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Research Article

A Comparative Study of CO_2 Emission Forecasting in the Gulf Countries Using Autoregressive Integrated Moving Average, Artificial Neural Network, and Holt-Winters Exponential Smoothing Models

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Forecasting is the process of making predictions based on past and present data, with the most common method being trend analysis. Forecasting models are becoming increasingly crucial in uncovering the intricate linkages between large amounts of imprecise data and uncontrollable variables. The main purpose of this article is to compare CO_2 emission forecasts in Gulf countries. In this study, the autoregressive integrated moving average (ARIMA), artificial neural network (ANN), and holt-Winters exponential smoothing (HWES) forecasting models are used to anticipate CO_2 emissions in the Gulf countries on an annual basis. This study attempts to predict time series data on CO_2 emissions in the Gulf countries using statistical tools. The current analysis relied on secondary data gathered from the United States Energy Information Administration (EIA). The study's findings show that the ARIMA (1,1,1), Holt-Winters exponential smoothing, ARIMA (1,1,2), and ARIMA (2,1,2) models do not outperform the artificial neural network model in estimating CO_2 emissions in the Gulf countries. This study gives information on the current state of CO_2 emission forecasts. This study will aid the researcher's understanding of CO_2 emissions forecasts. In addition, government agencies can use the findings of this study to develop strategic plans.

1. Introduction

This research aims to forecast CO_2 emissions in Gulf countries. Gulf countries have long dominated the oil and gas industry. They produce around 35 and 25 percent of the world's natural gas and crude oil, respectively, and are its major crude oil producers. CO_2 is the most significant greenhouse gas emitted by human activity. Carbon dioxide exists in the atmosphere naturally as part of the Earth's carbon cycle (the natural circulation of carbon among the atmosphere, oceans, soil, plants, and animals) [1].

According to Saudi government plans, multiple measures have been taken towards predicting the country's future. ARIMA (1,0,0), ARIMA (0,1,1), ARIMA (1,1,2), and ANN suitable models were used for predicting the total revenue and expenditure of Saudi Arabia [2]. The expected growth of CO_2 emissions of China has suddenly increased throughout the selected period of the study [3]. The regression analyses had been employed for 25 countries, and the statistical analyses indicated that eleven countries had a significant trend [4]. The gray prediction method was used to forecast the future CO_2 emissions for the period of 2010–2012 in Taiwan, and the study showed that CO_2 emissions would increase over the next three years [5]. The CO_2 data of 1999–2009 had been used to predict the future trend by using gray method (GM) [6].

Recently, many studies have combined ARIMA, Holt-Winters exponential smoothing, and ANN methods for CO_2 emission predictions. Prediction of CO_2 emissions based on the time series data has been analyzed, compared, and

interpreted using ARIMA and other forecasting models [7–11]. The forecasting models are significantly important methods applied in numerous areas of scientific studies. The researchers have used various prediction models in their studies for the prediction of CO_2 emissions and the other regions [12–19].

Here are some other forecasting prediction approaches. A proposed hybrid model is unique in that it combines the advantages of ARIMA and ANNs in modeling linear and nonlinear behaviors in the data set. Furthermore, the computational experience illustrates the new combination model's effectiveness in obtaining more accurate forecasting than earlier methodologies [20]. A hybrid technique that integrates both ARIMA and ANN models is used to exploit the various characteristics of ARIMA and ANN models in linear and nonlinear modeling. And, the results show that merging the models can be a helpful method for enhancing the forecast accuracy of each model alone [21]. The proposed hybrid ARIMA-ANN model was compared to individual ARIMA and ANN models and different current hybrid ARIMA-ANN models using simulated and experimental data sets such as sunspot data and energy prices, as well as stock market data. According to the results from all of these data sets, the proposed hybrid model exhibits higher prediction accuracy for both one-step-ahead and multistage-ahead forecasts [22]. Two additive hybrid approaches and five multiplicative hybrid methods were investigated to estimate the monthly retail and wholesale prices of regularly used vegetable crops, notably tomato, onion, and potato [23]. The R package Forecast-TB was created to assess the accuracy of various forecasting approaches as a function of time series data set features. In addition, Forecast-TB illustrated raw time series dataset to evaluate forecasting comparison analysis as a function of dataset attributes [24]. The improved chicken swarm optimization (ICSO) algorithm, also known as ICSO-SVM, is presented to optimize SVM parameters. Finally, the novel hybrid model is used to forecast CO_2 emissions from residential energy use in Shanghai, China. The simulation results show that the ICSO-SVM model surpasses the other models when it comes to forecasting accuracy. Furthermore, the ICSO-SVM model's thorough examination of influencing elements and remarkable performance in predicting CO_2 emissions can provide relevant researchers and policymakers with more breakthrough points for residential CO_2 emission reduction [25].

