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Impact of fuel prices on electricity price using the predictive power of ANN-GA, LRM: Evidence from Iran

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Abstract

In Iran, the energy price is very much influenced by the dollar price. However, this price is highly fluctuated due to various reasons. The emergence of the pandemic, the covid-19, from one part and the financial sanctions on the economy from another, cause the high volatility on this foreign currency. First, in this study, we converted the IRR (Iranian currency) into the same dollar rate of the year, contributing to the impact of exchange rate volatility in the model. Then, we forecast the price of all three principal fuels that affect the cost of electricity production, and then we forecast the electricity prices using ANN_GA and the historical data. This study also examines the fundamental and exacerbating causes in recent years, especially in 2018 when we faced an unprecedented increase in dollar prices in the Iranian market when the U.S. withdrew from the joint comprehensive plan of action (JCPA), and its effects are still visible. We intend to investigate the impact of these fluctuations on the future electricity market. In the end, we examine that which variables (fuel prices) would affect electricity prices the most using a linear regression model.

Keywords: Forecasting, fuel prices, ANN, GA, energy prices, linear regression model

1- Introduction

The officials believe that regarding the localization of the electricity industry through domestic enterprises, there is little problem in the electricity industry due to currency changes. Besides foreign exchange openings and government currency allocation of the dollar with the price of 4225 Tomans for producers of goods and services, these issues have led us to see a slight increase in the cost of electricity in recent years (Singhal and Swarup, 2011). In the previous year (2021), the cost of electricity per kilowatt/hour Electricity prices of steel, aluminum, copper, primary metals and metal ores, refineries, and petrochemical industries will increase from 80 Tomans to 300 Tomans per k/h (between $0.02 to $0.07 per k/h), according to Note 15 of Budget Law 1400 (2021) in the audit report of the planning and budget organization.

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However, the electricity industry has announced it would still be 80 tomans per k/h. Finally, the cabinet allowed the ministry of energy to cite articles 1 and 2 of the subsidies targeting act that increased average utility tariffs by 7% since February without restructuring[1]. Although actual reports show that the government's inability to stabilize the exchange rate has bankrupted many electrical contractors during the economic crisis of the previous year so far, and if the fluctuations continue happening like this, we will see many companies and factories disappear. And the pandemic effect, which started to feel in 2019 on the economy of Iran, was another cause of this disaster and economic instability. In general, we can say that the non-economic and political factors fluctuate the foreign exchange market in the short term. Still, economic issues such as getting out of the recession or economic growth are factors that can create relative stability in the currency market over the long term (Aggarwal et al., 2009). It should also be noted that before the recent nuclear talks in Vienna, which have just begun, we saw very sharp currency fluctuations between 2019 and 2021(from almost 11000 tomans per $1 and soared to nearly 30000 tomans per 1$ in the free market during the past three years).

Francis Galton first used the concept of regression in 1877. His study showed that the height of born children from tall parents tends to go back to the person's average height. He stated in his famous article that, although there is a tendency for tall parents to have tall children and short parents to have short children, the average height of parents of any given older class tends or regresses toward the average height of the whole society. In general, the new interpretation of the regression is quite different from the previous one (Zhang and Ma, 2011). Regression analyzes the study of the dependence of one variable (one variable) on one or more variables (explanatory variable) which by estimating or predicting the average or average value of the first type variable when the second time variable values are known or specified (in duplicate sampling). Suppose the variable dependency is examined on only one explanatory variable. In that case, such a study is known as simple or bivariate regression analysis. Still, if the dependence of one variable is reviewed on more than one explanatory variable, it is introduced as compound regression (Fan et al., 2016).

Artificial neural networks (ANN) or connectionist systems are computing systems like biological neural networks that constitute animal brains. An ANN is based on a collection of connected units or nodes called artificial neurons. A biological brain can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it can signal neurons connected to it (Mahdiani and Khamehchi 2016). Warren McCulloch and Walter Pitts (1943) opened the subject by creating a computational model and introducing some functions for neural networks for the first time. These functions are trained on historical data after connecting each other with adaptive weights, and they are used to make future predictions. Also, in this paper, we want to reduce ANN's projection for future prices as much as possible, so we utilize the ANN in combination with GA[2] (Viegas et al., 2016 April).

