Predicting US Energy Consumption Utilizing Artificial Neural Network

Mohammad Pasandidehpoor[1] mohammad.pasandidehpoor@inesctec.pt;

João Mendes-Moreira[1,2] jmoreira@fe.up.pt; Soulmaz Rahman Mohammadpour[3] soulmaz.mohammadpour@gmail.com; Ricardo Teixeira Sousa[1] ricardo.t.sousa@inesctec.pt

[1] Institute for Systems and Computer Engineering (INESC TEC), Technology and Science, Faculty of Engineering, University of Porto, Portugal

[2] Department of Informatics Engineering, Faculty of Engineering, University of Porto, Portugal;

[3]Department of Industrial Engineering, Faculty of Industrial and Mechanical Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran;

Corresponding Author: mohammad.pasandidehpoor@inesctec.pt

Abstract

Today, the increasing importance of energy resources in the formation and growth of economic processes, as well as the necessity of utilizing these resources based on environmental considerations and sustainable economic and social development, highlights the issue of identifying and studying the factors affecting energy consumption. In addition, due to the limitation of energy resources, forecasting the demand for energy consumption in the future has become very important. Therefore, this chapter proposed a smart prediction methodology to predict the US energy consumption via using machine learning (ML) methodologies. It proposes artificial neural networks (ANN) to predict energy consumption in the United States from 2021 to 2030. In addition, it investigates a vast range of influencers on energy consumption and selects four influencers on energy consumption during the years from 1990 until 2020 including population, gross domestic product (GDP), crude oil production, and inflation rate. Finally, this research presents the volume of future US energy consumption at a high level of accuracy which maximum value of ANN-PB algorithm error equaled to 2.5%.

Keywords: Energy consumption, Prediction, Artificial neural network, Global climate change, Machine learning

1. Introduction and Literature Review

In recent years, due to the increasing complexity and developments of the international community, energy consumption played a key role in the economy and politics of the nations. Moreover, the main pillars of maintaining political stability and economic power are the accurate pursuit of energy sector prospects and the adoption of appropriate strategies. In addition, economic and trade conditions warn of the necessity of a prediction plan for energy consumption. Predicting energy consumption is an important subject in managing consumption and meeting energy requirements. Therefore, the country's officials should try to control the energy supply and demand parameters desirably by predicting energy consumption as accurately as possible and planning correctly in directing consumption. The expansion of information technology applications in various fields, including the necessity of smart decision-making processes, has become an increasing trend. The use of machine learning (ML)-based methods appears as a key solution to meet these necessities. ML utilizes a set of tools for intelligent processes in various applications.

The most important economic growth factor in the United States, as the world's most powerful economy, is affordable energy access. Therefore, economic growth causes a rise in welfare, security, and social international stability. Hence, the importance of economic growth causes to concentrate on the prediction of future energy consumption to supply, manage, and allocate this critical factor. As a result, this chapter focuses on providing a reliable methodology to predict the US energy consumption utilizing an artificial neural network (ANN). The rest of the section reviews the literature and presents the chief gap-filling contributions of our research.

SÖZEN et al. (2006) proposed the prediction of the energy consumption model by using the multi-layer feed-forward (MLFF) algorithm. This study examined the four neurons in the input layer including year, population, installed capacity, and gross generation during the years from 1953 until 2000. Moreover, it validates the presented model in 3 years 1965, 1981, and 1997. SÖZEN & Arcaklioglu (2007) presented a net energy consumption prediction model for Turkey. The mentioned study considered gross national product and gross domestic product as input of the neural network. Moreover, it used scaled conjugate gradient (SCG) and Levenberg-marquardt (LM) algorithms for providing a prediction model. PEREA et al. (2009) analyzed the greenhouse energy consumption prediction by concentrating on ANOVA and mean comparison procedures for evaluating the variance between actual and predicted volumes. Ekonomou (2010) provided an accurate tool for predicting energy consumption in Greece. This study has stated that this proposed approach with high accuracy prediction can have a significant impact on energy policies. Uzlu et al. (2014) propose a configuration for ANN- TLBO (teaching-learning-based optimization) model to predict Turkey energy consumption from 2013 to 2020. Aydin et al. (2016) presented the model for highlighting the world's highest energy consumer country. The mentioned study evaluated the data related to China, the United States, Russian Federation, India, Japan, Canada, Germany, Brazil, South Korea, and France for predicting their future values utilizing the ANN method. Zhou and Chen (2019) presented multiple decomposition-ensemble methodologies to predict energy consumption in China. This approach helps to improve the prediction accuracy to have a reliable prediction. Lee et al. (2020) represented the energy consumption model in Vietnam to help plan geo-locational energy demands. This model by focusing on the urban population growth afforded to predict the amount of energy demand in particular regions or cities. Zhou and Chen (2021) provided a China energy consumption prediction model by using multivariate linear regression (MLR) and long short-term memory neural network (LSTM).

