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A Study on the Fuel Consumption Demands of the Jordanian Residential Sector

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Abstract

Fuel consumption analysis has become crucial for the local government of Jordan and decision makers for securing economic stability and environmental protection. The current study employs an Artificial Neural Network (ANN) to analyze and estimate fuel use and demand in Jordan's residential sector. Throughout the investigation, five criteria are assessed: population (P), income level (IL), electricity unit price (E$), fuel unit price (F$), and ambient temperature (AT). From 1985 to 2020, data on fuel use and independent variables are gathered from official government reports and literature sources. Therefore, ANN is used to model, to analyze and estimate fuel use and demand in Jordan's residential sector. The results of this study showed that in the Jordanian residential sector fuel demands are mainly driven by the population and fuel price. Additionally, the present ANN model findings accuracy outperforms the literature models. Thus, the current ANN model is combined with time series analysis to forecast the fuel demands in Jordan’s household sector for the next decade. The findings of this study are expected to be helpful for the decision makers in the country for developing reliable and productive planning for future energy policies in the household sector..

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Keywords: Artificial Neural Networks (ANN), Energy, Residential Sector, Sustainability, Time Series Analysis.

1. Introduction

Fuel has long been the foundation of both developed and developing countries’ energy production systems. Much research has been conducted to address the issues connected with its use [1,2]. It is responsible for environmental issues such as air pollution and global warming, as well as societal negative consequences such as health problems and population quality of life [3-5]. Because of their critical significance in today's energy systems, their uneven distribution also raises worries about energy security. In economic terms, the insecurity of markets and pricing is also a disadvantage in their utilization. Furthermore, they are nonrenewable resources, raising concerns about their depletion and availability for current and future generations. All of the problems raised above lead to unsustainable energy systems and the search for innovative ways to reduce the negative consequences of energy systems. Despite the efforts of governments and other stakeholders throughout the world, it is possible to confirm that achieving sustainable energy systems remains a problem [6].

Jordan is a developing country in the Middle East, and like the rest of the region, it is attempting to secure its energy supplies, including fuel. Therefore, according to the International Energy Agency (IEA), Jordan's residential sector consumed 16% of total fuel consumption in 2020 [7]. The country is classified as a non-oil-producing country. As a result, Jordan imports crude oil and natural gas from its neighbors (Egypt, Iraq, and Gulf nations). However, the current framework circumstances, such as frequent pauses in Iraq's oil production and continuous delays in Egypt's natural gas supply, make it critical and difficult for Jordan to meet its energy demands [8].

Several studies have been performed on the study of fuel used for various markets, one of which is automobiles. Zargarnezhad et al. [9] conducted a study about fuel usage in cars operated by energy firms that have been predicted using artificial neural networks. Maintenance, servicing, and monitoring are all included in the fleet of vehicles. The network's input data included the vehicle's number of cylinders, displacement volume, number of valves, type, and weight, and these inputs were the main factors affecting fuel consumption. Since fuel is one of the forms of energy, research was carried out for Ecuador country by Verdezoto et al.[10] about several factors affecting energy consumption in the household sector four levels of disaggregation are considered the dominant factors and the four levels are population location, availability of power, examines end uses, and technology issues. The last level is connected to the kind of energy sources.

Going back to Jordan, Al-Ghandoor et al. [11] conducted investigation research on fuel usage analysis and forecasting in Jordan's residential sector. As a consequence of the findings, the population is the most important component in the fuel consumption model.

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All Jordanian domestic electricity analysis studies are rather out of date, with data dating back to before 2006. To bridge this research gap, the current study uses the Artificial Neural Network (ANN) technique to estimate and anticipate Jordanian residential fuel usage of updated data in the range of 1985 to 2020. This study also forecasts fuel demand for the next decade, and the results are expected to be valuable in developing productive and accurate planning for Jordan's future home fuel strategy.

The structure of this paper begins with a comprehensive description of the residential sector of Jordan along with the influencing factors on the electricity consumption levels and demands in this segment. Followed by the modeling and analysis procedure using the artificial neural networks, subsequently. The ANN model results, validations, and comparison with literature are detailed accordingly. Afterwards, the methodology used to forecast the energy needs in Jordan's residential sector is presented. Finally, the influence of each factor on electricity demands is particularly presented and discussed in great detail.

2. Jordan's Residential Sector

2.1. Overview

As stated earlier, Jordan is severely reliant on imports to cover its domestic energy needs, with just 8% of its energy generated locally. It imported 403.500 tons of Liquefied Petroleum Gas (LPG), 3608.8 thousand tons of Egyptian natural gas, and roughly 5241.8 thousand tons of crude oil and oil products in 2018[12]. Moreover, local fuel and electricity costs in Jordan are highly impacted by global pricing as well as foreign political factors. As a result, depending on the global scenario, this will have an impact on fuel consumption in Jordan's residential sector. Additionally, Jordan's total population rises every year, which impacts the annual state budget in general, resulting in a shift in the per capita proportion of national income. As a consequence, the most relevant criteria that determine fuel consumption in Jordan's residential sector are population (P), income level (IL), electricity unit price ($E\$$), fuel unit price ($F\$$), and ambient temperature (AT). Each parameter is thoroughly described below. Such variables were previously discussed in literature in Jordan and other countries [13-23].

2.2. Population (P)

Residential fuel demand would rise as the population, the number of dwellings, and the quantity of energy-consuming equipment grew. During the years 1985 to 2020, population statistics were acquired from prior literature sources [11] as well as the Department of Statistics (DOS) annually [24] (1985-2009, literature,2007-2020, DOS). From 1985 to 2012, the population grew gradually and smoothly, as seen in Fig.1. Nonetheless, there has been a large rise since 2012 as a result of Syrian refugees. For example the population number in the year 2010 was approximately 6 million but right after the Syrian conflict and refugees this number went up to 9.5 million. This shows the considerable change in the population number in the country.

2.3. Income level (IL)

The income level (IL) is defined as the ratio of the population (P) to gross domestic product (GDP). As income levels improve, so will the living standards, leading to an increase of using energy. GDP statistics for this study were obtained from past literature sources [11] as well as the Central Bank of Jordan's (CBJ) annual releases [25] from 1985 to 2020. (1985-2009, literature,2010-2020, CBJ). Fig.2 demonstrates a fall in wages according to the circumstances of the Gulf War in the late 1980s with decrease from almost \$2500 per capita to less than \$1500 per capita, and a similar decline in income level is demonstrated from 2013 to 2018 owing to the Syrian crisis(from \$3500 per capita to \$2800 per capita). Additionally, the significant expansion from 2007 to 2012 is attributed to Iraqi investors' rapid economic progress.