Many papers have been written regarding forecasting the different fuel prices such as crude oil, natural gas, and coal with linear and nonlinear regression models. In 2011 Ma and Zhang predicted the coal price index by a new partial least-square (PLS) regression (Zhang and Ma, 2011). They have collected the daily coal price index for twenty days and fitted the function between the output variable and components by the linear, quadratic, and exponential model, which improved the PLS regression model. For forecasting crude oil prices, an ICA-based support vector regression scheme was used by Fan et al. (2016). The paper utilized independent component analysis (ICA) to analyze crude oil prices, which are decomposed into several separate components corresponding to various types of influential factors that affect oil prices. They also proposed an ICA-based support vector regression scheme called ICA-SVR to predict crude oil prices. Later in 2018, Dbouk and Jamali employed linear and nonlinear models to predict daily oil prices (Dbouk and Jamali, 2018). They evaluated the two different models in forecasting daily oil prices. The competing forecast of oil prices was generated from parsimonious linear models that needed no parameter estimation. They used two linear models that exploited the informational content of oil demand and the increasing

[1] barghnews.com
[2] Genetic Algorithm

correlation between oil and equity prices. The nonlinear model which they employed was an artificial neural network. They considered a neural network trained using the genetic algorithm and an ANN with fuzzy logic called a bagged neural network. Finally, in 2009 Joutz and Villar presented a paper about the relationship between crude oil and natural gas prices (Villar and Joutz, 2006). They examined the time series econometric relationship between the Henry Hub natural gas price and the West Texas Intermediate (WTI) crude oil price. They concluded that when data have unit roots, such analysis is faulty. The relationship dynamics suggested a 1-month temporary shock to the WTI of 20 percent has a 5-percent contemporaneous influence on natural gas prices. Still, they found out it is decomposed to 2 percent in 2 months. In the following year, 2020, Anand and Suganthi forecasted the future energy demand of one state in India, using an artificial neural network (ANN) optimized by particle swarm optimization (PSO) and by Genetic Algorithm (GA). The results obtained using the hybrid ANN-PSO models were compared with those of the ARIMA, hybrid ANN-GA, ANN-BP, and linear models, and they concluded that Among all the hybrid ANN models, ANN-PSO models are the best fit models in all the time series (Anand and Suganthi, 2020). In 2021, Sharma et al. published a paper regarding combining the genetic algorithm with the artificial neural network for stock market forecasting. They propose an intelligent forecasting method based on a hybrid of an Artificial Neural Network (ANN) and a Genetic Algorithm (GA) and use two U.S. stock markets. They proved that the GA and ANN hybrid model's accuracy for the two stock markets is greater than that of the single ANN (BPANN) technique, both in the short and long term (Sharma et al., 2021). Finally, in the same year, panda et al. (2021) conducted a research on Load Forecasting using Metaheuristic Techniques. They explained the work of ANN thoroughly with backpropagation (BP), genetic algorithm (GA), as well as particle swarm optimization (PSO) for short-term load forecasting (STFL). In the end, they compared the result of GA and PSO by simulation, and after that, it concluded, the PSO-BP is a suitable method for STLF using ANN.

We conduct these studies, analyses, and forecasting because we would be able to plan more efficiently in our industrial and residential sections by having the fuel prices that belong to the future. Hence, we will have an outlook for exporting natural gas and crude oil and importing coal if needed as the feed for thermal power plants. By knowing which parameters (fuel prices) may affect the electricity price the most, we can decide what kind of power plant we can build in the future to be more profitable and save the natural resources as much as possible (Rokhsari et al., 2020).

This paper aims to investigate the regression method to investigate the effects of future fuel prices (crude oil, natural gas, and coal), which directly affect electricity prices. We also forecast future electricity prices using an artificial neural network (ANN) coupled with G.A. to obtain more accurate results.

The paper is organized as follows. Section 2 is about the data. We explain how and where we obtained them and their timetable and from what date to another, they extend and how the forecast has been conducted on the data. We show the dollar volatility during recent years and finally convert all prices in dollar in exerting their effect. In section 3, the modeling and analysis of data for all four prices and some testing approaches to proving the regression model's validity are conducted. Finally, the last section, section 4, has to do with the discussion of the conclusion. We reexamine the three factors affecting the electricity price by calculating any influence effect in percentage and briefly discuss the model's concise testing.

2- Data and the exchange volatility

This section has to do with the data, how we achieved them, and their timetable. Also, we explain the software we used to forecast the data to assess our analysis in the future and investigate and evaluate the impact of the data on our main one, which is the future price of the electricity.

First, we convert the prices of fuels(crude oil, natural gas, and coal) to the U.S dollar to examine its impact on all the prices, then see what price of fuels affects the cost of electricity the most in the future (10 years later). The exchange rate volatility in the last ten years_ from 2012 to 2021_is as the following chart.

