forward neural network is used for forecasting in this study. In feed-forward neural networks signals flow from the input layer to the output layer. The neurons connect from one layer to the next layer, not to the previous layer or within the same layer (Mihalakakou *et al*., 2002). Among the several learning algorithms, back-propagation algorithm is the most suitable method for training multilayer feed-forward networks (Ermis *et al*., 2007).

A sample feed-forward neural network is shown in Fig. 1. The network is composed of an input layer, some hidden layers and an output layer. Each layer has a certain number of neurons which are the basic processing elements of ANN. Neurons are connected with the other neurons in further layers and each connection has an associated weight (Nasr *et al*., 2003). Each neuron is an operation unit in ANN. The process starts with summation of weighted activation of other neurons through its incoming connections. Then the weighted sum is passed through an activation function and this activated value is the output of the neuron (Kalogirou, 2001). The Sigmoid function:

$$f(x)=\frac{1}{1+e^{-x}} \tag{1}$$

is commonly used as an activation function.

The net input of neuron j is:

$$net_j = \sum_i w_{ij} x_i + \theta_j \quad (2)$$

where x_i's are the outputs of the neurons in the previous layer, w_{ij} is the synaptic weight of neuron i to neuron j and θ_j is the bias which is the constant value of the sigmoid function (Sahin *et al.*, 2004).

The most important section of ANN is training. While training the ANN, the weightings between neurons are estimated (Murat and Ceylan, 2006). In the learning phase, an input is presented to network along with the desired output (y_p) and the weights are adjusted to produce the desired output. The most popular learning algorithm is the Back-propagation (BP) algorithm. BP is a gradient descent algorithm which improves the resulting performance of the ANN by reducing the total error by adjusting the weights along its gradient. RMSE (Root Mean Square Error) is the most widely used error value which is calculated as:

$$E = \frac{1}{2}\sum_k (y_k - o_k)^2 \quad (3)$$

where, o_k is the output vector and k is the index for output units (Kalogirou, 2001). During back-propagation learning, weights are modified according to their contribution to the error function:

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} \quad (4)$$

where, η is the learning rate which determines the magnitude of changes to be made in the parameter (Sahin *et al.*, 2004). The performance can be analyzed with RMSE, however RMSE can be quite high or low depending on the unit of variables. In order to calculate the performance of different forecasting models, Relative Error (RE) can be used:

$$RE = \frac{\sum_k (y_k - o_k)^2}{\sum_k {y_k}^2} \quad (5)$$

ANN has been used for modelling and prediction of clean energy systems by many researchers. Modelling and design of a solar team generating plant, modelling and performance prediction of solar water heating systems, estimation of heating loads of buildings and prediction of air flow are some examples where ANN is applied (Kalogirou, 2001). However, ANN has not been used for estimating hydroelectric generation. One of the aims of this study is using ANN for modelling of a different field in clean energy production and the feed-forward back-propagation ANN is applied for forecasting the hydroelectric generation within a framework formed by a cognitive map.

APPLICATION

Cognitive mapping: There are many agents determining hydroelectric generation. In order to obtain an exclusive and detailed list of factors a cognitive map is used. Factors that affect hydroelectric generation are determined from literature.

Hydroelectric generation is greatly affected by climate. Global warming, drought, precipitation, evaporation, runoff (stream flow), temperature, humidity, radiation, wind speed and soil moisture are climatic parameters for hydroelectric generation. There are factors other than climate that could affect the availability of hydroelectric generation. The factors include water withdrawals, deliveries and consumptive use (Munoz and Sailor, 1998). In addition to these factors breakdowns, maintenance, efficiency and installed capacity of hydroelectric plants govern the generation (Eroglu, 2006). Also electric consumption is determinative for energy production and the number of household and amount of CO_2 pollution are factors that affect electric consumption directly. Population, index of industrial production, oil price, electricity price, Gross National Product (GNP) and Gross Domestic Product (GDP) are economic indicators used for forecasting energy consumption and production (Kermanshahi and Iwamiya, 2002). So there are 29 driving forces which affect hydroelectric generation directly and indirectly.

After the factors are identified, relations between factors are scaled by asking the experts. -1, 0 and 1 are used for scaling. "-1" refers to a negative relation and "1" refers to a positive relation between the factors. "0" means any change of a certain factor does not have any effect on those factors which connect with 0.