Furthermore, two proposed time series decomposition methods are developed for short-term forecasting of the CO_2 emissions of electricity consumption for five European countries [26]. In addition, a hybrid approach based on artificial neural networks and an agent-based architecture has been described for forecasting carbon dioxide (CO_2) emissions from various energy sources in the city of Annaba using actual data. The development is based on Algerian gas and electricity data provided by the national energy company [27].

For forecasting CO_2 emissions in the Gulf countries, the autoregressive integrated moving average (ARIMA), Holt-Winters exponential smoothing, and artificial neural network (ANN) forecasting models were proposed in this study. The ARIMA, Holt-Winters, and ANN forecasting techniques are the most widely used among the various forecasting methods chosen for this study.

The observations of CO_2 emissions ranging from 1960 to 2014 of the Gulf countries were chosen to predict CO_2 emissions. The findings of the ARIMA, ANN, and Holt-Winters exponential smoothing models were examined to find the best match in this study. This comparison identified the best fit for predicting CO_2 emissions.

2. Materials and Methods

Research methods and materials are summarized in the following. The data used for the ARIMA, ANN, and HWES models were primarily collected from the publicly available source. Minitab version 17 and Zaitun Time Series software have been used to run the models, respectively.

2.1. Data. CO_2 emissions data of Gulf countries were collected from the US EIA between 1960 and 2014. The data were measured in metric tons per capita.

2.2. Auto Regressive Integrated Moving Average (ARIMA). ARIMA models are capable of representing both stationary and nonstationary time series data. Remember that stationary processes have a fixed range of variation. At the level, nonstationary methods have no natural constant mean. ARIMA (p, d, q) models provide an approach to time series forecasting and describe the data's autocorrelations. ARIMA consists of autoregressive (p), different (d), and moving average (q). The proposed ARIMA models used in this study are as follows:

ARIMA (1,1,1):

$$\widehat{Y} = \varnothing_0 + Y_{t-1} + \varnothing_1 \left(Y_{t-1} - Y_{t-2}\right) - \omega_1 \varepsilon_{t-1}. \quad (1)$$

ARIMA (1,1,2):

$$\widehat{Y} = \varnothing_0 + Y_{t-1} + \varnothing_1 \left(Y_{t-1} - Y_{t-2}\right) - \omega_1 \varepsilon_{t-1} - \omega_2 \varepsilon_{t-2}. \quad (2)$$

ARIMA (2,1,2):

$$\widehat{Y} = \varnothing_0 + Y_{t-1} + \varnothing_1 \left(Y_{t-1} - Y_{t-2}\right) + \varnothing_2 \left(Y_{t-2} - Y_{t-3}\right) - \omega_1 \varepsilon_{t-1} - \omega_2 \varepsilon_{t-2}. \quad (3)$$

Here, we have the following:

$\widehat{Y}$ is the predicted value in the time series

Y_{t-1} and Y_{t-2} are the response variables at time lags $t-1$ and $t-2$

ε_{t-1} and ε_{t-2} are the errors in previous time periods

$\varnothing_0, \varnothing_1, \varnothing_2, \omega_1$, and ω_2 are the coefficients to be estimated [28, 29]

ARIMA models are the most comprehensive time series for forecasting applications. This paper uses ARIMA models to anticipate CO_2 emissions in Gulf countries and compares them to other models.