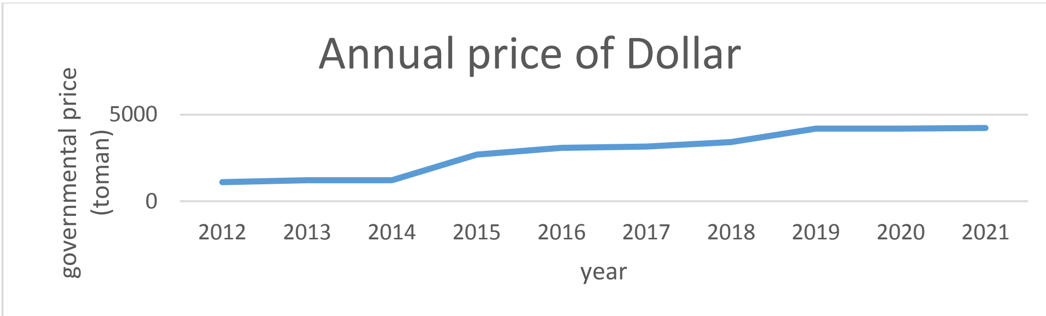

Fig 1. The annual price of the governmental dollar (declared by the central bank)

As you can see, since the governmental rate of dollar is allocated to the power plants and imports (if necessary, such as coals), we convert the prices to these dollar rates.

We obtained the hourly electricity prices of energy from the power plant of Damavand-Tehran, for the last ten years. We converted them to monthly prices, so the computations have been accelerated. The historical data for crude oil and natural gas for the previous ten years (from 2012 to 2021) is achieved from the website of NIOC[3], and coal prices are downloaded from the website of the energy exchange of Iran.

Matlab Simulink is utilized to predict the future prices (from 2021 to 2030) of fuels and energy using ANN and the programming language of R for statistical computation. And, it obtains the coefficients of correlation with the linear regression method and examines the different impacts of fuel prices on electricity prices. Some of the volatility exchange reasons which influence the price of fuels to generate energy, leading to electricity price volatility itself, are listed in the following table (Alagidede and Ibrahim, 2017).

Table 1. Reasons for exchange volatility

Demand-side	Background: -hyper-growth liquidity disproportionate to fundamental economic factors
Demand-side	Resonator: -Expectation factors • Statements by some government officials about increasing the exchange rate • Statements by U.S. officials about withdrawal from JCPOA agreement and imposition of new sanctions -decrease in the interest rate of banks in August 2018 -increasing demand for asset conversion to maintain asset value -increasing speculative demand -increasing demand for foreign travel -smuggling exchange rate to Soleimanie, Harat and…for issuing notes - Covid-19 pandemic and related restrictions - ongoing Nuclear talks
Supply-side	Background: -the existing restrictions for supplying the exchange rate for the central bank -lack of a proper mechanism for banknotes distribution and outsourcing management to exchanges -exchange rate allocation by presenting the national card without restriction and the need for a person's presence -restrictions on the entry of passenger's exchange rate into the country from neighboring countries - Covid-19 pandemic and related restrictions - ongoing Nuclear talks

[3] Natural Iranian oil company

3-Model and analysis

3-1- Forecasting the future price of fuels

First of all, a robust data bank is needed for building the model, which we already explained where we obtained our data for the past ten years in the previous section. Our goal is to use past data to forecast the fuel prices (oil, natural gas, and coal) in the next time series that is ten years later. The artificial neural network proved to be a strong tool for predicting future fuel prices based on past monthly prices. The output is the fuel prices, and the input is some data points preceding the output point.

ANN architecture of a single neural network and multi neural network layers are as follows. However, a multi neural network layer has more than one hidden layer in the middle of the input and output level.

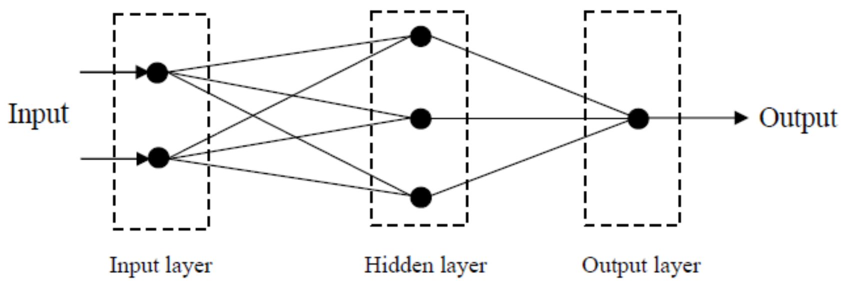

Fig 2. The model of a single neural network layer

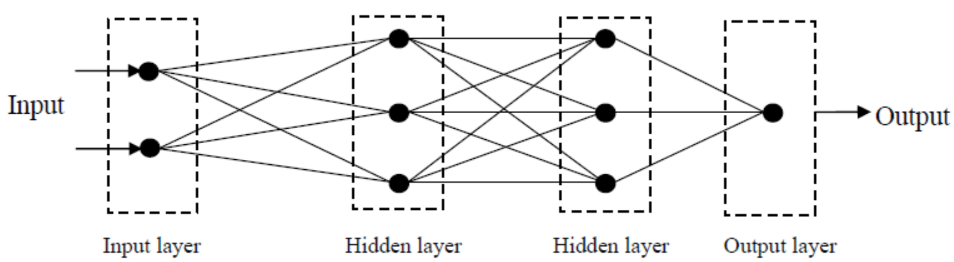

Fig 3. The model of a multi neural network layer

In prediction prices by ANN, if the number of points is minimal, the model cannot predict it well because of insufficient data. On the other hand, if the number is vast, some prices caused by previous phenomena (which are not available anymore) influenced the prediction. Thus, the ANN is applied with G.A. so that the G.A. optimizes the number of prior points and hidden layers (Wongsinlatam and Sompui, 2014). The properties of ANN and G.A. are listed in tables 2 and 3, respectively. Many considerations must be considered for using the ANN model, such as the size and frequency of data, network architect, number of hidden layers, and activation function.