Experts who define relations between factors defined above are academicians at Istanbul Technical University. Due to the fact that the whole pairwise comparison matrix is very big (29×29), a fragment of relations based on 7 variables is given in Table 1. The matrix is read from row to column. For example, hydroelectric generation affects installed capacity positively which means that if hydroelectric generation increases installed capacity will increase. The resulting aggregated map of the matrix is shown in Fig. 2.

A model for analysing the cognitive map is evaluated by using MATLAB. According to the results of the

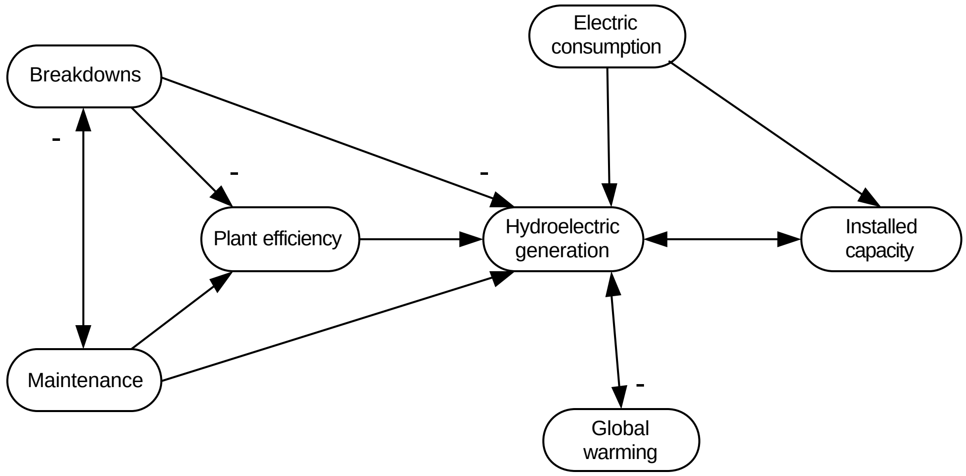

Fig. 2: A sample part of cognitive map for hydroelectric generation

Table 1: A part of the pairwise comparison matrix

	Hydroelectric generation	Breakdowns	Maintenance	Electric consumption	Plant efficiency	Installed capacity	Global warming
Hydroelectric generation	0	0	0	0	0	1	-1
Breakdowns	-1	0	1	0	-1	0	0
Maintenance	1	-1	0	0	1	0	0
Electric consumption	1	0	0	0	0	1	0
Plant efficiency	1	0	0	0	0	0	0
Installed capacity	1	0	0	0	0	0	-1
Global warming	1	0	0	0	0	0	0

model, drought is the most central variable which means that the sum of outcoming from and incoming to each variable of drought is bigger than the other variables. The model searches the effect on the variables of central variable change. The iterations are continued until the system converges to an equilibrium state. This state shows the variables influenced by a change that occur in the drought. So the driving forces for hydroelectric generation are determined. Electric consumption, installed capacity, global warming, runoff, temperature, drought, population, energy consumption, GDP and GNP are the factors that were revealed through CM. Electric consumption, installed capacity, population, energy consumption, GDP and GNP are used as inputs for an ANN forecasting model. As the yearly value of runoff and temperature cannot be obtained and global warming and drought are not quantitative, they cannot be used for forecasting hydroelectric generation.

Energy forecasting with ANN: Data is collected from different sources. Hydroelectric generation and electric consumption are collected from the Turkish Electricity Transmission Company. Population, GDP and GNP are collected from the Turkish Central Bank. Energy consumption is collected from the Ministry of Energy and National Resources.

The general shape of the ANN model is given in Figure 3 which places electric consumption, installed capacity, population, energy consumption, GDP and GNP in the input layer and hydroelectric generation in output layer. All data are normalized between 0 and 1. The neural network tool of MATLAB is used for forecasting. The data are divided into three parts. First 25 data are used for training, next 5 data are for validation and remaining 5 data are used for testing the network. Back-propagation is used for training the model. The learning rate is generally taken less than or equal to 0.2 (Alpaydýn, 2004). Hence, it is taken 0.2 in this study.

Identifying an appropriate neural network topology for a specific problem is not an easy task. For determining the number of hidden units and learning rate, experiments with different topology are performed. The minimum point of validation error seems to be the appropriate neural network architecture for estimating the hydroelectric generation. Different numbers of hidden units (1-30) are applied and each topology is trained 100 times. Validation errors of these networks are compared and a neural network with 26 hidden units gives the best results. Therefore 26 hidden units are used in hidden layer.