Table 1 Comparison of the contributions of different authors.

Author	**Year**	**Area**	**Input layer**	**Energy type prediction**	**Method**	**Time period**
SÖZEN et al.	2006	Turkey	Population, and gross generation, installed capacity and years	Net energy consumption	ANN	Model based
SÖZEN and Arcaklioglu	2007	Turkey	Gross national product and gross domestic product	Net energy consumption	ANN	Model based
PEREA et al.	2009	Mexico	Temperature, humidity, time, and power consumption	Greenhouse energy consumption	ANN	Model based
Ekonomou	2010	Greek	Yearly ambient temperature, installed power capacity, yearly per resident electricity consumption, and gross domestic product	Energy consumption	ANN	[2005–2008, 2010, 2012, 2015]
Uzlu et al.	2014	Turkey	Gross domestic product,	Energy consumption	ANN	[2013-2020]

			population, import, and export			
Aydin et al.	2016	China, the United States, Russian Federation, India, Japan, Canada, Germany, Brazil, South Korea and France	Gross domestic product, population, import, and export	World's highest consumers	ANN	[2007-2012]
AVAMI & BOROUSHAKI	2011	Iran	Gross domestic product, population	Energy consumption	ANN	Model based
Zhou and Chen	2019	China	gross domestic product, population, industry proportion of GDP	Energy consumption	multiple decomposition-ensemble	[2017-2021]
Lee et al.	2020	Vietnam	Urban growth factors, population, and nighttime light intensity	Energy consumption	ANN	Model based
Zhou and Chen	2021	China	Gross domestic product, industry percentage in GDP, population	Energy consumption	multivariate linear regression (MLR), long short-term memory neural network (LSTM)	[2020-2024]
Our research		United States	Gross domestic product (GDP), population, crude oil production,	Energy consumption	ANN	[2021-2030]

			and inflation rate			

Table 1 represents the literature segmentation into two categories of future prediction studies and model base studies. In the model base studies, most of the research used the ANN method, and it shows the high levels of acceptability of this method for the prediction process. Moreover, this literature review clearly shows that gross domestic product and population play key roles in energy consumption and have a direct impact on it. According to the literature review, this chapter tries to provide a novel prediction model to forecast future US energy consumption utilizing the ANN method to help the policies related to the future levels of energy consumption and production in the developing world's energy markets environment.

2. Variable Selection and Datasets Used

Two important factors in predicting architecture include choosing effective variables as input and provide the correct database to train data. This section introduces selected variables and data used in this research. The size of the input vector should not be increased or decreased. Instead, it should be selected with care that it fits to the entire dataset.

2.1. Selection of Predictor Variables

The first process in designing an AI network architecture is to determine the input parameters as predictor variables that affect the outputs. Choosing the right variables is a crucial factor in designing a potent network with accurate forecasting.

Energy consumption forecasts influence by many economic and demographic key indexes. The most important indicators included GDP and population; other factors depend on these variables such as imports, exports, employment rate, industrial production, gross national product, industry proportion of GDP, industry percentage in GDP, installed power capacity, yearly per resident, electricity consumption, power consumption, and urban growth factors (SÖZEN et al. 2006; SÖZEN and Arcaklioglu 2007; PEREA et al. 2009; Ekonomou 2010; Uzlu et al. 2014; Aydin et al. 2016; AVAMI & BOROUSHAKI 2011; Zhou & Chen 2019; Lee et al. 2020; Zhou & Chen 2021). According to the literature, GDP and population data are considered to be the most effective determinants for a country's energy consumption. Moreover, other variables are subsets of GDP and population. On the other hand, they have impact on GDP such as imports, exports, gross national production and population such as urban growth factor. This study also proposes and uses crude oil production (Tiwari 2015; Wanjala & Kinyanjui 2018) and inflation rate (Mohsin et al. 2018) as most effective variables that have direct impact on GDP.