Table 2. The artificial neural network parameters

Parameter	Value
Data division	Random
Training	Levenberg_Marquart
Performance	Mean Square Error
Stop tolerance	1.00E_05

Table 3. The Genetic Algorithm parameters

Property name	Property value
Population type	Integer vector
Population size	110
Fitness scaling	Rank
Selection function	Stochastic uniform
Elite count	4
Crossover function	Scattered
Crossover fraction	0.8
Mutation function	Uniform
Mutation probability	0.05
Migration	Forward
Max generation	220
Max stall generation	50
Function tolerance	1.00E-06

The genetic algorithm optimizes backward points, and ANN forecasts future prices. If we utilize them together, G.A. attempts to decrease ANN's prediction error as much as possible (Mahdiani and Khamehchi 2016). Training plays a significant role in the creation of the proper model. For this purpose, the data is divided into two parts, the first part is used for training the model, and the second one is for testing it. For monthly prediction, 80 percent of data is used for training, which is 88 points, and the rest is used for testing the model. After running the model, G.A. concluded that 36 backward points and two hidden layers are suitable for prediction. It can be deducted that there is no accuracy improvement for more than two hidden layers. Therefore two hidden layers are chosen. Tables 4, 5, and 6 show the statistical properties of the model for all three different fuels.

Table 4. Statistical properties of the model in this study case for crude oil ($ per barrel)

Monthly data	points	Max	Mean	Median	r
train	88	107.65	72.92	63.44	0.96
test	22	103.75	101.34	102.64	0.98

Table 5. Statistical properties of the model in this study case for natural gas ($ per metric ton)

Monthly data	points	Max	Mean	Median	r
train	88	4.61	3.43	3.49	0.98
test	22	5.86	3.35	3.15	0.97

Table 6. Statistical properties of the model in this study case for coal ($ per ton)

Monthly data	points	Max	Mean	Median	r
train	88	223.2	105.6	110.6	0.99
test	22	94.75	73.67	74.73	0.95

The convergence of the genetic algorithm is illustrated in figures 4, 5, and 6 for all three sets of data. Since the number of iteration is small, then the method is quick. So we coupled ANN with G.A. to predict the data for the next ten years with minor error and more accuracy.

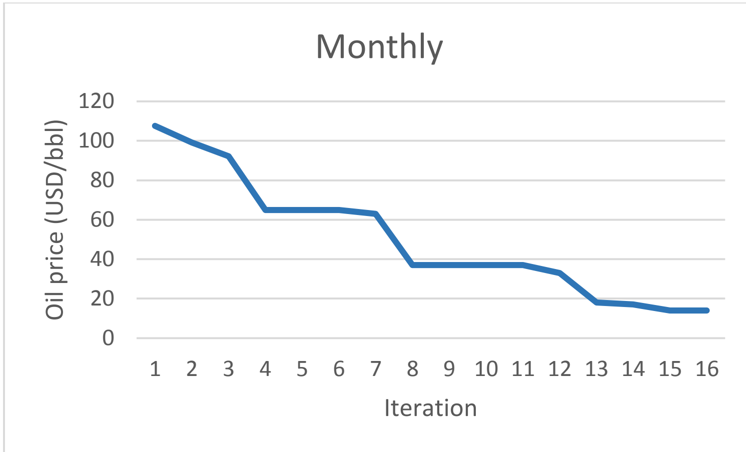

Fig 4. The convergence of the genetic algorithm for running the neural network for crude oil

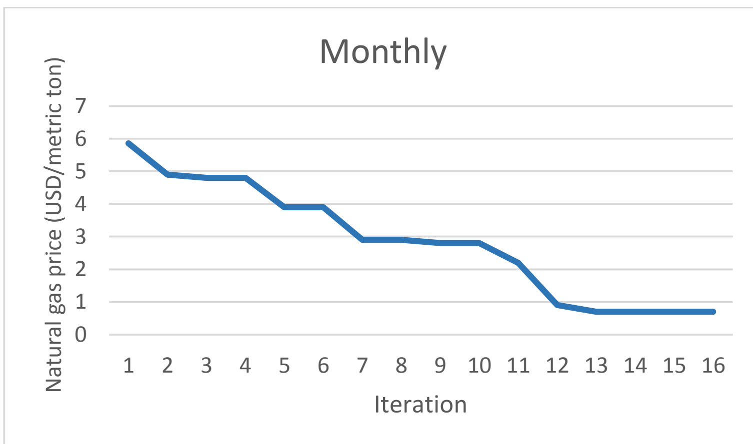

Fig 5. The convergence of the genetic algorithm for running the neural network for natural gas