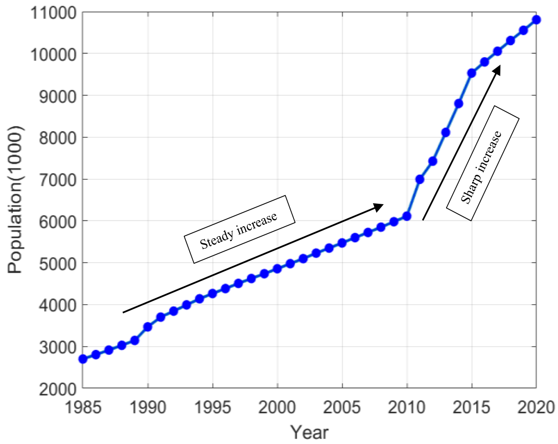

Figure 1. Population in Jordan for the period 1985 to 2020.

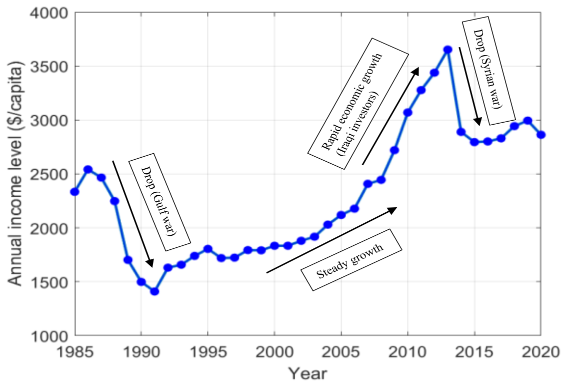

Figure 2. Income level in Jordan for the period 1985 to 2020.

2.4. Electricity unit price ($E\$$)

In reaction to rising electricity prices, people are expected to use more energy-efficient equipment or shift to alternative sources of energy, resulting in lower than expected rates of electricity usage. Electricity unit prices were obtained from prior literature sources [11] from 1985 to 2006, as well as the National Electric Power Company (NEPCO) annual report [26] from 2007 to 2020. Electricity prices continue to climb year after year, as seen in Fig.3, however, there have been two large rises. The first occurred in 2009 and 2010 where the price went up by 2.5 cents per KWh, and the second in 2014 and 2015 in which the price rise was by 3 cents per KWh.

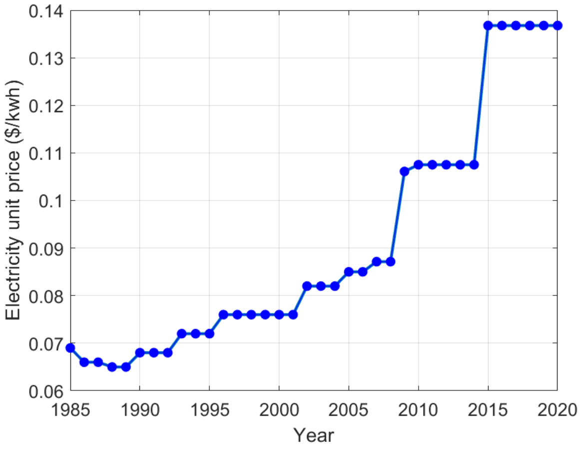

Figure 3. Electricity unit price in Jordan for the period 1985 to 2020.

2.5. Fuel unit price ($F\$$)

Kerosene, Liquefied petroleum gas (LPG), and diesel are the most commonly utilized fuels in Jordan's residential sector for space heating and, to a lesser extent, household water heating. As the unit price of fuel rises, families are expected to reduce their fuel consumption or switch to electricity as a fuel alternative. In this analysis, the weighted average price of diesel, LPG, and kerosene is employed as a variable. The fuel unit pricing data were acquired from prior literature sources [11] spanning the years 1985 to 2006, as well as yearly releases from the Ministry of Energy and Mineral Resources (MEMR) from 2007 to 2020 [27]. Figure 4 illustrates that because the Jordanian government supported fuel prices from 1980 to 2000, fuel prices did not vary. Following that, government assistance was withdrawn, and the country was put to a free pricing regime. The price shift from 2005 to 2020 is determined by worldwide fuel costs, which are heavily influenced by global political actions and conflicts. Over the course of 20 years, the fuel unit price went from \$6 per fuel unit to almost \$17 per fuel unit.

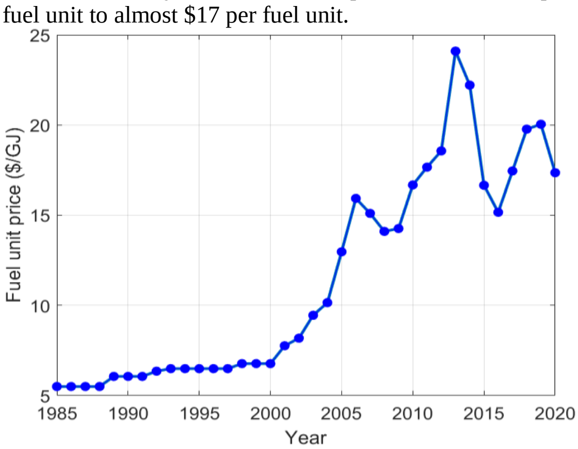

Figure 4. Fuel unit price in Jordan for the period 1985 to 2020.

2.6. Ambient temperature(AT)

The most major meteorological aspect that may have an influence on energy use is ambient temperature. Because frigid winters and scorching, dry summers need greater use of space heating and cooling equipment, energy use may be closely related to ambient temperature during either season. The difference in yearly average temperatures between summer and winter, rather than the average annual temperature, may be the more significant climatic variable. Furthermore, the averaged minimum yearly temperature was subtracted from the averaged maximum yearly temperature to compute the value of ambient temperature. The Climate Change Knowledge Portal (CCKP) [28] was used to collect ambient temperature data. As seen in Fig.5, weather conditions have changed relatively little over the last 36 years. As a result, it is projected that weather conditions have little impact on fuel use.