2.2. Datasets

Table 2 and Table 3, respectively, represent the train data set and the test data set used in the provided model from 1990 to 2020. Time Series Split was utilized for splitting the data which provides a set of test indices to split a time series data sample that are observed at fixed intervals and typically higher than the test indices that were used before. After doing the Time Series Split method train data set, select the data from 1990 to 2015, and after testing set, select the data from 2016 to 2020. Five categories of data were collected from different international sources including GDP (IEA 2020), population (Macrotrends 2021), Inflation rate (USDA 2021), Crude oil production (Annual Energy Outlook 2021), and energy consumption (IEA 2020).

Table 2 The train data set.

Year	**GDP (Billions of US $)**	**Population**	**Crude oil production (million barrels per day)**	**Inflation Rate**
1990	6004.733	252120309	5.484399	5.398
1991	6264.54	254539370	5.667232	4.235
1992	6680.803	256990613	6.520586	3.0288
1993	7013.738	259532129	7.494121	2.9517
1994	7455.288	262241196	8.789389	2.6074
1995	7772.586	265163745	9.446493	2.8054
1996	8259.771	268335003	8.851521	2.9312
1997	8765.907	271713635	9.371356	2.3377
1998	9293.991	275175301	10.964088	1.5523
…	…	…	…	…
2015	18354.372	320878310	13.763157	0.1

Table 3 The test data set.

Year	**GDP (Billions of US $)**	**Population**	**Crude oil production (million barrels per day)**	**Inflation rate**
2016	16919603.42	323015995	13.566243	1.3
2017	17304243.03	325084756	13.451651	2.1
2018	17798638.66	327096265	13.348973	2.4
2019	18292645.57	329064917	13.283369	1.8
2020	18587190	331002651	13.173889	0.9

To conduct future projections from 2021 to 2030, different forecasts were obtained from four databases: the GDP from OECD, population from Macrotrends (2021), inflation rate from USDA 2021, and crude oil production from Annual Energy Outlook (2021).

3. Methodology

Artificial intelligence as a new science has made our world today very different from a few decades ago, and technology owes much of its progress to it. One of the most important methods of artificial intelligence is the ANN method. Inspired by the neural network of the human brain, it seeks to develop information processing. The neural network helps to train our computer to respond appropriately to events, instead of dictating what needs to be done. Each neuron in this network is a processing element and solves different problems along with other processing elements. The learning process of this neural network is just like the human brain (Dreyfus 2012). Humans from birth are gradually taught to solve their problems by testing and learning. Eventually, they understand that in each situation they respond appropriately to the situation. The artificial neural network begins to learn in the same way from the beginning of formation so that it can eventually respond appropriately to a particular situation. The structure of the artificial neural network is designed to copy the method of data processing in humans. In this structure, numerous nodes work side by side in parallel with the goal of overall processing. Each of these nodes is a data structure. This data structure is placed in a communication network with each other and this network is trained and learned by humans. The structure of the artificial neural network is designed to copy the method of data processing in humans. In this structure, numerous nodes work side by side in parallel with the goal of overall processing. Each of these nodes is a data structure (Kankal et al. 2011). This data structure is placed in a communication network with each other, and this network is trained and learned by programmers through selected algorithms. This research among different algorithms in the ANN method chose the Backpropagation (BP) algorithm (Rumelhart et al. 1986) as modeling methodology.

3.1. Back-propagation Algorithm

A neural network is a network or circuit of neurons, or in other words, an artificial neural network, composed of artificial neurons or nodes. One of the most widely used methods in neural networks is the BP algorithm (Ediger wt al. 2007; Yan et al. 2008; Nourani et al. 2012). The algorithm, known as chain rule, is utilized to successfully train a neural network. Backpropagation, in simple terms, performs a backward pass across a network after each forward pass while modifying the model's parameters (weights and biases) to attain the lowest error. Fig. 1 represents the training scheme for ANN-BP.