2.3. Artificial Neural Network (ANN). Time series forecasting has significantly benefited from the use of neural networks. As a result, the use of neural networks to forecast time series is gaining popularity.

ANNs have solved many forecasting problems. Because neural networks are generally complex, they are beneficial for capturing the complex underlying relationship in many real-world problems. In addition, neural networks are potentially more versatile forecasting applications because they can detect linear and nonlinear structures in a problem. Several academics have investigated and reported on the ability of neural networks to describe linear time series ([2, 30] and others). This study used an artificial neural network which is known as a neural network. It consists of an input layer of neurons or nodes, one or two hidden neurons, and a final layer of output neurons. A neuron is an information-processing unit that is fundamental to the operation of a neural network. The artificial neurons we use to build our neural networks are genuinely primitive compared to those found in the brain [28, 29]. The proposed ANN model is as follows:

$$¥ = \varphi\left(\sum_{j=1}^{n} ₩_j x_j + ₺\right). \tag{4}$$

Here, we have the following:

¥ denotes the output signal

x_n indicates the input signals

$₩_n$ denotes the synaptic weights of the neuron

φ denotes the activation function

₺ denotes the bias

Figure 1 represents the general model of ANN.

This study applies the artificial neural network (ANN) technique to forecast CO_2 emissions in Gulf countries.

2.4. Holt-Winters Exponential Smoothing. This paper also uses the Holt-Winters method to predict CO_2 emissions. This method is applicable if the time series data have trend and seasonal effects. In addition to the alpha and beta smoothing factors, a new parameter is added called gamma (γ) that controls the influence's seasonal component. The equations used in this model are as follows.

The exponentially smoothed series or level estimate is given as

$$L_t = \alpha\left(\frac{Y_T}{S_{T-M}}\right) + (1-\alpha)\left(L_{t-1} - T_{t-1}\right). \tag{5}$$

The trend estimate is given as

$$T_t = \beta\left(L_t - L_{t-1}\right) + (1-\beta)T_{t-1}. \tag{6}$$

The seasonality estimate is developed as

$$S_t = \gamma\left(\frac{Y_T}{L_t}\right) + (1-\gamma)S_{t-s}. \tag{7}$$

The forecast for m periods into the future is written as

$$F_{t+m} = \left(L_t + mT_t\right)S_{t-s+m}. \tag{8}$$

Here, we have the following:

Y_T is the new observation

L_T is the current level estimate of series

L_{T-1} is the previously smoothed level

α is the smoothing constant for the level

β is the smoothing constant for trend estimate

T_t is the current trend estimate

T_{t-1} is the previously smoothed trend

γ is the smoothing constant for seasonality estimate

S_t is the seasonal component estimate

S_{t-s} is the previous seasonal component

m is the number of seasons in a year

s is the length of seasonality (number of periods in the season)

t is the time period

$0 \le \alpha \le 1$; $0 \le \beta \le 1$; and $\le \gamma \le 1$ [28, 29]

This study also compares the Holt-Winters exponential smoothing model to other models in order to predict CO_2 emissions in the Gulf countries.

2.5. Accuracy Measures of the Forecast Models. In this study, we analyzed the different errors of forecast models for comparing to each other, which are mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE) [28, 29].

2.5.1. Mean Absolute Error (MAE). The mean absolute error (MAE) measures the accuracy of fitted time series values. MAE expresses accuracy in the same units as the data, which helps conceptualize the amount of error and is calculated by the following formula:

$$\text{MAE} = \frac{1}{\text{number of observations}\,(n)} \cdot \sum_{\text{time }(t)=1}^{n} \left|\text{response variable}_t - \widehat{\text{predicted value}}_t\right|. \tag{9}$$

2.5.2. Mean Squared Error (MSE). The mean squared error (MSE) is a more sensitive measure of a substantial forecast error than MAE, and the following formula estimates it:

