Prediction of the Electricity Demand in the Market: An Application of Optimization and Machine Learning

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ABSTRACT:
In this study, the combination of Gray Wolf Optimization and Artificial neural networks (GWO-ANN) algorithm was applied to predict the long-term electricity demand in Iraq, considering the nonlinear trend and uncertainties in the variables affecting it. The results indicate that the population and gross domestic product are significant explanatory variables for long-term energy demand, consistent with previous studies. Compared to other intelligent methods, the GWO-ANN algorithm requires less data for modeling and optimally designs the ANN structure. The modeling and forecasting model outperform the ANN in simulating and predicting the long-term energy demand. Based on the most likely scenario, the predicted electricity demand in Iraq will reach approximately 415 GWh. Electricity is a critical factor in the development of societies and is utilized in various economic sectors.

KEYWORDS: Electricity Demand, Gray Wolf Optimization, Artificial Neural Networks, Predictive Modeling.

1. INTRODUCTION

Electricity is a crucial factor in the economic and social development of any country, as it plays a significant role in all sectors of the economy [1]–[3]. Especially in the region of West Asia and the Persian Gulf, where the energy issue is subject to the most severe international sanctions [4]–[6]. In the current era of industrialization and urbanization, energy demand is growing at an unprecedented rate, particularly in developing countries [7], [8]. The increasing demand for electricity has become a significant concern for policymakers, as it directly affects economic growth, environmental sustainability, and social welfare [9]. Therefore, accurate and reliable forecasting of electricity demand has become a vital task for policymakers, energy planners, and investors [10]–[12].

Numerous methods have been proposed to forecast electricity demand, such as statistical methods, machine learning algorithms, and artificial intelligence techniques [13]–[15]. Among these methods, Artificial Neural Networks (ANNs) have gained considerable attention in recent years due to their ability to handle complex and nonlinear relationships between the input and output variables [16], [17]. However, the performance of ANNs is highly dependent on the quality and quantity of data used for training the model [18]. Moreover, selecting the optimal architecture of ANNs can be a challenging task, particularly when the input-output relationship is complex [19], [20].

To overcome these limitations, several hybrid

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models have been proposed to enhance the predictive accuracy of ANNs [21]. Among these models, the Grey Wolf Optimization Algorithm (GWO) has emerged as a powerful optimization algorithm for enhancing the performance of ANNs [22]. The GWO algorithm is a metaheuristic optimization algorithm inspired by the hunting behavior of grey wolves [23]. The GWO algorithm has been successfully applied in various fields, such as image processing, power system operation, and renewable energy systems [24].

In the context of energy demand forecasting, several studies have applied the GWO-ANN algorithm for improving the accuracy of the forecasting models. For example, Behzadi et al. [25] applied the GWO-ANN algorithm for predicting the electricity demand, and the results indicated that the proposed model outperformed other forecasting methods. Similarly, Hafeez et al. [26] used the GWO-ANN algorithm for energy consumption forecasting in smart grid, and the results showed that the GWO-ANN algorithm can accurately forecast the electricity demand with high precision.

In this study, we propose a novel hybrid model based on the GWO-ANN algorithm for forecasting the electricity demand in Iraq. The proposed model aims to predict the long-term trend of electricity demand in Iraqi market, taking into account the uncertainty in the variables affecting it and its nonlinear trend. Moreover, the proposed model optimizes the ANN architecture using the GWO algorithm to enhance the accuracy and robustness of the model.

2. MARERIALS AND METHODS

In this paper, the use of artificial neural network and Grey Wolf Optimization (GWO) algorithm in solving optimization problems is investigated. Specifically, we explore the application of these methods in the context of long-term demand for electric energy over a 40-year period (1981-2021) in Iraq.

2.1. Artificial Neural Networks

Artificial Neural Networks (ANNs) are a type of machine learning model inspired by the structure and function of the human brain. ANNs are composed of multiple interconnected nodes, or neurons, that work together to process input data and produce an output.

The neurons in an ANN are organized into layers, with each layer performing a specific type of computation. The input layer receives raw data, and subsequent layers transform the data into increasingly abstract representations. The final output layer produces the network's prediction.