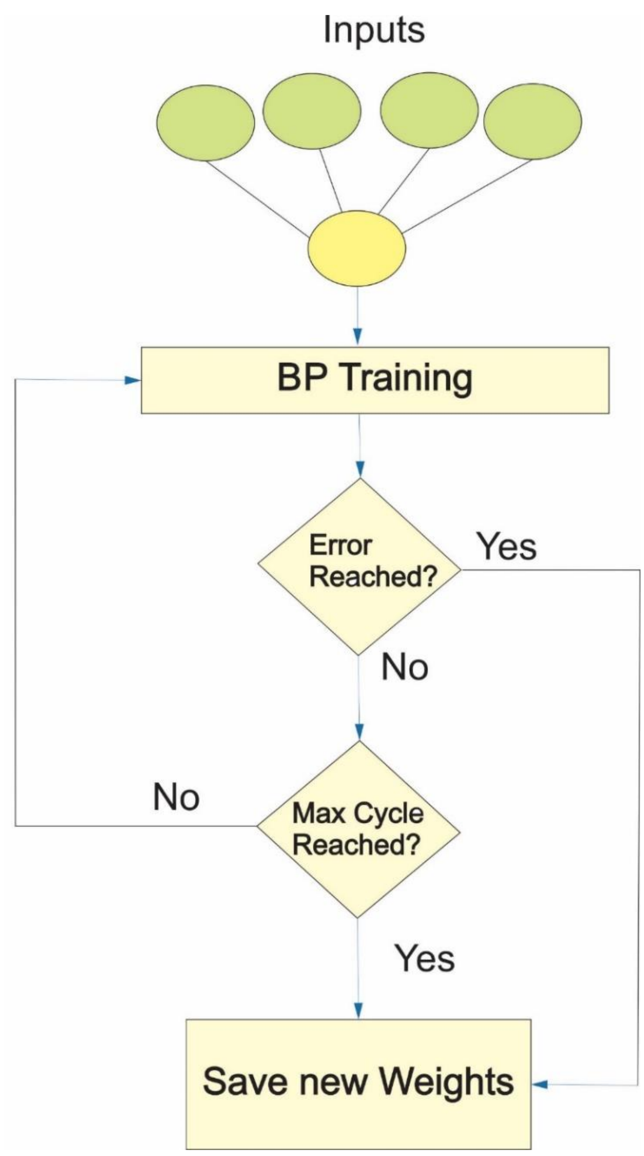

Fig. 1. Proposed training scheme for ANN-BP.

The most common architecture for a BP network is the Feed Forward network (SAZLI 2006). Feedforward networks often have one or more hidden layers of sigmoid neurons and use a linear final layer (Rajput & Verma 2015). The presence of multiple layers of neurons with a nonlinear transmission function allows the network to learn the linear and nonlinear relationship between inputs and outputs. The linear output layer allows the network to have an output that is out of range. If the output is in the desired range, the Log-sigmoid transfer function (logsig) is used in the linear layer. Fig. 2 shows the structure of a feed-forward network for the proposed energy consumption prediction model.