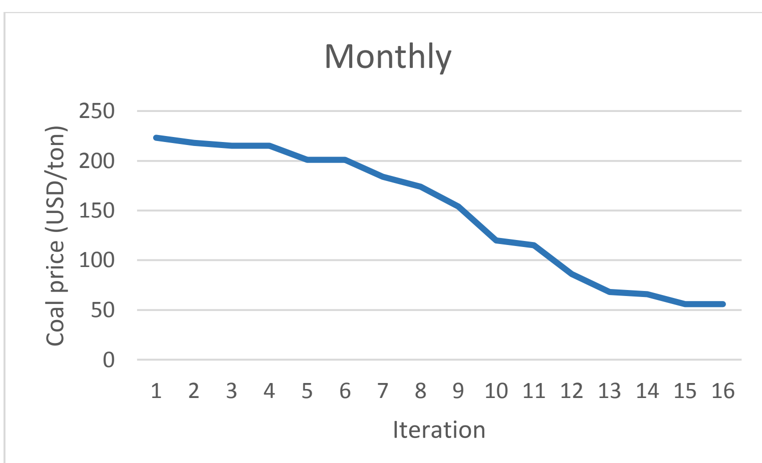

Fig 6. The convergence of the genetic algorithm for running the neural network for coal

So as it is desired to predict the fuel prices in the future, it is highly recommended to use a more extensive database, and the model is better to be built by ANN-GA rather than ANN alone (Bin Khamis and Yee, 2018).

3-2- Forecasting the future price of electricity

This section deals with forecasting the electricity prices based on historical data, which is a challenging task to do. Predicting the hourly market clearing prices (MCP) in daily power markets is the most critical task and basis for any decision-making to maximize benefits. But since we have had the hourly clearing prices for the past ten years, we predict the next decade with an artificial neural network. This method is the most proper tool to map the complex interdependencies between electricity prices, historical load, and other factors (Singh, et al., 2020 february). The neural network structure is a three-layer B.P.[4] network (two hidden layers and one output layer). We separated the electricity price prediction from fuel price prediction because the result of price forecasting using a neural network model indicates that these prices in the deregulated market are highly dependent on the trend in load demand and clearing price (C.P.) (Chinmoy et al., 2019). Three factors may influence the market and prices: historical MCPs that calculated its monthly price, system loads, and fuel prices that we already predicted. Again the neural network is trained with the data of 88 months out of 110 monthly collected data as before, and the rest is for testing the model. Historical information on electricity prices and also past load demands establish the crucial inputs for forecasting electricity prices (Román-Portabales et al., 2021). The inputs to the neural network forecast are brought in table 7.

Table 7. Neural network input for electricity price forecasting

No	Parameter	Inputs information	Relation
1	Day of week	3257 days (May 2021 to June 2030)	t
2	Historical price information	3257 (2605 for training and 652 for testing)	P(t)
3	Load demand	3257 days demand for the country	D(t)
4	Change in demand		D(t)-D(t-1)
5,6,7	fuel prices (crude oil, natural gas, coal)	For 110 months, as we used historical monthly price in the previous sections	F(t)