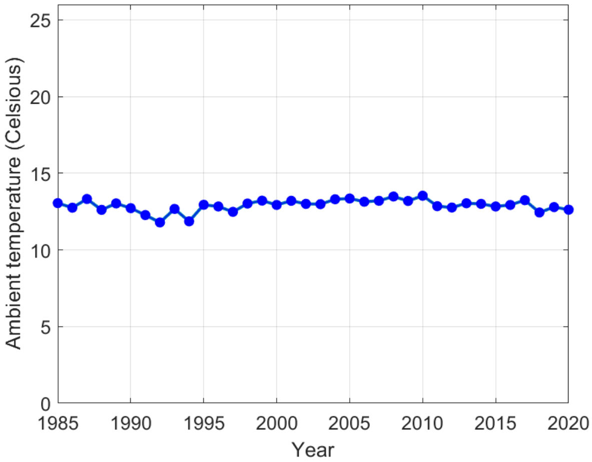

Figure 5. Ambient temperature in Jordan for the period 1985 to 2020.

2.7. Fuel consumption (F)

Fuel consumption (F) data in 1000-ton oil equivalent (1000 toe) are gathered from previous literature source [11], as well as yearly releases from the Ministry of Energy and Mineral Resources (MEMR) [27] for the years 1985 through 2020 (1985-2006, literature,2007-2020, MEMR).As seen in Fig.6, fuel usage continues to rise year after year. Despite this, there has been a significant increase since 2005 as a result of Syrian refugees and conflict.Table 1 presents the whole set of data examined in this study.

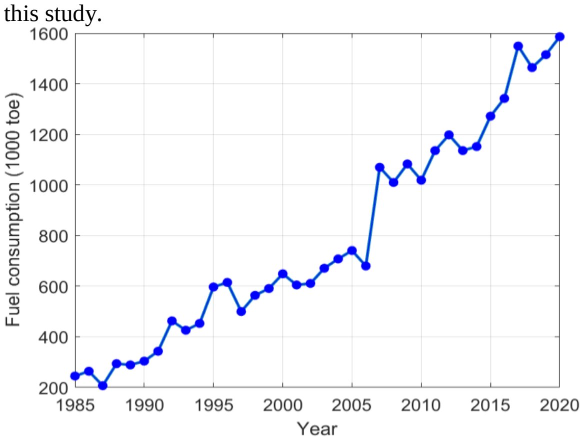

Figure 6. Fuel consumption in Jordan for the period 1985 to 2020.

In fact, literature studies have shown that other factors like the price of the electric device, efficiency of the house appliances and the residential type would have a comparable influence on the energy demands and consumption of the household sector [29]. However, due to the lack of access on such data in Jordan, the authors did not include them in the present study.

3. Analysis using Artificial Neural Networks

Artificial neural networks (ANNs) are a type of artificial intelligence that is based on the computerization of human abilities. When comparing typical computer processing to the way the human brain functions, it must be remembered that traditional computer processing occurs in a totally different way. The human brain's complex, nonlinear, and parallel working allows it to surpass even the greatest traditional computers in certain areas, including pattern recognition and perception [30, 31]. By duplicating the human biological information processing system, artificial intelligence has been able to augment the capabilities of computers. ANNs, in particular, are capable of replicating the biological neural network seen in the human brain, allowing them to identify patterns and predict future values.As a result, ANNs can effectively and correctly solve nonlinear regression issues [32,33].Artificial neural networks are widely used in a variety of sectors. Prediction, which is the practice of anticipating future patterns or events, is one of the most well-known. Forecasting is also used in a range of other areas, such as forecasting weather, asset values, and economic downturns [34,35].

Each ANN has an input layer, an output layer, and several hidden layers. Each hidden layer, as shown in Fig.7, is made up of a number of processing components known as neurons. To create an ANN, first, train it by examining a large number of input patterns and comparing them to their corresponding outputs. The neural network then models the findings and moves them to the hidden layer, where the neurons define the weight. Through the transfer function, the weight is then transmitted from the neurons to the input layer. As a result, the appropriate output predictions are sent to the output layer. A typical ANN method is as follows:

$$Y_j = f(\theta_j + \sum_{i=1}^{n} w_{ji} X_i) \quad (1)$$

where: θ_j is the bias at the hidden layer; n is the number of neurons in the hidden layer; w_{ji} the connection weight between the input variable and the hidden layer; X_i is the input variable; Y_j is the output variable; f is the transfer function [36].

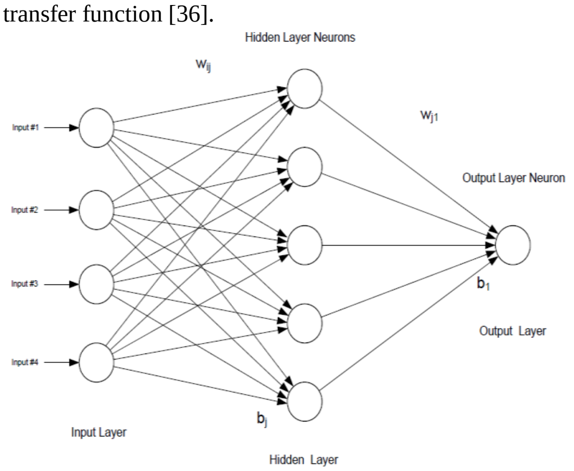

Figure 7. Typical ANN architecture [33].

The ANN approach was utilized in this work to anticipate Jordan's household fuel usage while taking into account all of the previously listed influencing factors ($P, IL, E\$, F\$$, and AT). Before beginning the ANN modeling process, all components, including the fuel use F, are normalized using the following equation to have values between 0 and 1, as advised by the ANN:

$$normalized\ value = \frac{input\ value - minimum\ value}{maximum\ value - minimum\ value} \quad (2)$$

Also, Appendix 1 divides the data into training, validation, and testing data, 70%, 15%, and 15%, respectively, chosen at random by the ANN. To find the optimum ANN design, 100 networks with varying numbers of hidden layers and neurons are examined.The root mean square error (RMSE) between predicted values ($F_{predict,i}$)and true values ($F_{actual,i}$) of fuel consumption was calculated for each network using the following formula:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_{actual,i} - F_{predict,i})^2} \quad (3)$$

As a result, the ANN with the lowest root mean square error (RMSE) is employed in the current study to conduct the fuel consumption analysis and projections.

4. Results and Discussion

4.1. ANN Model Results

As previously stated, many ANNs were evaluated in order to select the most accurate artificial intelligence network. Fig.8shows the RMSE values of each network, with network 58 having the lowest RMSE value of 15.25. This network is made up of 8 hidden layers, each with 6 neurons. Appendices 2, 3, and 4 show the whole set of training, validation, and testing data, with the ANN selecting 70%, 15%, and 15% at random. Appendices 5 and 6 also show the network's weights and biases. Furthermore, the amount of the weight indicates relevance; a negative weight indicates that increasing the input reduces the output.

