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Forecasting CO_2 Emission in Gulf Countries Using ARIMA, ANN, and Holt-Winters Exponential Smoothing Models: A Comparative Analysis

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Abstract

Forecasting involves making predictions based on historical and current data, with trend analysis being one of the most commonly used approaches. Forecasting models have become increasingly vital in revealing complex relationships within large datasets, often influenced by uncertain and uncontrollable variables. The primary objective of this study is to compare CO_2 emission forecasts across Gulf countries. To achieve this, the forecasting models—Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN), and Holt-Winters Exponential Smoothing (HWES)—were employed to project annual CO_2 emissions. The analysis utilizes secondary data sourced from the United States Energy Information Administration (EIA). This research employs statistical tools to model time series data and evaluate the forecasting performance of various approaches. The results indicate that ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (2,1,2), and the Holt-Winters Exponential Smoothing models do not outperform the ANN model in predicting CO_2 emissions across the Gulf region. The findings contribute to a deeper understanding of CO_2 emission trends and forecasting accuracy in the Gulf countries. This study not only supports researchers in the field of environmental data analytics but also provides valuable insights for government agencies in formulating data-driven strategies to manage and reduce emissions.

Keywords
CO_2 emissions, Forecasting, ARIMA, Artificial Neural Network (ANN), Holt-Winters, Gulf countries.

1. Introduction
This research aims to forecast CO_2 emissions in Gulf countries using time series forecasting models. The Gulf region, comprising countries such as Saudi Arabia, the United Arab Emirates, Qatar, Kuwait, Bahrain, and Oman, has historically played a dominant role in the global oil and gas industry. These countries produce approximately 35% of the world's natural gas and 25% of crude oil, making them major contributors to global carbon emissions.

Carbon dioxide (CO_2) is the most significant greenhouse gas released through human activities, especially the combustion of fossil fuels. Although CO_2 is a natural part of the Earth's carbon cycle, circulating through the atmosphere, oceans, soil, and living organisms, its increasing concentration due to industrial activities has become a primary environmental concern (EPA, 2021).

Recognizing the environmental challenges, Gulf countries such as Saudi Arabia have begun implementing measures to predict and manage future emissions. For example, ARIMA models such as ARIMA (1,0,0), ARIMA (0,1,1), and ARIMA (1,1,2), along with Artificial Neural Networks (ANNs), have been previously applied to forecast economic

indicators, including total revenue and expenditure, in Saudi Arabia (Alam, 2020). Similarly, studies from other regions also report rising CO_2 emissions, such as in China, where a significant increase in emissions was observed over the selected study period (Auffhammer & Carson, 2008). Regression analysis across 25 countries found statistically significant emission trends in 11 countries (Köne & Büke, 2010). In Taiwan, the grey prediction model was used to forecast CO_2 emissions for 2010–2012, showing a continued rise (Lin et al., 2011). Likewise, the Grey Model was applied to data from 1999 to 2009 to predict CO_2 trends in another study (Yilmaz & Yilmaz, 2013).
Recently, numerous studies have explored and compared forecasting techniques such as ARIMA, Holt-Winters Exponential Smoothing (HWES), and ANN for predicting CO_2 emissions. These models are particularly effective in analyzing time series data (Abdullah & Pauzi, 2015; Jiang et al., 2018; Jothikannan & Dinesh Kumar, 2017; Nyoni & Bonga, 2019). Researchers have widely used these models across different countries and contexts to predict CO_2 emissions and other environmental or economic variables (Alam, 2019; Awel, 2018; Ersen et al., 2019; Hosseini et al., 2019; Kitworawut & Rungreunganun, 2019; Olabemiwo et al., 2017; Sen et al., 2016; Urrutia et al., 2019).

In addition to standalone models, hybrid forecasting methods have also gained popularity. These models combine the strengths of ARIMA and ANN to handle both linear and nonlinear patterns in data. Studies have shown that such combinations improve forecast accuracy over traditional single models (Wang et al., 2013; Zhang, 2003). For instance, hybrid ARIMA–ANN models have demonstrated superior performance when tested on data sets such as energy prices, sunspot activity, and stock markets (Babu & Eswara, 2014). Other studies have employed hybrid additive and multiplicative models to forecast the prices of agricultural products, such as tomatoes, onions, and potatoes (Purohit et al., 2021).