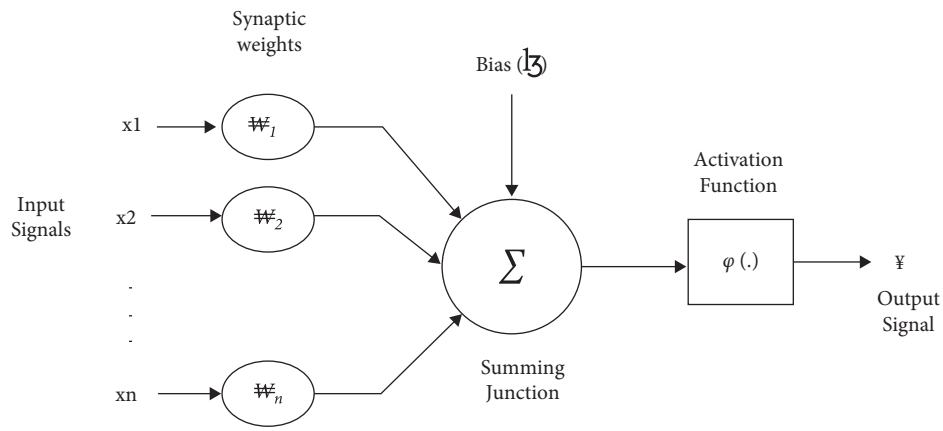

Figure 1: General model of a neuron.

$$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n}\left(\text{response variable}_t - \widehat{\text{predicted value}}_t\right)^2. \quad (10)$$

2.5.3. Root Mean Square Error (RMSE). The root mean square error (RMSE), like the MSE, penalizes significant errors but has the same units as the forecast, so its magnitude is easily interpreted.

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}}. \quad (11)$$

2.5.4. Mean Absolute Percentage Error (MAPE). The mean absolute percentage error (MAPE) measures the accuracy of fitted time series values. MAPE expresses accuracy as a percentage, and the following formula estimates it:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|\text{response variable}_t - \widehat{\text{predicted value}}_t\right|}{\text{response variable}_t}. \quad (12)$$

After the analysis for errors, we compare the accuracy measures of the forecast models. Less MAPE and less RMSE often are the best way to define the best forecast.

Following that, we present the outcomes of the ARIMA, ANN, and HWES model implementations.

3. Results and Discussion

3.1. Predicted Value of CO_2 Emissions (Metric Tons per Capita) Using the Various Forecasting Models. The proposed forecasting models will assist GCC nations in determining the best fit model to predict CO_2 emissions.

It is evident from Table 1 and Figure 2, the CO_2 emissions of the GCC countries will continue increasing over the years except for Kuwait. Table 1 shows that the model ARIMA (1,1,1) is the best fit for predicting CO_2 emissions of Oman, Saudi Arabia, Bahrain, Kuwait, UAE, and Qatar according to their sequence of accuracy measures.

From Table 2 and Figure 3, we conclude that the CO_2 emissions of the GCC countries will continue increasing over the years except for Kuwait. Table 2 shows that the model ARIMA (1,1,2) is the best fit for predicting CO_2 emissions in Oman, Saudi Arabia, Bahrain, Kuwait, UAE, and Qatar based on the sequence of accuracy measures.

It is evident from Table 3 and Figure 4, the CO_2 emissions of the GCC countries will continue increasing over the years, except for Kuwait and Qatar. Table 3 shows that the model ARIMA (2,1,2) is the best fit for predicting CO_2 emissions of the kingdom of Saudi Arabia, Oman, Bahrain, Kuwait, and Qatar according to their sequence of accuracy measures.

From Table 4 and Figure 5, we conclude that the CO_2 emissions of the GCC countries will continue increasing and decreasing over the years except for Kuwait. It is evident from Table 4 that the model ANN is the best fit for predicting CO_2 emissions of Oman, Saudi Arabia, Bahrain, UAE, Kuwait, and Qatar according to their sequence of accuracy measures.

From Table 5 and Figure 6, we can say that the CO_2 emissions of KSA will continue increasing and decreasing over the years. Also, it seems that the CO_2 emissions of the UAE, Kuwait, Bahrain, and Qatar will continue declining over the years except for Oman. It is evident from Table 5 that the model of Holt-Winters exponential smoothing is the best fit for the prediction of CO_2 emissions of Oman according to their accuracy measures.