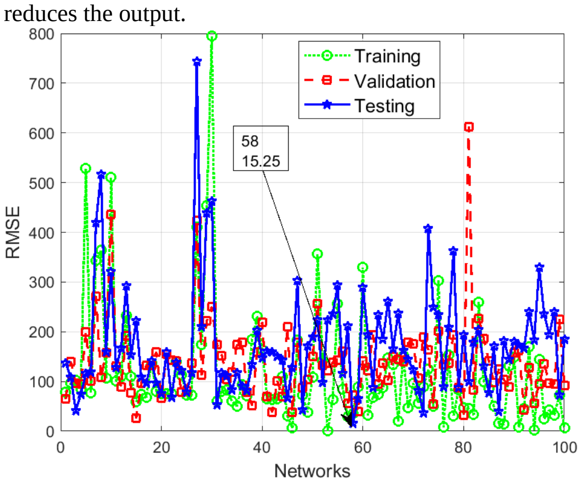

Figure 8. RMSE for training, validation, and testing sets vs networks.

Fig.9 represents the ANN predicted against actual values of fuel use in Jordan's residential sector for training, validation, testing, and full data sets. This graph shows that almost all data points for all data sets cluster around the normal line, indicating that the ANN is well-trained.To obtain higher trust in the created network, the values of the mean absolute percentage error (MAPE) and the coefficients of determination (R^2) are computed and investigated. The MAPE is provided by:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|F_{predict,i} - F_{actual,i}|}{F_{actual,i}} * 100\% \quad (4)$$

The MAPE was found to be 3.00%, a very low error value showing the outstanding accuracy of the present ANN model, and the R^2 was found to be 0.99, suggesting a very excellent quality match.

4.2. Comparison with Literature

The predictions of the current ANN model are compared to the literature model accessible in [11]. Table 7 summarizes the findings of this comparison.

After comparing the two models (ANN and literature), the results in Appendix7 show that the current ANN model's fuel consumption estimations are in strong agreement with the real fuel consumption data. To demonstrate, the ANN model's fuel use value in 2012 was 11931000-toe, which is quite close to the actual amount of 1198 1000-toe with a 0.41% error. Moreover, the literature model anticipated a fuel consumption value of 760.7 1000-toe in 2007, whereas the actual value was 1070 1000-toe, showing low performance and accuracy. As seen in Fig.10, the present ANN beats the literature model with much lower error values.

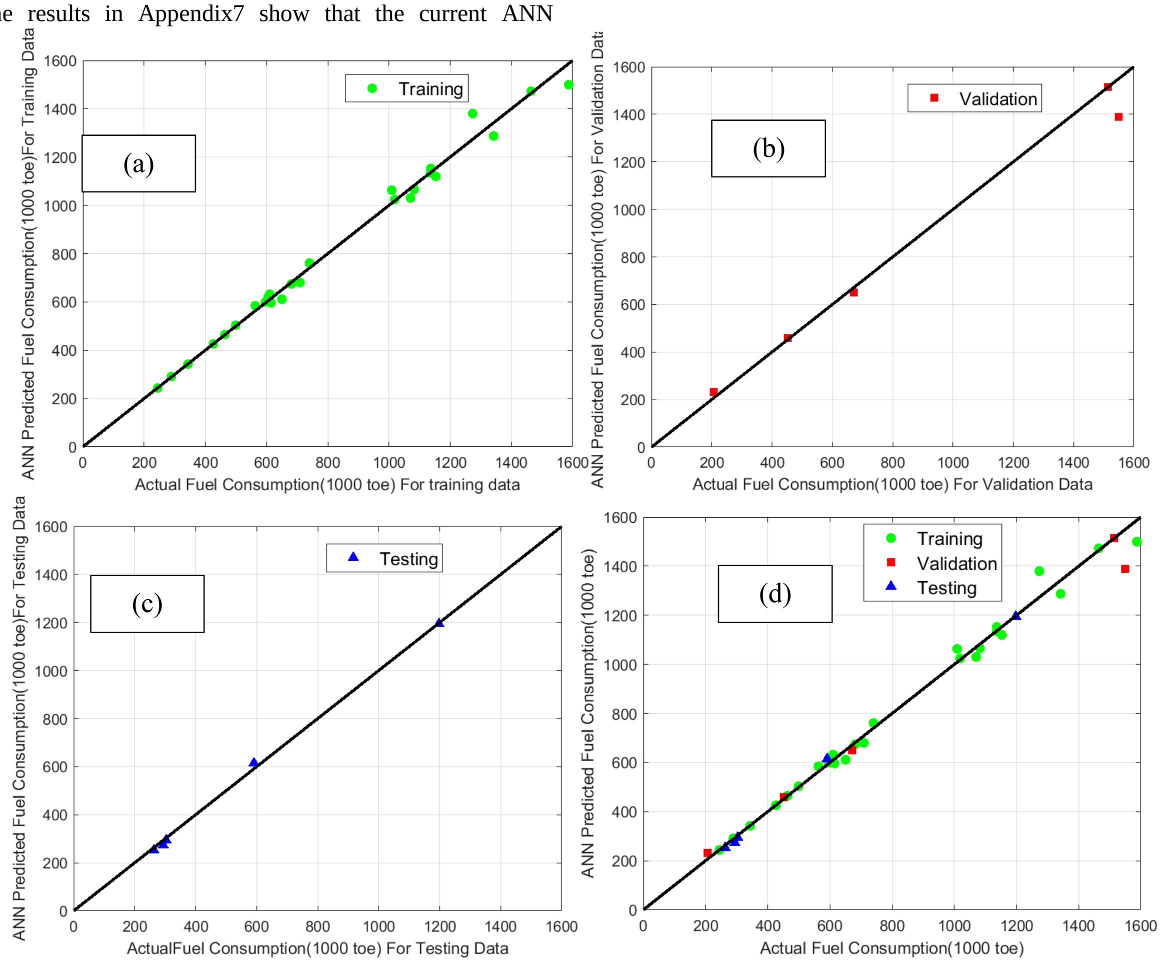

Figure 9. Actual fuel consumption (1000 toe) vs ANN predicted fuel consumption (1000 toe) (a) Training Data (b) Validation Data (c) Testing Data (d) All Data.