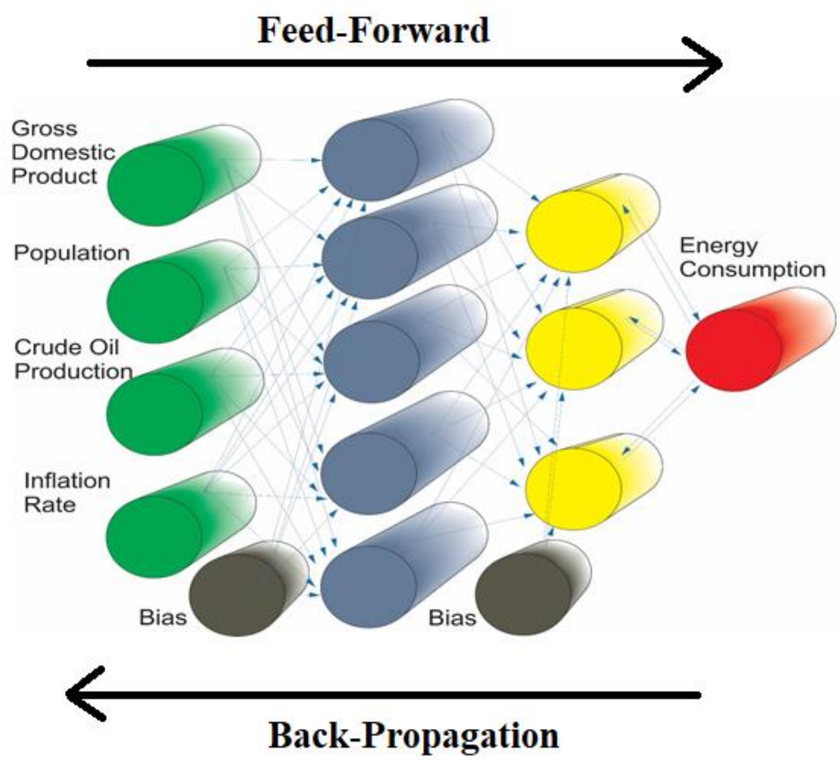

Fig. 2. Feed-forward network for proposed energy consumption prediction model.

3.2. Error Estimation

The current research utilized mean squared error (MSE) (Khoshnevisan et al. 2013) for estimating in the feed-forward BP network (Khoshnevisan et al. 2013) which is illustrated in Eq. (1).

$$MSE = 1/n \sum_{i=1}^{n} (output - predicted)^2 \quad (1)$$

where predicted is the output value obtained by the neural network, the output is the exact output value, and n is the number of patterns. Weights in the network are updated by the amount of Δw_{ij}, given as Eq. (2) (Uzlu et al. 2014).

$$\Delta wij = \eta \frac{\partial E}{\partial wij} \quad (2)$$

The *wij* is the weight vector which depends on the training error function. In order to know the steepest descent at each point in the training error function, the derivative of *E* with respect to each component of the weight vector, in the downward sloping direction must be computed. Furthermore, η is the learning rate, which determines the magnitude of changes to be made in the learning parameter. The performance of a trained ANN model is evaluated with the average MSE (relative error) (Karasu 2010), which measures how close the predicted energy consumption path predicted lies to the true energy consumption path output.

3.3. Proposed Feed-Forward Back-propagation Network

As can be seen in Fig. 2, this study used a feed-forward BP network to model the prediction of energy consumption. The network was trained with US historical data including GDP, population, inflation rate, and crude oil production values. Table 4 shows that the best convergence values of BP for ANN training are related to 4-5-3-1 ANN architecture and the maximum value of ANN-BP algorithm error equaled to 2.5%.

Table 4 The best convergence values of BP for ANN training.

ANN architecture	**ANN Backpropagation algorithm error (%)**
4-5-3-1	2.5
4-5-2-1	2.6
4-5-4-1	3
4-6-2-1	2.8
4-6-3-1	3
4-6-4-1	2.8

The basic configuration related to the ANN-BP method can be observed in Table 5. A four-layer network, including two hidden layers, was selected. After the input and output variables were selected, the optimal number of neurons in the hidden layer was determined by using a trial-and-error procedure, varying the number of hidden neurons from 5-2 to 6-4. Through this process, a network consisting of one input layer with four neurons, two hidden layers with 5 and 3 neurons, and one output layer with one neuron was chosen. The maximum number of epochs were set to 300 for the Back-propagation algorithm.

Table 5 The basic configuration related to ANN-BP method.

Feature	**Answer**
Number of hidden layers:	Double hidden layer
Network structure (input-hidden-output neurons):	4-5-3-1
Evaluation of training process:	Error (MSE)
Transfer function (1st hidden layer- 2nd hidden layer):	Logarithmic- sigmoid (logsig)
Transfer function (2nd hidden layer-3rd hidden layer):	Linear function (Purelin)
Training Epochs:	300

4. US energy consumption prediction Results

This section presents US energy consumption prediction results utilizing the proposed model. The input data including GDP (IEA 2020), population (Macrotrends 2021), inflation rate (USDA 2021), and crude oil production (Annual Energy Outlook 2021) were found from different resources. According to the literature review, most of the studies chose GDP, population, import, and export but his chapter afforded to introduce two valuable influencers to the literature including inflation rate and crude oil production. These two influencers have a direct impact on energy consumption. Table 6 provides the US energy consumption prediction utilizing the proposed model 2021 to 2030. Moreover, it can be seen in Fig. 3 that the best training performance MSE is 0.85786 at epoch 254.

Table 6 Future prediction of energy consumption in the USA.