During training, an ANN adjusts the weights of the connections between neurons in order to minimize the difference between the network's output and the desired output. This process is typically done using a variant of the backpropagation algorithm.

One of the key advantages of ANNs is their ability to learn and generalize from complex, high-dimensional data sets. This makes them useful for a wide range of applications, including image and speech recognition, natural language processing, and predictive modeling [27].

2.2. Grey Wolf Optimization Algorithm

The Gray Wolf Optimization (GWO) algorithm is a metaheuristic optimization algorithm that is inspired by the social hierarchy and hunting behavior of gray wolves in the wild. Like other metaheuristic algorithms, the GWO algorithm is used to find the optimal solution to a given optimization problem, without requiring knowledge of the problem's analytical form.

The GWO algorithm is based on the idea of simulating the social hierarchy and hunting behavior of gray wolves in the wild. In the algorithm, a group of candidate solutions, called a pack, is initialized and evolves over time based on the behavior of the wolves. The pack is composed of alpha, beta, and delta wolves, which represent the most dominant and successful individuals in the pack.

During each iteration of the algorithm, the position of each wolf is updated based on its own position, as well as the positions of the alpha, beta, and delta wolves. This is done using a set of mathematical equations that are designed to simulate the hunting behavior of the wolves, which involves a combination of exploration and exploitation.

The ability of the GWO algorithm to efficiently search large solution spaces for the optimal solution without requiring a large number of function evaluations is one of its primary advantages. This makes it particularly useful for optimization problems with a large number of variables or a high computational cost [28].

2.3. Model Evaluation

There are two categories of electric energy demand forecasting models: short-term forecasts and long-term forecasts. The first type relates to demand on an hourly, weekly, and monthly basis. This type of prediction is crucial for distribution companies. Due to the fact that its data is the foundation of daily production and, in the event of an inaccurate forecast, directly affects the distribution companies' purchase costs, its accuracy is crucial. Due to the effects of temperature and price on electricity consumption, variables such as temperature, weather changes, and seasonal changes are typically included in this type of predictive model. The annual and even multi-year projections of future electricity demand are made. This information is essential for expanding production capacity, making investment decisions, analyzing profits, and budgeting for businesses. In other words, the demand behavior will vary according to the modeling time period (long-term or short-term) and these effective variables. If the model in question is seasonal (short-term), air temperature and humidity will have a substantial impact on electricity demand. However, if the demand modeling is annual (long-term), because the annual changes in weather and climate are very small, the temperature and humidity will not vary significantly from year to year. As a result, the presence of these variables in long-term models is not ideal. Additionally, the diversity of the country's climate will be the long-term reason for excluding atmospheric variables from macro and national modeling.

On the other hand, due to the unique characteristics and high economic efficiency of electric energy, the likelihood of substituting it with other products is low, and the pricing policy will have little impact on its consumption. Due to price discrimination and the existence of different prices in different sectors and even within a single sector (such as the prices of electric bridges in the domestic sector), it is also difficult to provide a single index that accurately demonstrates the behavior of energy supply and demand.

Energy has been essential to life and the growth of human societies. The population as a whole, influences not only the total amount of energy consumption, but also the per capita energy consumption resources and the energy consumption pattern; as a result of its rapid growth, it is a driving force for the population. Consequently, population can be considered one of the most significant factors influencing energy demand.

According to economic theories, an increase in consumer income will increase their purchasing power, and an increase in purchasing power will increase their consumption of essential goods. With an increase in income, the most important indicator of which is gross domestic product, it is anticipated that the demand for electricity will also rise. Consequently, it can be stated that the increase in production in these nations results in a rise in energy consumption. *E* represents the annual demand for electric energy, while *P* and *GDP* per capita represent the population and gross domestic product, respectively.

$$E = f(GDP, P) \tag{1}$$

3. SIMULATION OF ENERGY AND ELECTRICITY DEMAND

In this study, an artificial neural network model was created and trained using MATLAB software. Identifying and creating a suitable structure for the artificial neural network prior to beginning its training by the neural network was necessary and very effective for achieving the desired outcomes. The creation of an appropriate structure is heavily influenced by the researcher's preferences and level of expertise. In some instances, the created structure may not be optimal, and alternative structures may be utilized. In this study, the problem of identifying and creating the optimal structure of the neural network using the optimization algorithm is addressed by combining the gray wolf algorithm and artificial neural network. It is the annual electric energy consumption.