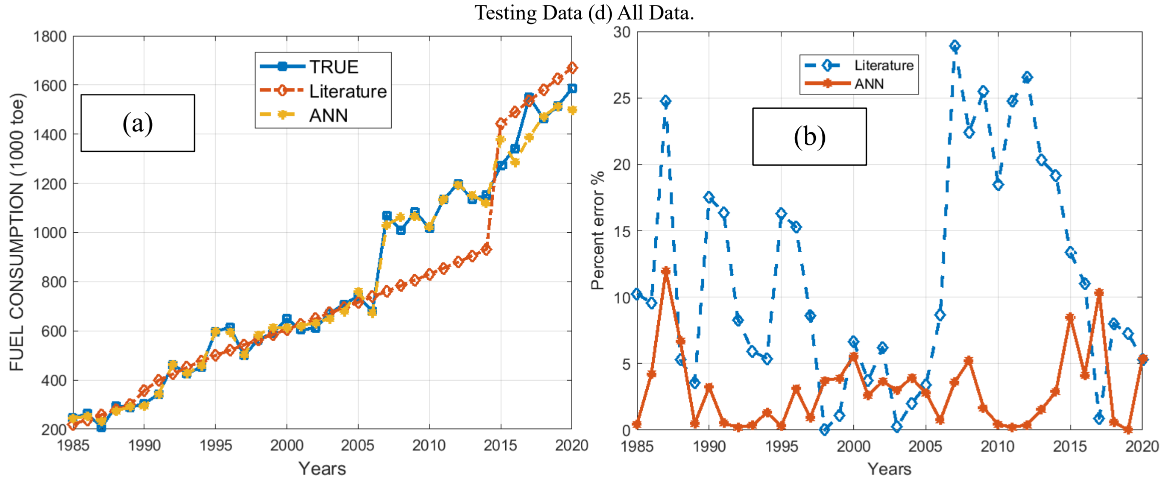

Figure 10. Comparison between the ANN model and previous literature model of reference [11]. (a)True value with literature and ANN values (b) Percentage error for true value with literature and ANN errors.

It is crucial to note that the reference model [11] was built on out-of-date data (1985-2006), and its precision was not tested at the time. As a consequence, it is reasonable to state that the recently constructed ANN can consistently calculate Jordan's residential sector's fuel consumption levels and should be utilized with confidence to predict Jordan's future demands in this critical sector.

4.3 Fuel Predictions and Time Series Analysis

The current ANN-based fuel consumption model has been validated, and it can now be used to anticipate Jordan's residential sector's fuel demands over the next decade (2021-2030).To utilize this ANN model, the predicted values of the five independent variables ($E\$, F\$, W, I$, and P) in the years 2021 to 2030 must be calculated. This was accomplished through the application of time series analysis [37,38] In such cases, the double exponential smoothing forecasting time series technique is widely recommended.

Mathematically, the double exponential forecasting is formatted as:

$$Z_{t+m} = a_t + b_t m \tag{5}$$

where $Z_{t+m}$is the forecast after m the number of periods ahead to be forecast, a_t the forecasted intercept, and b_t the forecasted slope.

The intercept a_t and the slope b_t are estimated as follows:

$$a_t = 2S'_t - S''_t \tag{6}$$

$$0 \leq \alpha < 1 \tag{7}$$

where α is the smoothing constant used to weight recent and historical observations, and S'_t and $S''_t$the single and double exponential smoothing values respectively for time t. These S'_t and S''_t values are calculated as follows:

$$S'_t = \alpha Y_t + (1-\alpha)S'_{t-1} \tag{8}$$

$$S''_t = \alpha S'_t + (1-\alpha)S''_{t-1} \tag{9}$$

The more α is greater, the more importance is placed on the most recent observations. α should be chosen before starting the analysis. The projections are produced using many α's, and the α that produces a low mean square error and indicates anticipated future growth is selected.Note. The values of $(S'_1 = S''_1 = Y_1)$ in period $(t = 1)$.Table 1 shows the smoothing factors (α) calculated for each independent variable, and Table 2 summarizes their predicted values.

Table 1. Smoothing constants (α's) for the different variables.

	$E\$$	$F\$$	AT	I	P
Smoothing constant	0.25	0.35	0.12	0.2	0.4

The variables in Table 2 were normalized using the previously outlined manner and then utilized in the ANN model to anticipate fuel consumption levels between 2021 and 2030. Table 9 summarizes the data of the fuel use values from 1985 to 2030.

The influence of each independent variable on the amount of fuel consumed is seen in Fig.11. The influence of two factors on fuel use is depicted in Fig.11(a): population and fuel unit pricing. The figure depicts the influence of population on fuel use over fuel unit pricing. The role of the population in residential sector fuel utilization is confirmed by Fig.11(b). A similar trend for population may be seen in Fig.11 (c). According to Fig.11 (a-c), the most important factor impacting fuel consumption in Jordan's residential sector is population. More people equal more houses, which means higher fuel usage. Moreover, Fig.11(d) displays the fuel unit price and income level related to fuel use. Fuel prices have a significant influence on fuel use, but income level has minimal impact. This data implies that, regardless of fuel price, as income levels climb, so does fuel use. The influence of electricity unit price and income level on fuel use is not fully understood, as seen in Fig.11 (e). In summary, the most influential determinant on fuel use is population.

According to the bar graph, fuel use is expected to climb over the next decade in a rapid way. As a result, the government is highly subsidized in its efforts to utilize clean and renewable energy sources such as solar and wind energy. You may save money, increase our energy security, and minimize pollution caused by nonrenewable energy sources by using energy-saving devices. There are also smart building controls available, such as digital thermostats and lighting. These controls have the potential to reduce total energy consumption in both residential and commercial buildings. Additionally, smart building controls may increase efficiency and sustainability while cutting operating costs by reducing consumption.

Table 9 Projected values for the different variables.