3.2. Comparison of the Best Predicted CO_2 Emissions Values for 2025. The best prediction for the year 2025 is shown in Table 6 and Figure 7. As a consequence, ANN is the best model for the Gulf Countries based on the accuracy measures. It is not an easy task to create a neural network model for a time series forecasting assessment. As several software packages exist to assist users in building a neural network model, forecasters must understand many important issues surrounding the model construction. For example, the ANN software package does not need to produce the correct result

Table 1: Predicted value of CO_2 emissions (metric tons per capita) using the ARIMA (1,1,1) model and accuracy measures.

Year	KSA	UAE	KWT	BHR	QAT	OMAN
2015	19.8132	22.032	25.6859	23.8404	45.4081	15.336
2016	20.178	23.073	25.6503	24.1938	46.6756	15.6805
2017	20.5361	23.176	25.5865	24.5455	47.7162	15.9687
2018	20.8884	23.73	25.5289	24.8972	48.5749	16.2729
2019	21.2355	24.067	25.4699	25.2489	49.2879	16.5726
2020	21.5783	24.509	25.4113	25.6005	49.8844	16.8736
2021	21.9172	24.9	25.3526	25.9522	50.3873	17.1742
2022	22.2528	25.316	25.2938	26.3039	50.8154	17.475
2023	22.5855	25.719	25.2351	26.6555	51.1836	17.7757
2024	22.9156	26.129	25.1764	27.0072	51.5037	18.0764
2025	23.2436	26.536	25.1177	27.3589	51.7854	18.3771
MSE	2.728546	191.1273	39.47481363	7.50587707	199.110449	1.581776118
RMSE	1.651831	13.82488	6.282898506	2.739685579	14.1106502	1.257686812

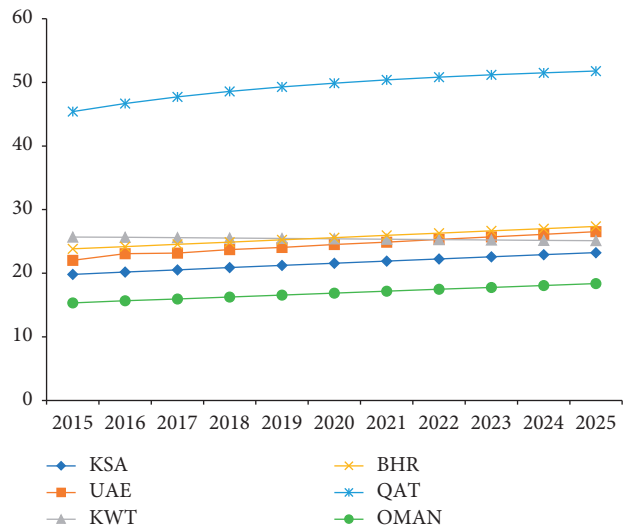

Figure 2: Predicted value of CO_2 emissions (metric tons per capita) using the ARIMA (1,1,1) model.

Table 2: Predicted value of CO_2 emissions (metric tons per capita) using the ARIMA (1,1,2) model and accuracy measures.

Year	KSA	UAE	KWT	BHR	QAT	OMAN
2015	19.8274	22.032	25.2979	23.0702	48.9564	15.2469
2016	20.2132	23.057	25.0196	24.1298	51.6403	15.6726
2017	20.5898	23.136	24.7665	24.0314	53.6255	16.0615
2018	20.9584	23.718	24.5337	24.6683	55.1167	16.4249
2019	21.3201	24.032	24.317	24.8383	56.2585	16.7705
2020	21.6757	24.489	24.1133	25.3048	57.1533	17.1038
2021	22.026	24.87	23.92	25.583	57.8735	17.4285
2022	22.3717	25.291	23.735	25.9808	58.4702	17.7472
2023	22.7135	25.691	23.5567	26.3026	58.9796	18.0617
2024	23.0517	26.102	23.3837	26.6726	59.4272	18.3734
2025	23.387	26.508	23.2149	27.0121	59.8312	18.683
MSE	2.69729	191.0923	36.73398116	6.53011983	174.7189806	1.437520777
RMSE	1.64234	13.82361	6.06085647	2.555409914	13.21813075	1.198966545