In the pre-processing phase, to facilitate calculations and accelerate convergence, the function first converts the data to normal data between zero and one, and then divides it into two groups: training data from 1981 to 2011 and validation data from 2011 to 2021.

$$Z_n = (Z_r - Z_{min})/(Z_{max} - Z_{min}), \tag{2}$$

where, Z_r, Z_n, Z_{max} and Z_{min} represent the actual, normalized, the maximum, and minimum values of the data under investigation, respectively. Table 1 shows the statistics of the input and output variables.

Table 1. The maximum and minimum values of the variables under investigation in the years 1981 to 2021.

	Annual Energy Consumption	GDP per Capita	Population
Min	13.24×10^6 kWh (1981)	\$23 (1991)	14,067,260 (1981)
Max	171.12×10^6 kWh (2021)	\$10,217 (1990)	43,533,592 (2021)

After creating and training the artificial neural network model with training data and ensuring its generalizability, independent variables are predicted and re-entered into this model to predict future electric energy demand values.

4. EVALUATING THE EFFICIENCY OF SIMULATION AND FORECASTING

After constructing the GWO-ANN model, training and simulating electric energy demand using data from 1981 to 2021, we are currently evaluating its effectiveness at simulating and forecasting electric energy demand. In order to accomplish this, the output of the system must first undergo post-processing so that it can be compared with actual electric energy consumption values. In fact, the opposite of what was done in equation 1 must be performed.

The proficiency of the model was evaluated using the mean square error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) as

$$MSE = \frac{\sum_1^n (\widehat{Z_t} - Z_t)^2}{n}; \tag{3}$$

$$MAE = \frac{\sum_1^n |\widehat{Z_t} - Z_t|}{n}; \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (\widehat{Z_t} - Z_t)^2}{n}}, \tag{5}$$

where, n, Z_t and $\widehat{Z_t}$ are the number of observations, observed, and calculated values, respectively.

5. MODEL RESULTS

Fig. 1 depicts the results of simulation (1981 to 2011) and forecasting real values outside the realm of education (2011 to 2021) of electric energy demand. Examining electric energy demand using the simulation efficiency model and forecasting using this model demonstrates the system's performance in simulating and predicting the long-term demand for electric energy is satisfactory.

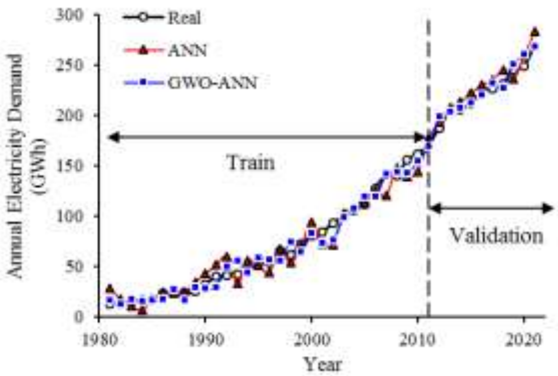

Fig. 1. Simulation results of training and verification data.

The performance of the ANN and GWO-ANN model to predict the long-term demand for electric energy is deemed acceptable based on the simulation and prediction efficiency evaluation results presented in Table 2.

Table 2. Model performance evaluation.

Model	Phase	MSE	MAE	RMSE
ANN	Train	0.002	0.034	0.044
	Validation	0.002	0.019	0.31
GWO-ANN	Train	0.001	0.023	0.028
	Validation	0.001	0.018	0.024

Based on the above results, it can be stated that the variables of population and GDP, as discussed earlier about their relationship with the long-term demand of electric energy, have not been able to explain the trend of the long-term demand of electric energy. As can be seen, the GWO-ANN model has a higher efficiency in simulating population variables and gross domestic product from 1981 to 2021, as all error criteria have the lowest value. In order to predict the future demand for electricity, this model can also be used with high confidence to predict the model's independent variables.