Year	$E\$$ (\$/kWh)	$F\$$ (\$/GJ)	AT (Celsius)	IL (\$/capita)	P(1000)	F(1000 toe)
2021	0.144	18.40	12.81	3025	11136	1539
2022	0.147	18.40	12.80	3051	11433	1546
2023	0.151	18.40	12.79	3076	11731	1551
2024	0.154	18.41	12.78	3102	12028	1556
2025	0.157	18.41	12.77	3128	12326	1559
2026	0.161	18.41	12.76	3153	12623	1561
2027	0.164	18.42	12.75	3179	12921	1563
2028	0.168	18.42	12.74	3204	13219	1565
2029	0.171	18.42	12.73	3230	13516	1566
2030	0.174	18.43	12.72	3256	13814	1567

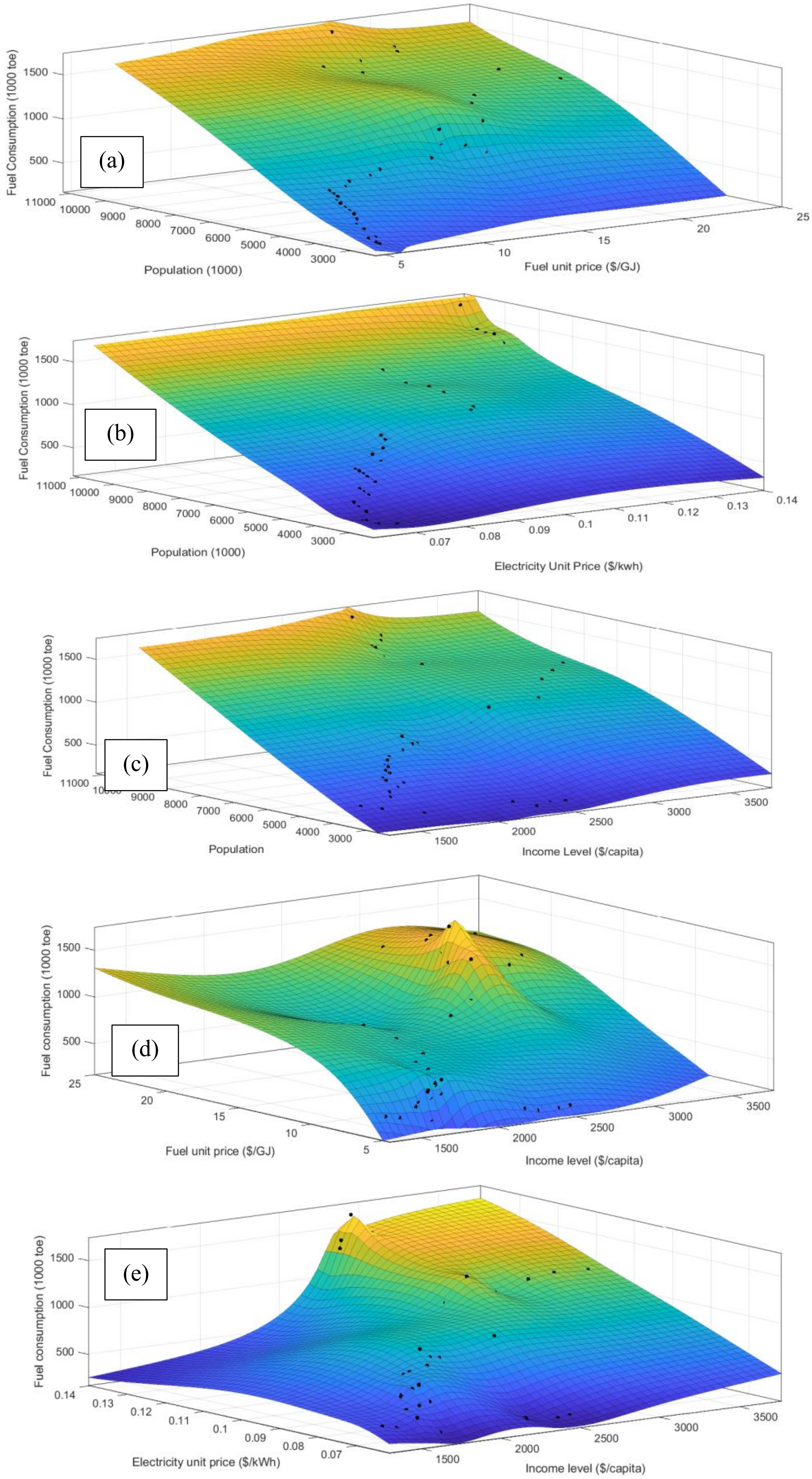

Figure 11. Surface chart for fuel consumption (1000 toe) in the z-axis with two factors in the x-axis and y-axis affecting it. (a) $F\$, P$ (b) $E\$, P$ (c) I, P(d) $I, F\$$(e)I, EP.

5. Conclusions

The artificial neural network approach was used in this paper to model, examine, and forecast Jordan's residential sector's fuel use. Data on population (P), income level (I), electricity unit price ($E\$$), fuel unit price ($F\$$), and ambient temperature (AT) were collected from various literature works and Jordanian government papers and put into this study to get a fuel consumption level model. Furthermore, the proposed neural network model has one hidden layer with four neurons. The ANN-based model demonstrated outstanding efficiency and accuracy, with RMSE, MAPE, and R^2values of 15.25, 3.00 %, and 0.99, respectively. In addition, the final neural network model's correctness was evaluated by comparing its outputs to actual electricity use data and a literature-based model. This artificial intelligence model was also used to forecast Jordan's household fuel requirements over the coming decade. Finally, this study discovered that the most significant variable influencing electricity is the unit price of electricity; so, Jordan's government should adopt legislation to manage this factor.

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List of abbreviations

ANN	Artificial Neural Network
DPSIR	Driving Forces-Pressures-State-Impacts-Responses
EIA	Energy Information Administration's
GDP	Gross Domestic Product
PSD	Public Security Department
DOS	Department of Statistics
MEMR	Ministry of Energy and Mineral Resources
NEPCO	National Electricity Power Company
CCKP	Climate Change Knowledge Portal
toe	Ton Oil Equivalent

Nomenclature

F	Fuel Consumption
$F_{actual,i}$	True Values of Fuel Consumption
$F_{predict,i}$	Predicted Values of Fuel Consumption
IL	Income Level
P	Population
$E\$$	Electricity Unit Price
$F\$$	Fuel Unit Price
AT	Ambient Temperature
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
R^2	Coefficients of Determination
Y_j	The Output Variable
θ_j	The Bias at The Hidden Layer
w_{ji}	The Connection Weight between The Input Variable and The Hidden Layer
X_i	The Input Variable
f	The Transfer Function
Z_{t+m}	The Forecast After m
m	The Number of Periods Ahead to be Forecast
a_t	The Forecasted Intercept
b_t	The Forecasted Slope
α	The Smoothing Constant
S'_t ,S''_t	The Single and Double ExponentialSmoothing Values Respectively for Time t

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Appendix 1. Data set for the residential sector fuel consumption used in the present study.