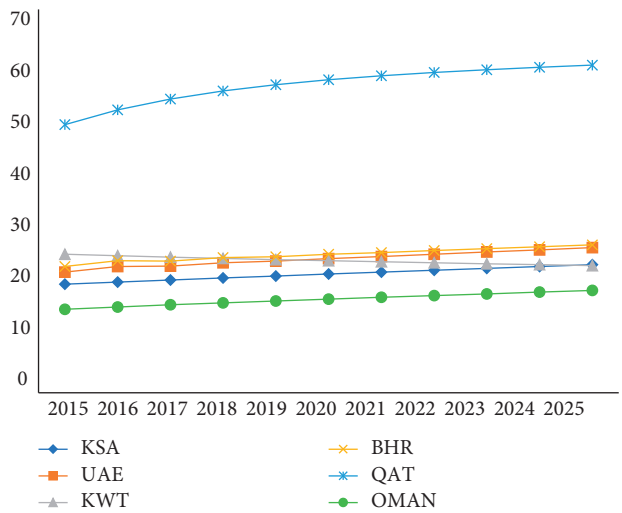

Figure 3: Predicted value of CO_2 emissions (metric tons per capita) using the ARIMA (1,1,2) model.

Table 3: Predicted value of CO_2 emissions (metric tons per capita) using the ARIMA (2,1,2) model and accuracy measures.

Year	KSA	UAE	KWT	BHR	QAT	OMAN
2015	19.2517	22.1399	25.3724	23.1818	40.0646	15.7528
2016	20.4422	23.0162	25.0809	24.4201	35.45	16.284
2017	20.2464	22.9346	24.8022	24.0725	32.4005	16.3999
2018	21.3706	23.329	24.5477	24.8493	32.5155	16.557
2019	21.1754	23.4278	24.3113	25.014	35.8467	17.0212
2020	22.2428	23.654	24.0898	25.418	40.8942	17.4425
2021	22.0535	23.7826	23.8803	25.7906	45.3509	17.637
2022	23.0715	23.9392	23.6807	26.11	47.2266	17.8727
2023	22.8924	24.0589	23.4891	26.4967	45.8029	18.2753
2024	23.8669	24.1797	23.3039	26.8318	41.9622	18.6406
2025	23.7007	24.2835	23.124	27.1969	37.7401	18.8833
MSE	2.48489	181.5921	36.79337864	6.342618621	197.9863674	1.380955048
RMSE	1.576353	13.47561	6.065754582	2.518455602	14.07076286	1.175140438

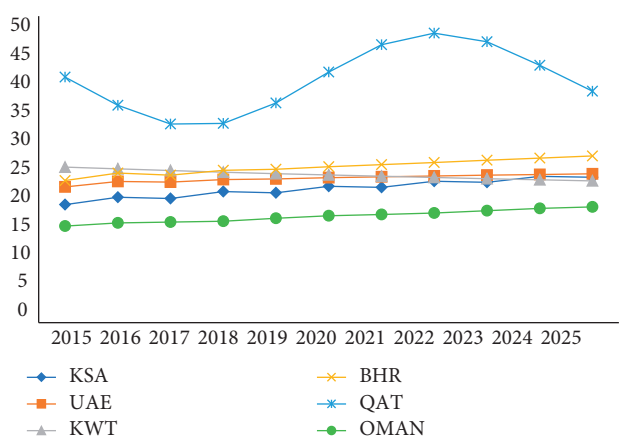

Figure 4: Predicted value of CO_2 emissions (metric tons per capita) using the ARIMA (2,1,2) model.

Table 4: Predicted value of CO_2 emissions (metric tons per capita) using the ANN model and accuracy measures.