Further advancements include tools like the R package Forecast-TB, which enables researchers to compare forecasting techniques based on dataset characteristics (Bokde et al., 2020). Additionally, machine learning-based optimization methods, such as the Improved Chicken Swarm Optimization–Support Vector Machine (ICSO-SVM), have been developed for forecasting CO_2 emissions from residential energy use, demonstrating improved performance over traditional models (Wen & Cao, 2020). Moreover, Bokde et al. (2021) proposed time series decomposition methods for short-term forecasting of CO_2 emissions from electricity use in five European countries. Similarly, Bouziane et al. (2021) applied a hybrid ANN and agent-based model to predict CO_2 emissions using real gas and electricity data from Annaba, Algeria. Singh and Dubey (2021) utilized deep learning on car telematics data, achieving high accuracy due to real-time sensor inputs. Ulku and Ulku (2022) employed machine learning methods to estimate greenhouse gas emissions, finding that these methods are effective in handling large and complex datasets. Thi et al. (2025) used traditional models, such as ARIMA and Holt-Winters, to forecast yearly CO_2 levels in Vietnam, demonstrating their long-term validity.

In this study, ARIMA, Holt-Winters Exponential Smoothing, and Artificial Neural Network models are applied to forecast CO_2 emissions in Gulf countries. These models were selected based on their widespread use and effectiveness in previous studies. Historical CO_2 emissions data from 1960 to 2014 were collected and analyzed. The forecasting results from each model were compared to identify the most accurate and suitable method for predicting future CO_2 emissions in the region. This research contributes to the growing body of literature on environmental forecasting and aims to support policy planning and sustainable development in the Gulf region.

2. Methods
The following is a summary of the research methods and materials utilized. The information used for the ARIMA, ANN, and HWES models was mainly gathered from publicly accessible sources. Minitab version 17 and Zaitun Time Series software were utilized to execute the models, respectively. Data on CO2 emissions from Gulf countries was gathered from the US EIA for the period spanning 1960 to 2014. The measurements were recorded in metric tons per individual.

2.1 Auto Regressive Integrated Moving Average (ARIMA)
ARIMA models can effectively represent both stationary and nonstationary time series data. Stationary processes exhibit a constant range of variation. At the level, nonstationary methods lack a natural constant mean. ARIMA (p, d, q) models offer a method for time series forecasting and characterize the autocorrelations within the data. ARIMA comprises autoregressive (p), differencing (d), and moving average (q) components. This study proposed the following ARIMA models (1-3):
ARIMA (1,1,1)

$$\widehat{Y} = \emptyset_0 + Y_{t-1} + \emptyset_1(Y_{t-1} - Y_{t-2}) - \omega_1\varepsilon_{t-1} \qquad (1)$$

ARIMA (1,1,2)

$$\widehat{Y} = \emptyset_0 + Y_{t-1} + \emptyset_1(Y_{t-1} - Y_{t-2}) - \omega_1\varepsilon_{t-1} - \omega_2\varepsilon_{t-2} \qquad (2)$$

ARIMA (2,1,2)

$$\widehat{Y} = \emptyset_0 + Y_{t-1} + \emptyset_1(Y_{t-1} - Y_{t-2}) + \emptyset_2(Y_{t-2} - Y_{t-3}) - \omega_1\varepsilon_{t-1} - \omega_2\varepsilon_{t-2} \qquad (3)$$

Where;
$\hat{Y}$ is the predicted value in the time series
Y_{t-1}, Y_{t-2} are the response variables at time lags t-1 and t-2
ε_{t-1} , ε_{t-2} are the errors in previous time periods
$\emptyset_0, \emptyset_1, \emptyset_2, \omega_1, \omega_2$ are the coefficients to be estimated. (Hanke & Wichern, 2005; Russell & Taylor, 2005)
ARIMA models represent a robust approach for forecasting in time series analysis. This study employs ARIMA models to forecast CO2 emissions in Gulf countries and compares these results with alternative models.