Year	$E\$$ (\$/kWh)	$F\$$ (\$/GJ)	AT (Celsius)	IL (\$/capita)	P (1000)	F(1000 toe)
1985	0.069	5.5	13.05	2334	2700	245
1986	0.066	5.5	12.75	2542	2805	264
1987	0.066	5.5	13.32	2466	2914	207
1988	0.065	5.5	12.61	2248	3027	294
1989	0.065	6	13.03	1703	3144	289
1990	0.068	6	12.72	1499	3468	304
1991	0.068	6	12.27	1410	3701	343
1992	0.068	6.4	11.79	1631	3844	463
1993	0.072	6.5	12.67	1658	3993	426
1994	0.072	6.5	11.86	1740	4139	453
1995	0.072	6.5	12.94	1805	4264	597
1996	0.076	6.5	12.83	1720	4383	615
1997	0.076	6.5	12.48	1724	4506	500
1998	0.076	6.8	13.02	1794	4623	564
1999	0.076	6.8	13.21	1792	4738	591
2000	0.076	6.8	12.93	1834	4857	649
2001	0.076	7.8	13.2	1834	4978	605
2002	0.082	8.2	13	1880	5098	611
2003	0.082	9.5	12.98	1918	5230	671
2004	0.082	10.2	13.3	2030	5350	708
2005	0.085	13	13.35	2119	5473	741
2006	0.085	16	13.14	2178	5600	680
2007	0.087	15.1	13.2	2107	5723	1070
2008	0.087	14.1	13.48	2574	5850	1010
2009	0.106	14.3	13.19	2720	5980	1083
2010	0.108	16.7	13.53	3069	6113	1019
2011	0.108	17.7	12.85	3277	6993	1136
2012	0.108	18.6	12.76	3439	7427	1198
2013	0.108	24.1	13.04	3653	8114	1136
2014	0.108	22.2	13	2889	8804	1152
2015	0.137	16.7	12.83	2795	9531	1272
2016	0.137	15.2	12.93	2801	9798	1342
2017	0.137	17.5	13.24	2830	10053	1549
2018	0.137	19.8	12.44	2943	10309	1464
2019	0.137	20	12.79	2994	10554	1515
2020	0.137	17.4	12.62	2863	10806	1586

Appendix 2. ANN training set.

Year	F, (1000 toe) training	$E\$$, (\$/kWh) training	$F\$$, (\$/GJ) training	AT (Celsius)	IL, (\$/capita) training	P, (1000) training
1985	245	0.069	5.5	13.05	2334	2700
1989	289	0.065	6	13.03	1703	3144
1991	343	0.068	6	12.27	1410	3701
1992	463	0.068	6.4	11.79	1631	3844
1993	426	0.072	6.5	12.67	1658	3993
1995	597	0.072	6.5	12.94	1805	4264
1996	615	0.076	6.5	12.83	1720	4383
1997	500	0.076	6.5	12.48	1724	4506
1998	564	0.076	6.8	13.02	1794	4623
2000	649	0.076	6.8	12.93	1834	4857
2001	605	0.076	7.8	13.2	1834	4978
2002	611	0.082	8.2	13	1880	5098
2004	708	0.082	10.2	13.3	2030	5350
2005	741	0.085	13	13.35	2119	5473
2006	680	0.085	16	13.14	2178	5600
2007	1070	0.087	15.1	13.2	2107	5723
2008	1010	0.087	14.1	13.48	2574	5850
2009	1083	0.106	14.3	13.19	2720	5980
2010	1019	0.108	16.7	13.53	3069	6113
2011	1136	0.108	17.7	12.85	3277	6993
2013	1136	0.108	24.1	13.04	3653	8114
2014	1152	0.108	22.2	13	2889	8804
2015	1272	0.137	16.7	12.83	2795	9531
2016	1342	0.137	15.2	12.93	2801	9798
2018	1464	0.137	19.8	12.44	2943	10309
2020	1586	0.137	17.4	12.62	2863	10806

Appendix 3. ANN validation set.

Year	F, (1000 toe) validation	$E\$$, (\$/kWh) validation	$F\$$, (\$/GJ) validation	AT (Celsius)	IL, (\$/capita) validation	P, (1000) validation
1987	207	0.066	5.5	13.32	2466	2914
1994	453	0.072	6.5	11.86	1740	4139
2003	671	0.082	9.5	12.98	1918	5230
2017	1549	0.137	17.5	13.24	2830	10053
2019	1515	0.137	20	12.79	2994	10554

Appendix 4. ANN testing set.

Year	F, (1000 toe) testing	$E\$$, (\$/kWh) validation	$F\$$, (\$/GJ) validation	AT (Celsius)	IL, (\$/capita) validation	P, (1000) validation
1986	264	0.066	5.5	12.75	2542	2805
1988	294	0.065	5.5	12.61	2248	3027
1990	304	0.068	6	12.72	1499	3468
1999	591	0.076	6.8	13.21	1792	4738
2012	1198	0.108	18.6	12.76	3439	7427

Appendix 5. Weights for the inputs and output, in addition to biases for the hidden layers, were obtained from the ANN model.

Weights						
	input					output
Neurons	$E\$$	$F\$$	AT	IL	P	F
K=1	0.738	1.090	0.760	-0.36	-0.95	0.285
K=2	0.996	-0.78	0.721	0.876	1.249	-0.02
K=3	0.649	1.001	-0.30	1.574	0.557	0.795
K=4	-1.29	0.940	-0.37	-0.63	-1.17	0.403
K=5	0.643	-0.12	-0.32	0.081	2.040	-0.93
K=6	-1.01	1.373	-0.80	0.525	0.538	0.462
Biases						
		Hidden Layers				
Neurons	Input Layer 1	Input Layer 2	Input Layer 3	Input Layer 4	Input Layer 5	Input Layer 6
K=1	-2.47	1.989	1.902	-1.89	1.887	-1.74
K=2	-1.14	-1.26	-0.89	1.109	1.178	-1.21
K=3	-0.76	-0.30	0.406	0.305	0.262	0.406
K=4	-0.64	-0.38	-0.22	0.346	-0.36	-0.22
K=5	1.468	0.989	-1.19	-1.22	-0.99	-1.17
K=6	-1.96	-1.44	-1.88	1.839	-1.82	-1.88
Neurons	Input Layer 7	Input Layer 8	output	-	-	-
K=1	1.887	1.843	0.352	-	-	-
K=2	1.174	-1.09	-	-	-	-
K=3	0.324	-0.49	-	-	-	-
K=4	0.245	0.356	-	-	-	-
K=5	1.131	-0.96	-	-	-	-
K=6	-1.88	-1.89	-	-	-	-

Appendix 6.Weights for hidden layers obtained from the ANN model.