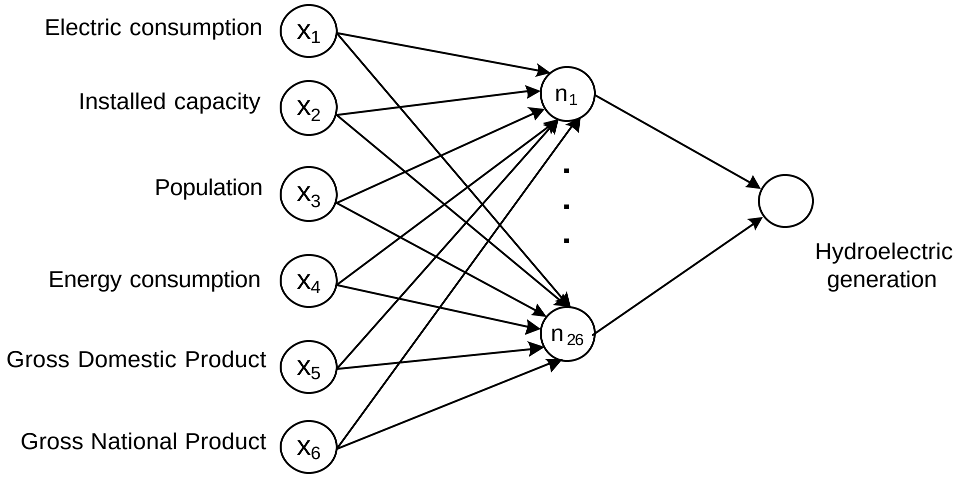

Fig. 3: ANN model

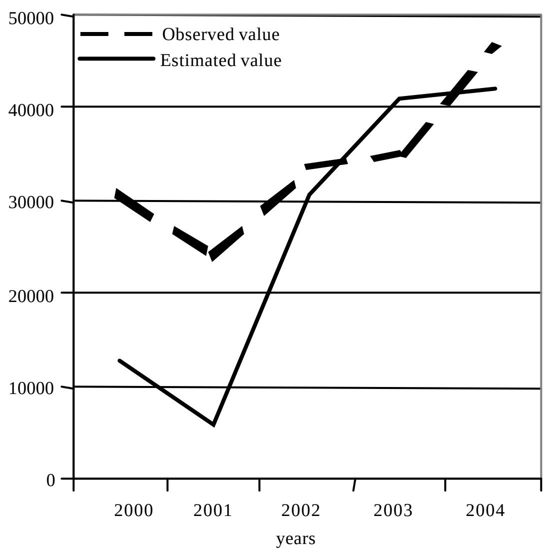

Fig. 4: Estimated hydroelectric energy generation between 2000 and 2004 with ANN

RESULTS

Test result of the neural network model is shown in Fig. 4. RMSE for the proposed model is 11909.285 and relative error is 0.117. Estimated values between 2000 and 2001 are in harmony with real values but the gap between estimated and real data is higher than the other years. In 2000, the big economic crisis caused a reduction in the Turkish energy sector like other industries. Electric generation by hydroelectric plants, also electric consumption, was higher than expected in 2000 and 2001.

A multivariate regression model which is a classical statistic forecasting technique is applied to estimate hydroelectric generation. SPSS is used for regression analysis. The proposed model was compared with the regression model. Relative error of regression is 0.267 while ANN is 0.117. In general, the ANN model gives a better forecasting performance than the regression model.

CONCLUSION

CM and ANN were used in the present study to forecast the annual hydroelectric generation values of China. When analyzing the testing error, it is obvious that remarkable success has been achieved in making accurate predictions. This study proposes a hybrid model which is composed of CM and ANN. CM is an efficient tool for reducing the number of inputs for understanding and analyzing the problem more easily and a neural network is able to estimate the hydroelectric generation with sufficient accuracy. Since the holonomy of national, regional and individual company requirements are considered in the study, the model achievements are adoptable for any size of clean energy production needs. The ability of an ANN to predict outcomes accurately depends upon the selection of proper weights during the ANN training. Due to the complex nature of training ANN, even simple functions can have very complex error surfaces. Since the nature of back-propagation is to converge locally, it can be demonstrated that solutions are highly dependent upon the initial random choice of weights. If these initial weights are located on a local grade which is probable, the back-propagation algorithm will likely become trapped in a local solution that may or may not be the global solution. Results found in this study can be compared with another training algorithm's results in future studies.

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