2.2 Artificial Neural Network (ANN)

The use of neural networks has significantly enhanced time series forecasting, leading to their increasing adoption for this purpose. Many forecasting challenges have been effectively addressed using artificial neural networks (ANNs) due to their ability to model complex correlations in real-world data. In contrast to conventional statistical approaches, neural networks can identify both linear and nonlinear patterns, making them very adaptable for predictive tasks.

Studies indicate that neural networks can proficiently represent linear time series (Alam, 2020; Zhang, 2001). This research employed an artificial neural network (ANN) model comprising an input layer, one or more hidden layers, and an output layer. Information processing in the network is executed by artificial neurons, which, while inspired by real neurons, are simplified in comparison (Hanke & Wichern, 2005; Russell & Taylor, 2005).

This work suggests the implementation of an ANN (4) model, which includes four input neurons that represent delayed time series data. This design facilitates the network's efficient learning of temporal relationships, hence enhancing prediction accuracy. The general model of an artificial neural network is illustrated in Figure 1. The present study employs the artificial neural network (ANN) methodology to predict CO2 emissions in Gulf nations.

$$\text{¥} = \varphi\left(\textstyle\sum_{j=1}^{n} \text{₩}_j x_j + \text{ɮ}\right) \qquad (4)$$

Where,
¥ denotes output signal
x_n indicates input signals
₩_n denotes Synaptic weights of the neuron
φ denotes Activation function
ɮ denotes bias

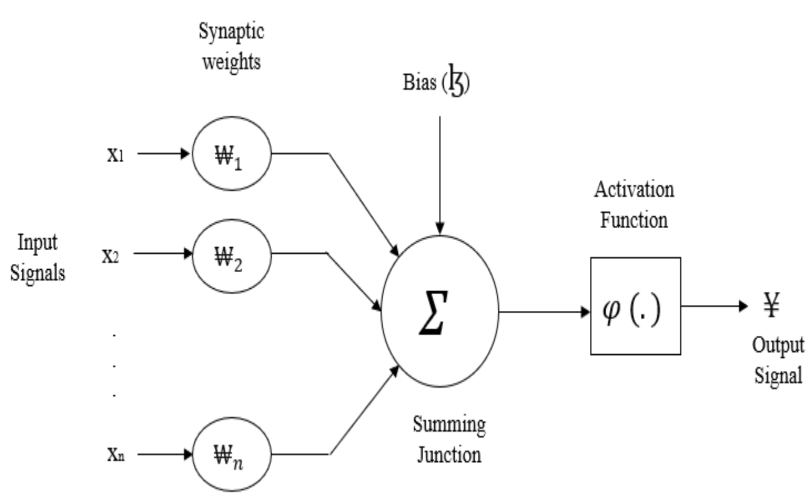

Figure 1. General Model of a Neuron

2.3 Holt-Winters Exponential Smoothing

This study employs the Holt-Winters method to forecast CO2 emissions. This approach is suitable when the time series data exhibits both a trend and seasonal influences. A new parameter, gamma (γ), is introduced alongside the alpha and beta smoothing factors to regulate the impact of the seasonal component. The equations utilized in this model are as follows.

The level estimate, derived from exponential smoothing, is expressed as follows:

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

The trend estimate is given as:

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

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:

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

where;
Y_T is the new observation
L_T is the current level estimate of the series
L_{T-1} is the previously smoothed level
α is the smoothing constant for the level
β is the smoothing constant for the trend estimate
T_t is the current trend estimate
T_{t-1} is the previously smoothed trend
γ is the smoothing constant for the 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
and
$0 \leq \alpha \leq 1$; $0 \leq \beta \leq 1$; $\leq \gamma \leq 1$. (Hanke & Wichern, 2005; Russell & Taylor, 20 05)
This analysis also compares the Holt-Winters Exponential Smoothing model with alternative models for forecasting CO2 emissions in Gulf nations.

3. Accuracy measures of the forecast models

This research examined forecasting model errors for comparative analysis, namely mean squared error (MSE) and root mean square error (RMSE) (Hanke & Wichern, 2005; Russell & Taylor, 2005).