Years	**Predicted energy consumption (Quadrillion British Thermal Unit)**
2021	95.3216
2022	98.4003
2023	99.5431
2024	99.8411
2025	99.7329
2026	99.7117
2027	99.7079
2028	99.6494
2029	99.596
2030	99.4224

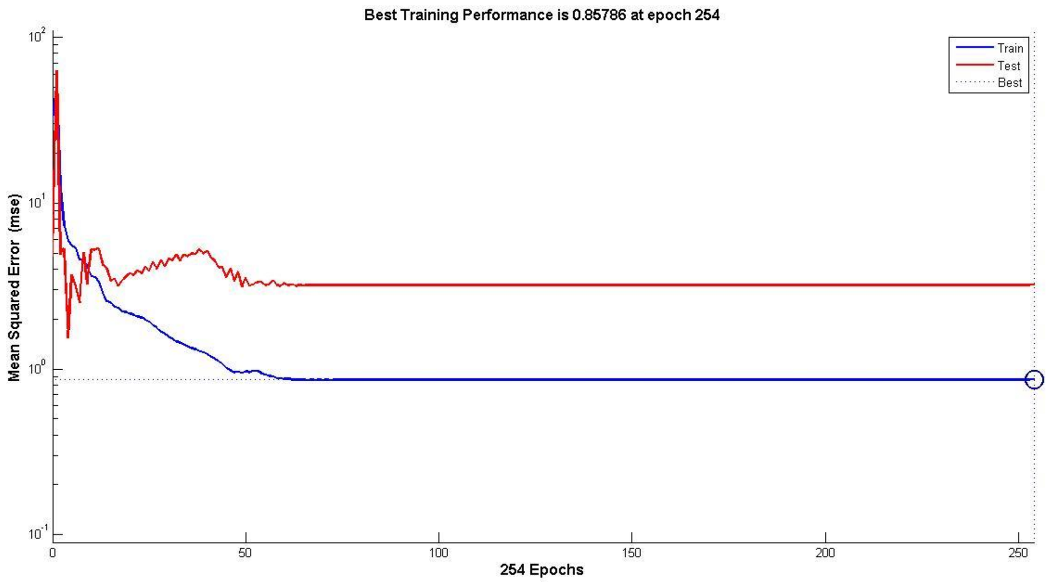

Fig. 3. The best training performance in MSE.

5. Conclusion

This study developed an energy consumption prediction model utilizing the ANN method by BP algorithm. The main contribution of this chapter is introducing novel influencers for estimating energy consumption. Based on the literature review, the inflation rate and crude oil production were not considered as input data for predicting energy consumption; meanwhile, the inflation rate has a direct impact on GDP (GDP as the most important input for all studies) and crude oil production has a direct impact on the level of consuming energy. Moreover, this study used to feed-forward BP network to model the prediction of energy consumption that the concept and structure of feed-forward BP cause to have a network with a high level of accuracy. The output of this study in Table 6 shows US energy consumption will increase from 2021 to 2024 in amount equal to 99.8411 (Quadrillion British Thermal Unit) and it is the highest amount of US energy consumption prediction in the next 10 years. During future years, the trend of energy consumption from 2024 till 2030 will approximately stay stable. As a result, this chapter with a high level of accuracy helps the government for allocating, saving, and managing energy consumption for the coming years. Future work of this chapter can concentrate on other algorithms of ANN such as TLBO, long short-term memory neural network (LSTM), and multivariate linear regression (MLR), developing a model by considering new influencers and inputs, which have a direct impact on energy consumption.

References

Annual Energy Outlook, the U.S. Energy Information Administration of the outlook for energy markets through 2050 (2021)

Avami A., Boroushaki M., (2011), Energy Consumption Forecasting of Iran Using Recurrent Neural Networks, Energy Sources Part B, Vol 6 pp339–347

Aydin G., Jang H., Topal E., (2016), Energy consumption modeling using artificial neural networks: The case of the world's highest consumers, Energy Sources, Part B: Economics, Plan. and Policy, Vol 11 pp. 212-219

Dreyfus S. E., (2012), Artificial neural networks, back propagation, and the Kelley-Bryson gradient procedure, Am. Inst. Aeronaut. Astronaut., Vol 13 pp. 926 – 928