[4] Back propagation

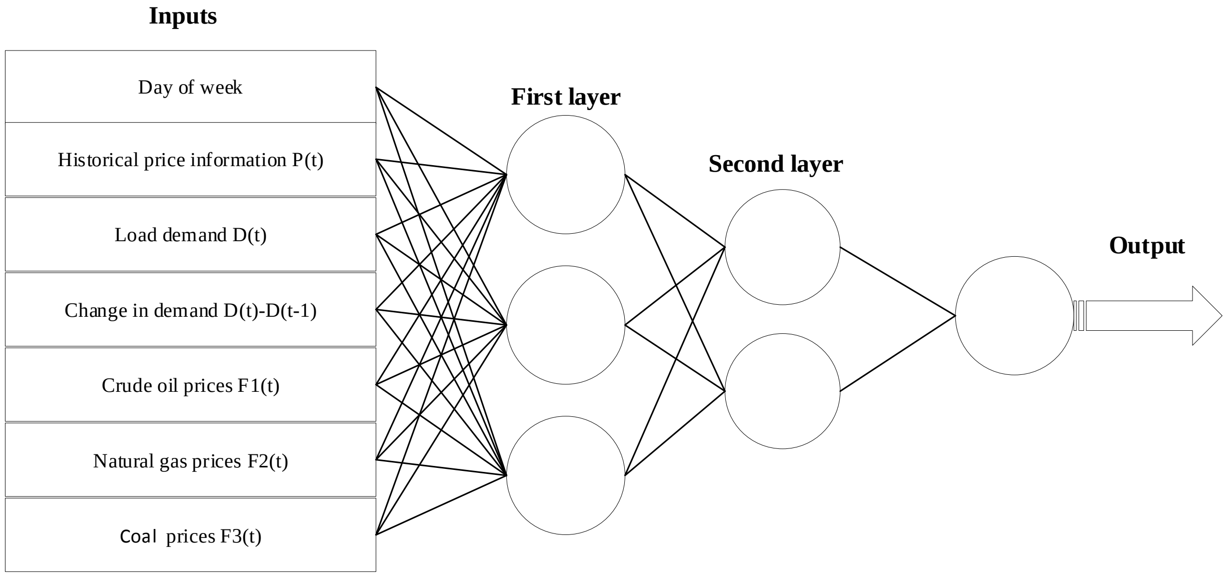

Fig 7. A neural network model for price forecasting

The first layer has three neurons and a tansig function, a transfer function calculating a layer's output from its net input, and the second layer has two neurons and a tansig function. The output layer contains one neuron with a linear function. Accurate price forecasting is crucial for electric utilities in a competitive environment created by the deregulation of the electricity industry. The powerful interdependence between load demand and electricity price should always be considered. The artificial neural network model was utilized to predict the daily energy market's clearing prices (MCP). Then we averaged them monthly for further investigations in the next chapter. However, electricity price forecasting can be more accurate by combining several fuzzy logic or dynamic clustering techniques. Still, the results in the next part indicate that the electricity prices are forecasted with reasonable accuracy (Tondolo de Miranda et al., 2018).

3-3- modeling and analysis using LRM

In this part, we want to investigate the impacts of variables _, which, in this case, are fuel prices (crude oil, natural gas, and coal) _on the response variable that is electricity price using linear regression of full model type.

A simple linear regression model can be expressed as follows.

$$y_i = \beta_1 + \beta_2 x_i + u_i \tag{1}$$

Where x_i represents an explanatory variable, y_i is the dependent variable and u_i represents the disturbance component of society. The random component of the society (u_i) is the representative or substitute for all deleted or forgotten variables that affect the dependent variable. Still, it does not exist in the regression model (or cannot fit for various reasons) (Faraway, 2016).

As stated, the stochastic component (disruptive component) is representative of all variables that are omitted from the model but affect y. Now the question is why these variables are not explicitly introduced into the model? In other words, why a component regression model does not extend to all possible variables? There are many reasons for this question. Some of them are listed below.

1. Theory may be flawed, meaning that we are unaware of the influence of some variables on the dependent variable. **2.** We may have little data on some variables. **3.** Gathering data on some variables may be

overwhelming relative to their impact on the model. **4.** Due to the random nature of the dependent variable, its full explanation is not possible, and the disturbance component can reflect it. **5.** An error measurement might have occurred. **6.** By applying the rule of Occam (describing phenomena even as simple as possible and not proven otherwise), it is desirable to simplify the regression model as much as possible (Fitzmaurice, 2016).
In this study case, our regression model equation is as follows.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \quad (2)$$

In equation (2), 'y' is the price of electricity and β is the coefficient and x_1 is the price of crude oil, x_2 is the price of natural gas, and x_3 is the price of coal. Using the programming language of R for statistical computation to obtain the coefficients of correlation with linear regression method and examining the different impacts of fuel prices on electricity prices, table 7 is brought as follows.

Table 8. Regression coefficients

P-Value	Coefficients	Parameters
0.000530	7.45367	Intercept
0.000226	2.10345	Natural gas
2.03e-16	0.34423	Crude oil
0.133674	0.23054	Coal

Regarding the presented model, as you can see in table 8, the most influential variable is the price of natural gas because most of the existing power plants in our country are combined-cycle power plants. In addition to the thermal power plant for greater energy production efficiency, a large section of the gas power plant next to them feeds on natural gas. The following influential parameters on the price of electricity are crude oil and coal, respectively. Due to the values of the p-value, all the proposed variables are 99% significant. Our H_0 hypothesis, as below, states that all coefficients are ineffective, is rejected (Harrell, 2015).

Statistical hypothesis $$\begin{cases} H_0 : \beta_0 = \beta_1 = \beta_2 = \beta_3 = 0 \\ H_1 : \beta_i \neq 0 \quad \forall i = 0,1,2,3 \end{cases} \quad (3)$$

For the whole model, the F-statistic with a degree of freedom 3 and 106 was used, higher than the critical value, so we accept the hypotheses H_0 and H_1, meaning that the model is significant. The R-square value obtained for the model is 65.53% which covers a relatively large amount of response variable (electricity price). R-square is expressed as the following equation. Regarding the satisfied value of R^2, this model can be referred to for price forecasting.

$$R^2 = \frac{SSR}{SST} = \frac{\sum(\hat{y}_i - \overline{y})^2}{\sum(y_i - \bar{y})^2} \quad (4)$$

Where SSR is the sum of square regression, and SST is the sum of the square total. R^2 is between 0 and 100%, the closer to 100%, the better the model is described.