3.1 Mean Squared Error (MSE)

The following formula calculates mean squared error (MSE), which is more sensitive to considerable prediction error than MAE.

$$\text{MSE} = \frac{1}{\text{n}} \sum_{t=1}^{n} (y_t - \hat{y}_t)^2 \tag{9}$$

3.2 Root Mean Square Error (RMSE)

Root mean square error (RMSE), like MSE, penalizes substantial mistakes but uses the same units as the prediction, making the size easier to understand.

$$\text{RMSE} = \sqrt{MSE} \tag{10}$$

Where,
n is the number of observations(n)
t indicates time

y_t is the response variable
$\hat{y}_t$ is the predicted value

Following the error analysis, we compare the accuracy metrics of the forecasting models. A lower MAPE and RMSE are often the optimal criteria for determining the most accurate prediction. Subsequently, we present the results of the ARIMA, ANN, and HWES model implementations.

4. Results and Discussion

4.1 Forecasted per capita CO_2 emissions (metric tons) using various predictive models

The suggested forecasting approaches aim to help GCC countries determine the most accurate model for estimating CO_2 emissions.

Table 1. Forecasted per capita CO_2 emissions 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. Forecasted per capita CO_2 emissions using the ARIMA (1,1,1) model

As illustrated in Table 1 and Figure 2, CO_2 emissions in the GCC countries are projected to continue rising in the coming years, except in Kuwait. Based on the accuracy metrics, Table 1 identifies the ARIMA (1,1,1) model as the most suitable for forecasting CO_2 emissions in Oman, Saudi Arabia, Bahrain, Kuwait, the UAE, and Qatar.

Table 2. Forecasted per capita CO_2 emissions 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

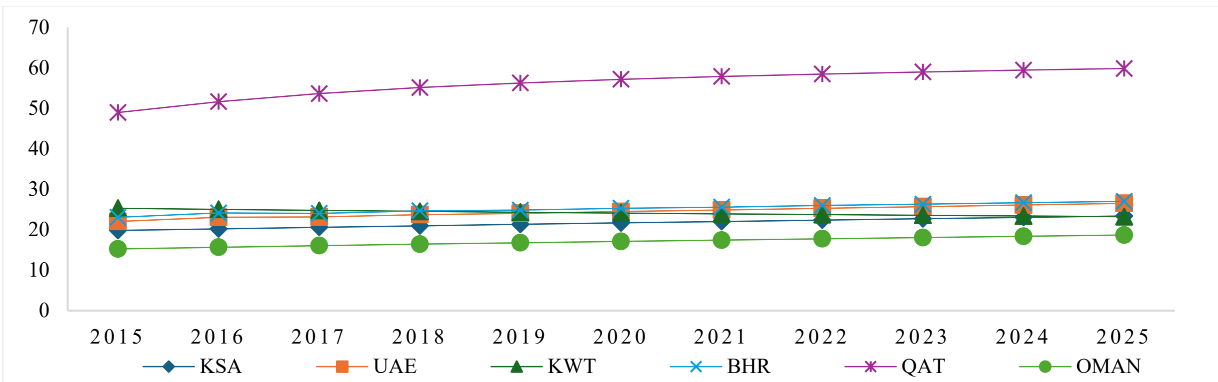

Figure 3. Forecasted per capita CO_2 emissions using the ARIMA (1,1,2) model

Table 2 and Figure 3 indicate that CO_2 emissions in the GCC countries are projected to continue rising over the years, except in Kuwait. Based on the accuracy measures, the ARIMA (1,1,2) model emerges as the most suitable for forecasting CO_2 emissions in Oman, Saudi Arabia, Bahrain, Kuwait, the UAE, and Qatar.