6. FORECASTING THE FUTURE TREND OF ELECTRIC ENERGY DEMAND

Due to the fact that electric energy cannot be stored on a large scale and the electricity industry's investment process is time-consuming. Consequently, a correct and logical forecast of the trend in electricity consumption is crucial for policymaking and management of electricity production and distribution; hence, this section of the study focuses on the long-term electricity consumption over the 2030.

The scenario method is one of the qualitative methods of the future, according to which we draw and imagine the future through the creation of hypothetical scenarios. Scenarios are a clear picture of the future that enable programmers to clearly identify the environment's issues, challenges, and opportunities. The scenario is a tool for analyzing policies and identifying future circumstances, threats, opportunities, requirements, and values. Due to the diversity of future factors and forces, as well as their complexity and interaction, the future cannot be accurately predicted. Therefore, futurists do not believe it is appropriate to select the most probable image of the future. Why should different programming scenarios be used? Consequently, if the scenario includes all possible future images, it can be regarded as a potent planning tool. The long-term energy forecast is presented in Table 3, along with the potential scenarios.

Table 3. Annual rate of independent variables based on different scenarios.

Variable	Scenarios			
	1	2	3	4
GDP	8%	5%	3%	1%
Population	2%	1.5%	1%	0.5%

After predicting the trend of independent variables, it is possible to predict the future trend of electricity demand until 2030 by substituting them into the GWO-ANN model developed in the previous section. Table 4 depicts the anticipated trend of electricity demand until 2030. The outcomes of scenario 1, which is considered an optimistic scenario, are evident. It indicates that energy consumption will reach 509.5 GWh in 2030, based on an overestimate.

The results of scenario 4, which is deemed a pessimistic scenario, indicate that the amount of energy consumed in 2030 will be approximately 388.3 GWh.

As an intermediate scenario, Scenarios 2 and 3 predict 2030 energy consumption of 429, 418 GWh, respectively. In addition, the GWO-ANN model predicts that this amount will be 414 GWh.

Examining the preceding results closely reveals that the forecast of the GWO-ANN model, which is based on the temporal trend of the historical data of the socio-economic variables of Iraq, is very similar to the forecast of scenarios 2 and 3. This indicates that scenarios 2 and 3 are extremely close to the historical data used in this study.

Table 4. The long-term demand trend of Energy Electric (GWh).

Year	Scenario				GWO-ANN
	1	2	3	4	
2022	290.81	290.81	290.81	290.81	290.81
2023	317.17	308.82	305.54	304.07	307.18
2024	365.72	341.10	331.67	327.47	336.37
2025	418.44	374.68	358.39	351.22	366.48
2026	424.86	378.61	361.47	353.93	369.97
2027	443.86	390.17	370.50	361.89	380.24
2028	482.84	413.58	388.68	377.87	400.98
2029	495.20	420.81	394.25	382.74	407.35
2030	509.50	429.11	417.61	388.30	414.66

7. CONCLUSION

Electricity plays a crucial role in the development of societies and is utilized as a factor of production in various economic sectors. In this study, the combined GWO-ANN algorithm was used to model and predict the future trend of the nation's long-term electric energy demand, taking into account the uncertainty in the variables affecting it and its nonlinear trend. In comparison to other intelligent methods, the employed algorithm requires less data for modeling and optimally designs the ANN structure. Similar to Azadeh et al. [29], the results of this study confirm the explanatory power of population and gross domestic product in the estimation of long-term energy demand. Comparing the efficiency of simulating and forecasting long-term energy demand using GWO-ANN and ANN demonstrate the superior predictive ability of the modeling and forecasting model. Based on the most likely scenario, he demonstrated that this level of demand will reach about 415 GWh.

According to the findings of the study, the presented algorithm is recommended for a better and more accurate forecast of the long-term demand for electric energy and the formulation of various energy policies for the nation. In addition, it is suggested that this technique be used in future studies to predict other energy carriers in various economic sectors. Considering the high predictive power of the proposed technique, future studies that compare this technique to other methods for predicting other economic variables can also demonstrate its efficacy.

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