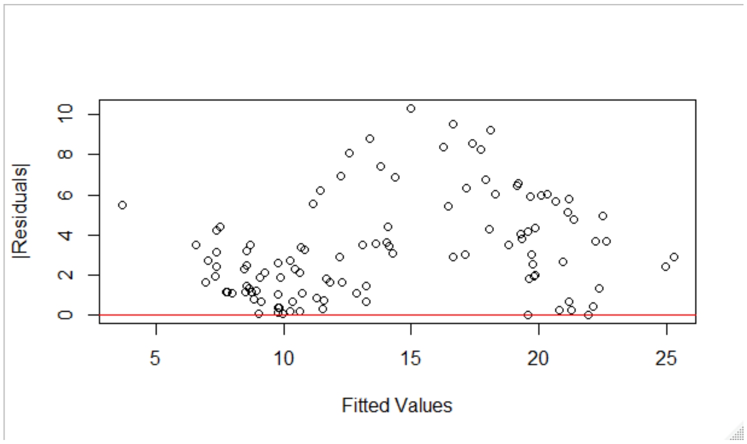

Fig 8. Fixed variance investigation

For investigating the variance being constant, we used residuals versus fit values, which in most studies this method is used for this purpose. In figure 8, you can see a predominant random state which indicates that the variance of the values remains constant. The red line represents the mean of the remaining values when they are not in an absolute value state, and as you can see, it is equal to zero. This is one of the basic assumptions of regression that is valid. The constant variance is also one of the basic assumptions of regression (Pilleboue et al., 2015).

To investigate of normality of residuals, we defined the Anderson-Darling test, which assumed the H_0 to be non-normal, with the p-value of 0.9912, the H_0 assumption is rejected at the 99% significant level, and residuals are normal, which proves that another regression assumption is valid (McDowell et al., 2016).

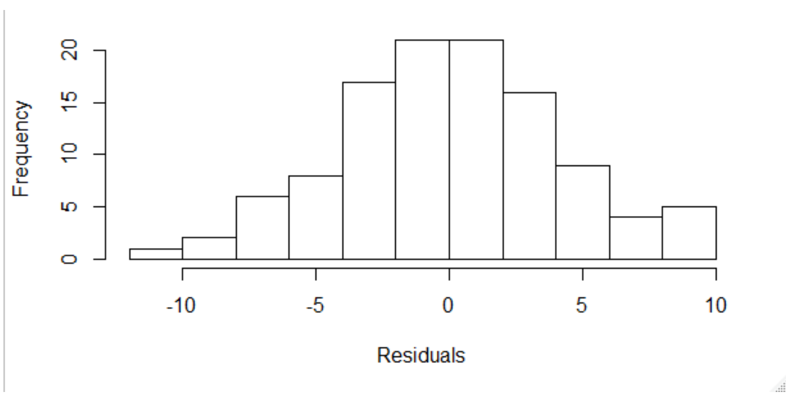

Fig 9. Histogram of Residuals

In the above figure, you see the histograms of residuals that confirm the validity of this test.

4-Discussion

In conclusion, we forecasted three different fuel prices (crude oil, natural gas, and coal) to understand their price change better and plan more efficiently for the future. We predicted them by the artificial neural network. We coupled it with the genetic algorithm for better accuracy because the input points are not much. We also wanted to reduce the ANN prediction error to optimize the previous issues. The GA determined that the number of hidden layers is better than 2, and it can be concluded that there is no accuracy movement for more than two layers. We took 80% of the data for training, and the rest is left for testing the model. Those prices affect the price of electricity the most. For forecasting electricity prices for the next ten years until 2030, we should notice that market-clearing prices (MCP) in daily power markets is the most crucial task and basis for any decision-making to maximize benefits. The structure of the neural network we used for electricity forecasting is a three-layer backpropagation network (two hidden layers and one output layer). Three factors may influence the market prices: historical MCPs that we calculated its monthly price, system loads, and fuel prices. In the end, we investigated the effect of each of the fuel prices on electricity prices by a linear regression model. The result showed us that the most influential variable is the price of natural gas, crude oil, and coal, respectively, by looking at their regression coefficient according to table 8. By some tests such as the value of R^2 and H_0 hypothesis, and also due to the values of the p-value, all the proposed variables are 99% significant. Therefore, our model was found to be valid and reliable.

This work can also be conducted and developed to other prices for future analysis and the number of exports and imports and different reasonable prices which affect them most. We can combine several techniques such as fuzzy logic or dynamic clustering in future studies for investigating more prediction accuracy.

References

Aggarwal, S. K., Saini, L. M., & Kumar, A. (2009). Electricity price forecasting in deregulated markets: A review and evaluation. *International Journal of Electrical Power & Energy Systems*, *31*(1), 13-22.