Table 3. Forecasted per capita CO_2 emissions 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

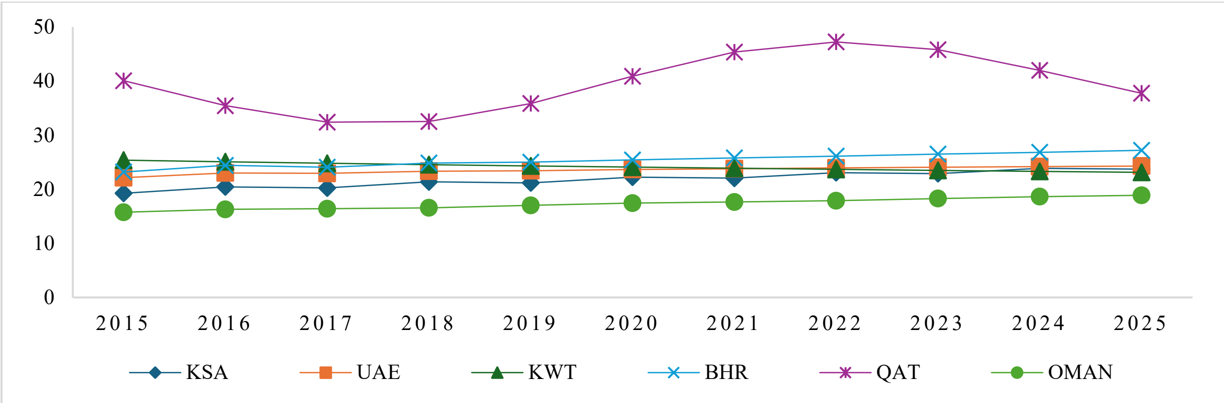

Figure 4. Forecasted per capita CO_2 emissions using the ARIMA (2,1,2) model

According to Table 3 and Figure 4, CO_2 emissions are expected to rise in most GCC countries, except for Kuwait and Qatar. The ARIMA (2,1,2) model provides the best forecasting performance for Saudi Arabia, Oman, Bahrain, Kuwait, and Qatar, as reflected by the accuracy scores.

Table 4. Forecasted per capita CO_2 emissions 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

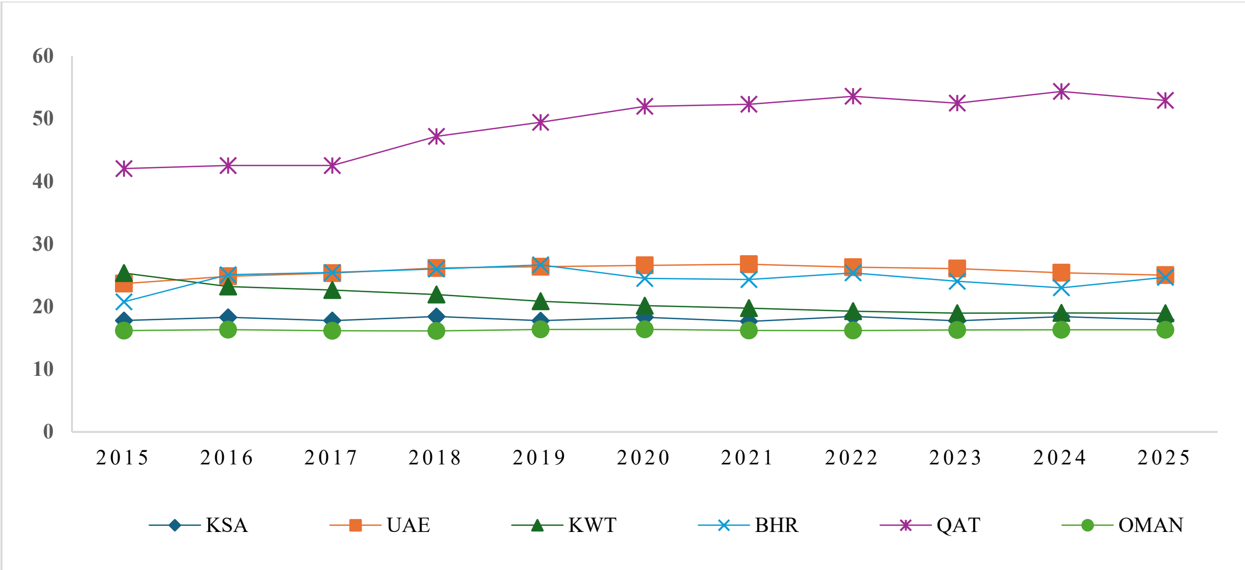

Figure 5. Forecasted per capita CO_2 emissions using the ANN model

Table 4 and Figure 5 suggest that CO_2 emissions in the GCC countries will experience both upward and downward trends over time, except in the case of Kuwait. According to the accuracy metrics in Table 4, the ANN model offers the best fit for predicting emissions in Oman, Saudi Arabia, Bahrain, the UAE, Kuwait, and Qatar.