Year	KSA	UAE	KWT	BHR	QAT	OMAN
2015	17.7764	23.6796	25.3525	20.7706	42.0368	16.169
2016	18.292	24.8476	23.213	25.0854	42.5176	16.3194
2017	17.77	25.348	22.6426	25.4424	42.5139	16.1421
2018	18.4168	26.1558	21.9359	26.0121	47.1656	16.1208
2019	17.7574	26.3692	20.8619	26.655	49.4236	16.355
2020	18.2973	26.5869	20.1502	24.4962	51.9579	16.3724
2021	17.6336	26.7628	19.7581	24.3246	52.2961	16.1978
2022	18.4311	26.2901	19.2751	25.3826	53.5767	16.1845
2023	17.7389	26.0693	18.9593	24.0357	52.4733	16.2648
2024	18.4094	25.403	18.9986	23.0032	54.3419	16.2966
2025	17.8752	25.0183	18.9484	24.6834	52.9035	16.2928
MSE	2.063634	13.94389	14.8509483	2.92500569	24.1817259	0.75614137
RMSE	1.436536	3.734152	3.85369282	1.7102648	4.91749183	0.8695639

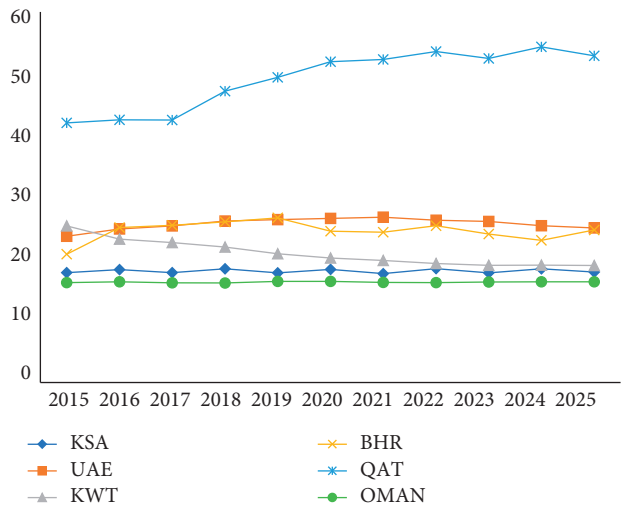

Figure 5: Predicted value of CO_2 emissions (metric tons per capita) using the ANN model.

Table 5: Predicted value of CO_2 emissions (metric tons per capita) using the Holt-Winters exponential smoothing model and accuracy measures.

Year	KSA	UAE	KWT	BHR	QAT	OMAN
2015	18.9619	18.3657	28.8636	22.8149	36.9647	17.7822
2016	20.3868	18.7049	28.8068	22.4036	36.5989	17.8181
2017	19.6537	17.3906	28.5948	22.6495	33.7156	18.6483
2018	21.1172	17.6846	28.5373	22.2406	33.2341	18.6652
2019	20.3454	16.4155	28.326	22.4841	30.4665	19.5143
2020	21.8477	16.6644	28.2677	22.0776	29.8692	19.5124
2021	21.0372	15.4404	28.0571	22.3187	27.2173	20.3804
2022	22.5781	15.6442	27.9982	21.9146	26.5044	20.3595
2023	21.729	14.4653	27.7883	22.1533	23.9682	21.2464
2024	23.3086	14.624	27.7287	21.7516	23.1395	21.2067
2025	22.4208	13.4902	27.5195	21.9879	20.7191	22.1125
MSE	5.300806	457.0809	129.2720698	38.3314634	496.415161	3.796661954
RMSE	2.302348	21.37945	11.36978759	6.19124086	22.2803761	1.94850249

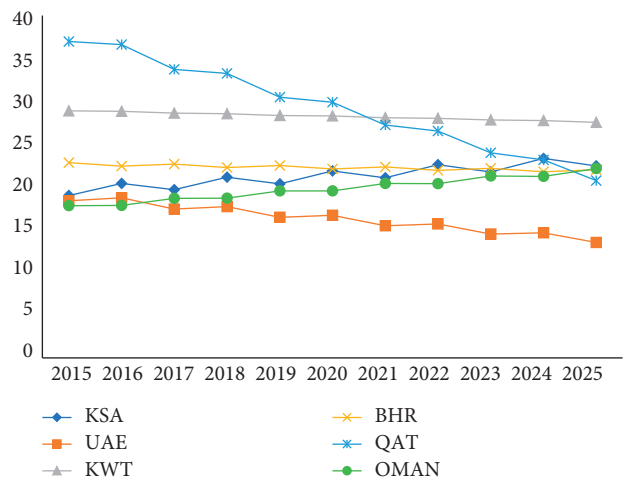

Figure 6: Predicted value of CO_2 emissions (metric tons per capita) using the Holt-Winters exponential smoothing model.