Alagidede, P., & Ibrahim, M. (2017). On the causes and effects of exchange rate volatility on economic growth: Evidence from Ghana. *Journal of African Business*, *18*(2), 169-193.

Anand, A., & Suganthi, L. (2020). Forecasting of electricity demand by hybrid ANN-PSO models. In *Deep learning and neural networks: Concepts, methodologies, tools, and applications* (pp. 865-882). IGI Global.

Bin Khamis, A., & Yee, P. H. (2018). A Hybrid Model of Artificial Neural Network and Genetic Algorithm in Forecasting Gold Price. *European Journal of Engineering and Technology Research, 3*(6), 10-14.

Chinmoy, L., Iniyan, S., & Goic, R. (2019). Modeling wind power investments, policies and social benefits for deregulated electricity market–A review. *Applied energy*, *242*, 364-377.

Dbouk, W., & Jamali, I. (2018). Predicting daily oil prices: Linear and non-linear models. *Research in International Business and Finance*, *46*, 149-165.

Fan, L., Pan, S., Li, Z., & Li, H. (2016). An ICA-based support vector regression scheme for forecasting crude oil prices. *Technological Forecasting and Social Change*, *112*, 245-253.

Faraway, J. J. (2016). *Extending the linear model with R: generalized linear, mixed effects and nonparametric regression models*. Chapman and Hall/CRC.

Fitzmaurice, G. M. (2016). Regression. *Diagnostic Histopathology*, *22*(7), 271-278.

Harrell, F. E. (2015). *Regression modeling strategies: with applications to linear models, logistic and ordinal regression, and survival analysis* (Vol. 3). New York: springer.

Mahdiani, M. R., & Khamehchi, E. (2016). A modified neural network model for predicting the crude oil price. *Intellectual Economics*, *10*(2), 71-77.

McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, *5*(4), 115-133.

McDowell, J. J., Calvin, O. L., & Klapes, B. (2016). A survey of residual analysis and a new test of residual trend. *Journal of the Experimental Analysis of Behavior*, *105*(3), 445-458.

Panda, S. K., Ray, P., & Mishra, D. P. (2021). Short term load forecasting using metaheuristic techniques. In *IOP Conference Series: Materials Science and Engineering* (Vol. 1033, No. 1, p. 012016). IOP Publishing.

Pilleboue, A., Singh, G., Coeurjolly, D., Kazhdan, M., & Ostromoukhov, V. (2015). Variance analysis for Monte Carlo integration. *ACM Transactions on Graphics (TOG)*, *34*(4), 1-14.

Rokhsari, A., Esfahanipour, A., & Ardehali, M. M. (2020). Computing optimal subsidies for Iranian renewable energy investments using real options. *Journal of Industrial and Systems Engineering*, *13*(Special issue: 16th International Industrial Engineering Conference), 16-29.

Román-Portabales, A., López-Nores, M., & Pazos-Arias, J. J. (2021). Systematic review of electricity demand forecast using ANN-based machine learning algorithms. *Sensors*, *21*(13), 4544.

Sharma, D. K., Hota, H. S., Brown, K., & Handa, R. (2021). Integration of genetic algorithm with artificial neural network for stock market forecasting. *International Journal of System Assurance Engineering and Management*, 1-14.

Singh, A., Singh, N. K., & Singh, P. (2020, February). Daily Electric Forecast for Various Indian Regions Using ANN. In *2020 International Conference on Electrical and Electronics Engineering (ICE3)* (pp. 95-100). IEEE.

Singhal, D., & Swarup, K. S. (2011). Electricity price forecasting using artificial neural networks. *International Journal of Electrical Power & Energy Systems*, *33*(3), 550-555.

Sompui, M., & Wongsinlatam, W. (2014). Prediction Model for Crude Oil Price Using Artificial Neural Networks. *Applied Mathematical Sciences*, *8*(80), 3953-3965.

Tondolo de Miranda, S., Abaide, A., Sperandio, M., Santos, M. M., & Zanghi, E. (2018). Application of artificial neural networks and fuzzy logic to long-term load forecast considering the price elasticity of electricity demand. *International Transactions on Electrical Energy Systems*, *28*(10), e2606.

Viegas, J. L., Vieira, S. M., Melício, R., Mendes, V. M., & Sousa, J. (2016, April). GA-ANN short-term electricity load forecasting. In *Doctoral Conference on Computing, Electrical and Industrial Systems* (pp. 485-493). Springer, Cham.

Villar, J. A., & Joutz, F. L. (2006). The relationship between crude oil and natural gas prices. *Energy Information Administration, Office of Oil and Gas*, *1*, 1-43.

Zhang, B., & Ma, J. (2011). Coal price index forecast by a new partial least-squares regression. *Procedia Engineering*, *15*, 5025-5029.