Ediger V. S., Akar S., (2007), ARIMA forecasting of primary energy demand by fuel in Turkey, Energy Policy, Vol 35 pp. 1701- 1708

EIA (2021) U.S. Energy Information Administration, https://www.eia.gov/energyexplained/us-energy-facts

Ekonomou L., (2010), Greek long-term energy consumption prediction using artificial neural networks, Energy, Vol 35 pp. 512-517

IEA Key World Energy Statistics (2020) https://www.iea.org/data-and-statistics/charts/gdp-by-scenario-2018-2030

Kankal M., Akpinar A., Komurcu M.I., Ozsahin T.S., (2011), Modeling and forecasting of Turkey's energy consumption using socio-economic and demographic variables, Appl. Energy, Vol 88 pp. 1927-1939

Karasu S., (2010), The effect of daylight-saving time options on electricity consumption of Turkey, Energy, Vol 35 pp. 3773-3782

Khoshnevisan B., Rafiee S., Omid M., Yousefi M., Movahedi M., (2013), Modeling of energy consumption and GHG (greenhouse gas) emissions in wheat production in Esfahan province of Iran using artificial neural networks. Energy, 52 333-338

Lee H. Y., Jang K. M., Kim Y., (2020), Energy Consumption Prediction in Vietnam with an Artificial Neural Network-Based Urban Growth Model, Energies, 13, 10.3390/en13174282

MacroTrends (2021) U.S. Population, https://www.macrotrends.net/countries/USA/united states/population

Mohsin M., Majeed M. K., Naseem S., (2018), Impact of Inflation Rate and Exchange Rate on GDP: Evidence from Pakistan, Am. J. of Res. 10.26739/2573-5616-2018-3-2-3

Nourani V., Sharghi E., Aminfar M. H., (2012), Integrated ANN model for earthfill dams seepage analysis: Sattarkhan dam in Iran, Artif. Intell. Res., Vol 1 pp. 22-37

Perea M. T., Ruiz G. H., Moreno J. R., Miranda R. C., Araiza E. R., (2009), Greenhouse Energy Consumption Prediction using Neural Networks Models, Int. J. Agri. Biol., 1814 - 9596

Rajput N., Verma S. K., (2015), Back propagation feed forward neural network approach for Speech Recognition, IEEE Xplore, DOI: 10.1109/ICRITO.2014.7014712

Rumelhart D. E., Hinton G. E., Williams R. J., (1986), Learning representations by back propagating errors, Nature, 533-536

Sazli M. H., (2006), A brief review of feed-forward neural networks, Communications Facul. Sci. Univ. Ankara, Vol 50 pp. 11-17

Sözen A., Arcaklioglu E., (2007), Prediction of net energy consumption based on economic indicators (GNP and GDP) in Turkey, Energy Policy, Vol 35 pp. 4981–4992

Sözen A., Arcaklioglu M. A., Arcaklioglu E., (2006), Forecasting Net Energy Consumption Using Artificial Neural Network, Energy Sources Part B, Vol 1 pp. 147–155

Tiwari A. K., (2015), On the dynamics of Indian GDP, crude oil production and imports, OPEC Energy Rev., Vol 39 pp. 162-183

USDA US Inflation Long-Term Forecast (2021) https://knoema.com/kyaewad/us-inflation-forecast-2021-2022-and-long-term-to-2030-data-and-charts

Uzlu E., Kankal M., Akpınar A., Dede T., (2014), Estimates of energy consumption in Turkey using neural networks with the teachingelearning-based optimization algorithm, Energy, Vol 75 pp. 295-303

Wanjala K., Kinyanjui A., (2018), Effect of Crude Oil Prices on GDP Growth and Selected Macroeconomic Variables in Kenya, J. Econ. Bus., Vol 1(3) pp. 282-298

Yan B., Zhang Q. H., Wai O. W. H., (2008), Prediction of sand ripple geometry under waves using an artificial neural network, Comput. Geosci., 34 pp. 1655-1664

Zhou C., Chen X., (2019), Predicting energy consumption: A multiple decomposition-ensemble approach, Energy 189, 10.1016/j.energy.2019.116045

Zhou C., Chen X., (2021), Predicting China's energy consumption: Combining machine learning with three-layer decomposition approach, Energy Rep., 5086-5099