Table 6: Best predicted value of CO_2 emissions for the year 2025.

Countries	Best prediction of CO_2 emissions (metric tons per capita) for the year 2025				
	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (2,1,2)	ANN	HWES
KSA	23.2436	23.387	23.7007	17.8752	22.4208
UAE	26.536	26.508	24.2835	25.0183	13.4902
KWT	25.1177	23.2149	23.124	18.9484	27.5195
BHR	27.3589	27.0121	27.1969	24.6834	21.9879
QAT	51.7854	59.8312	37.7401	52.9035	20.7191
OMAN	18.3771	18.683	18.8833	16.2928	22.1125

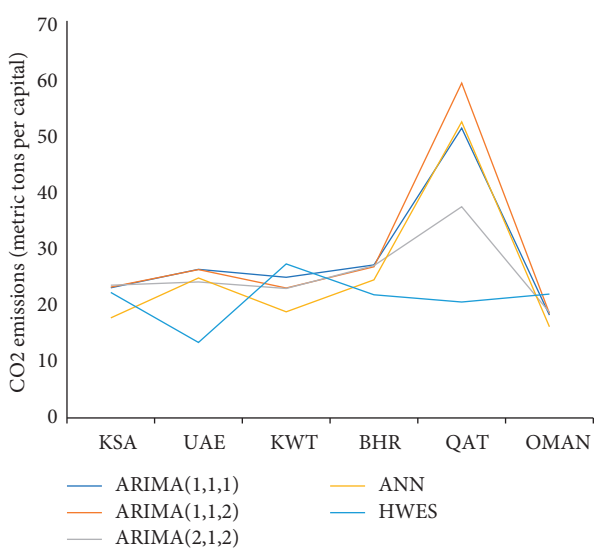

Figure 7: Best predicted values of CO_2 emissions for the year 2025.

for every data set. Since ANN software solves complex problems, it is often seen that ARIMA and HWES are suitable for linear time series compared to the ANN. In this study, ANN has proved to be a good model among the other models.

4. Conclusions and Recommendations

The main aim of the study is to predict the CO_2 emissions in Gulf countries. Autoregressive integrated moving average, Holt-Winters exponential smoothing, and artificial neural network models are the finest models with any changing pattern to predict the amount of any time series data. They are appropriate for at least fifty observations. In light of the accuracy measures, we concluded that the ANN model is the best fit for the Gulf countries in 2025.

The predicted value of CO_2 emissions in the Gulf countries for the year 2025 will be fluctuating compared to 2014. The outcomes of the research indicate that the researcher should concentrate on the models ANN, ARIMA (1,1,1), Holt-Winters exponential smoothing, ARIMA (1,1,2), and ARIMA (2,1,2) for predicting time series data regarding CO_2 emissions in the Gulf countries. In addition, the scope of this study is to identify the adequacy of the ANN model for this type of data set. Furthermore, researchers should focus on the kind of data because ANN requires an extensive data set, whereas ARIMA requires at least 50 observational data sets.

ANN, ARIMA, and HWES are the most commonly utilized forecasting models. Therefore, based on the data set, we applied these methods. Furthermore, the critical focus of future research will be on identifying the area and using

support vector machine (SVM) regression models and polynomial surface fit (PSF) models to predict the right field of study. Besides, in the subsequent study, we will compare forecasting models using the R package and Python.

Data Availability

Previously reported financial data were used to support this study and are available at (https://www.eia.gov/). These prior studies (and datasets) are cited at a relevant place within the text as reference [31].

Conflicts of Interest

The authors declare no conflicts of interest.

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