Input hidden Layer 2

Neurons	Weight 1	Weight 2	Weight 3	Weight 4	Weight 5	Weight 6
K=1	-0.06	1.175	0.845	0.217	-1.41	-0.35
K=2	1.720	0.085	-0.24	0.452	0.341	-0.39
K=3	0.638	-0.53	0.671	0.622	-1.51	0.520
K=4	-0.85	-0.01	0.760	1.301	0.160	-0.67
K=5	0.873	-0.64	0.952	-0.68	1.231	-0.64
K=6	-0.44	0.384	-0.88	0.899	0.987	-1.23

Input hidden Layer 3

Neurons	Weight 1	Weight 2	Weight 3	Weight 4	Weight 5	Weight 6
K=1	-0.47	1.013	-0.51	-0.52	-0.65	1.175
K=2	0.883	-0.51	-1.26	-0.59	1.255	0.340
K=3	-0.66	0.872	0.456	-0.41	-1.27	0.702
K=4	-1.09	-1.16	0.159	-0.78	0.898	0.458
K=5	-1.38	-0.65	-0.14	-0.42	1.413	-0.40
K=6	-1.24	-0.56	0.811	-0.01	0.810	0.585

Input hidden Layer 4

Neurons	Weight 1	Weight 2	Weight 3	Weight 4	Weight 5	Weight 6
K=1	0.439	0.813	1.053	-1.25	-0.30	-0.43
K=2	-0.64	1.213	-0.69	-0.30	1.041	0.351
K=3	-0.64	0.154	0.977	0.839	-1.50	0.310
K=4	0.909	0.796	-0.39	-0.88	0.494	-0.90
K=5	-0.90	-1.11	-0.23	-0.38	0.661	1.066
K=6	0.929	-0.25	-0.13	0.681	-0.51	-1.36

Input hidden Layer 5

Neurons	Weight 1	Weight 2	Weight 3	Weight 4	Weight 5	Weight 6
K=1	-0.84	-0.20	0.805	0.871	0.931	0.731
K=2	-1.33	-0.49	-0.82	-0.77	0.097	-0.54
K=3	-0.08	-0.32	1.323	0.290	0.968	1.160
K=4	-0.36	0.519	0.214	-1.02	1.030	-0.99
K=5	-0.50	-0.94	-0.97	0.711	-1.14	0.295
K=6	-0.09	1.668	0.704	-0.62	-0.32	-0.07

Input hidden Layer 6

Neurons	Weight 1	Weight 2	Weight 3	Weight 4	Weight 5	Weight 6
K=1	1.134	0.553	-0.09	-1.38	0.849	-0.06
K=2	0.204	0.979	1.381	0.510	0.600	-0.67
K=3	-0.52	1.459	-0.84	0.542	0.443	0.126
K=4	0.111	-0.70	-0.22	-0.23	-0.19	-1.72
K=5	-0.90	0.562	0.419	-1.20	-0.05	-0.92
K=6	-0.68	-0.91	-0.56	0.930	-0.84	0.604

Input hidden Layer 7

Neurons	Weight 1	Weight 2	Weight 3	Weight 4	Weight 5	Weight 6
K=1	-1.05	0.187	0.507	-0.97	-0.30	-1.04
K=2	-0.31	0.964	0.811	0.172	-1.27	0.536
K=3	-0.93	-1.07	0.370	-0.60	0.556	-0.97
K=4	0.870	-1.13	-0.15	-0.64	-1.25	-0.24
K=5	0.711	-0.68	-0.79	1.139	-0.40	-0.69
K=6	-1.04	0.604	0.133	1.059	-0.70	0.685
			Input hidden Layer 8			
Neurons	Weight 1	Weight 2	Weight 3	Weight 4	Weight 5	Weight 6
K=1	-0.66	0.316	-0.92	1.076	-0.97	0.357
K=2	0.958	-0.10	0.959	1.156	-0.66	0.061
K=3	0.251	-0.00	1.701	0.863	0.056	0.067
K=4	0.666	0.119	-1.09	0.914	0.945	-0.36
K=5	-0.33	0.713	1.064	-0.79	0.089	-1.34
K=6	-0.79	0.857	-0.50	0.581	-0.68	-1.06

Appendix 7 Comparison between ANN model and previous literature model of reference [11].

Year	F,true (1000 toe)	F, ANN (1000 toe)	error %	F, literature (1000 toe)	error %
1985	245	243	0.81	219.9	10.24
1986	264	252	4.54	238.6	9.58
1987	207	231	11.5	258.1	24.73
1988	294	274	6.80	278.4	5.3
1989	289	290	0.34	299.3	3.57
1990	304	294	3.28	357.3	17.53
1991	343	341	0.58	399	16.32
1992	463	463	0	424.5	8.29
1993	426	427	0.23	451.2	5.92
1994	453	458	1.10	477.3	5.37
1995	597	598	0.16	499.7	16.29
1996	615	595	3.25	521	15.28
1997	500	504	0.8	543	8.6
1998	564	585	3.72	563.9	0.005
1999	591	614	3.89	584.5	1.09
2000	649	612	5.70	605.8	6.65
2001	605	620	2.47	627.4	3.71
2002	611	633	3.60	648.9	6.21
2003	671	650	3.12	672.5	0.23
2004	708	680	3.95	694	1.97
2005	741	761	2.69	716	3.36
2006	680	675	0.73	738.7	8.64
2007	1070	1031	3.64	760.7	28.89
2008	1010	1062	5.14	783.5	22.42
2009	1083	1064	1.75	806.7	25.5
2010	1019	1023	0.39	830.5	18.49
2011	1136	1133	0.26	854.8	24.74
2012	1198	1193	0.41	879.7	26.56
2013	1136	1153	1.49	905.1	20.31
2014	1152	1118	2.95	931.1	19.17
2015	1272	1380	8.49	1442.1	13.37
2016	1342	1286	4.17	1489.8	11.01
2017	1549	1388	10.3	1535.5	0.87
2018	1464	1472	0.54	1581.3	8.01
2019	1515	1515	0	1625.1	7.27
2020	1586	1499	5.48	1670.2	5.31