Table 5. Forecasted per capita CO_2 emissions using the Holt-Winters exponential smoothing 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

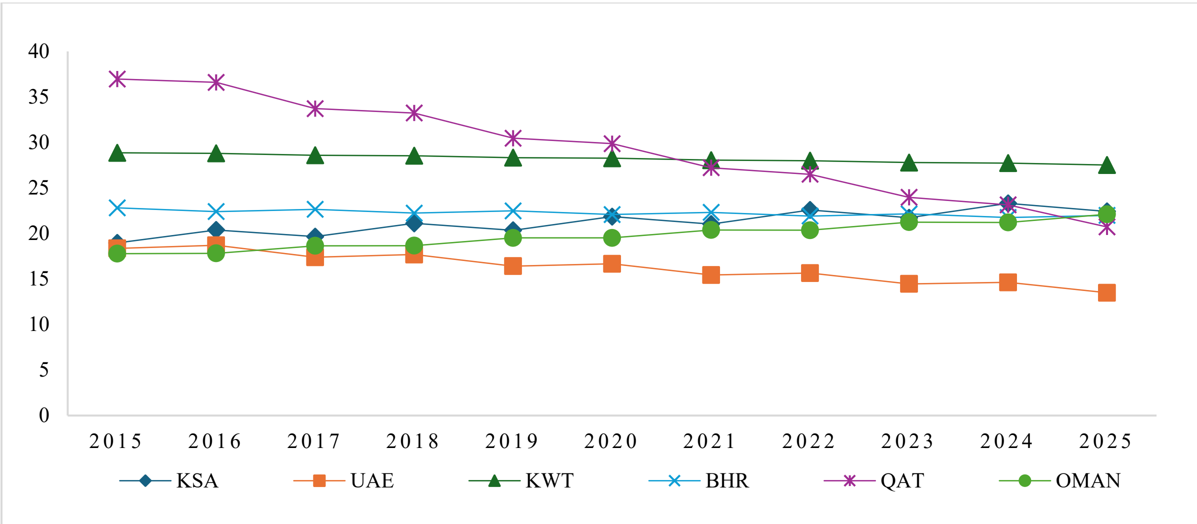

Figure 6. Forecasted per capita CO_2 emissions using the Holt-Winters exponential smoothing model

Table 5 and Figure 6 indicate that CO_2 emissions in Saudi Arabia are likely to follow a fluctuating trend over time. Meanwhile, emissions in the UAE, Kuwait, Bahrain, and Qatar appear to be in continuous decline, except in Oman. Based on the accuracy metrics presented in Table 5, the Holt-Winters Exponential Smoothing model provides the best forecasting performance for CO_2 emissions in Oman.

4.2 Comparative Analysis of Best-Fit CO_2 Emission Predictions for 2025

Table 6 and Figure 7 present the best prediction results for the year 2025, indicating that the Artificial Neural Network (ANN) model outperforms others in terms of accuracy for the Gulf Countries. Developing a neural network model for time series forecasting is inherently complex. Although several software tools are available to support the construction of ANN models, forecasters must understand the key challenges associated with them. Notably, ANN software does not always yield optimal results across all datasets. While ANNs excel in modeling non-linear patterns, traditional methods such as ARIMA and Holt-Winters Exponential Smoothing (HWES) are often more effective for linear time series. Despite these considerations, the ANN model demonstrated superior performance in this study compared to other forecasting approaches.

Table 6. Best Predicted CO_2 Emissions (Metric Tons per Capita) – 2025

Countries	Various Models				
	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

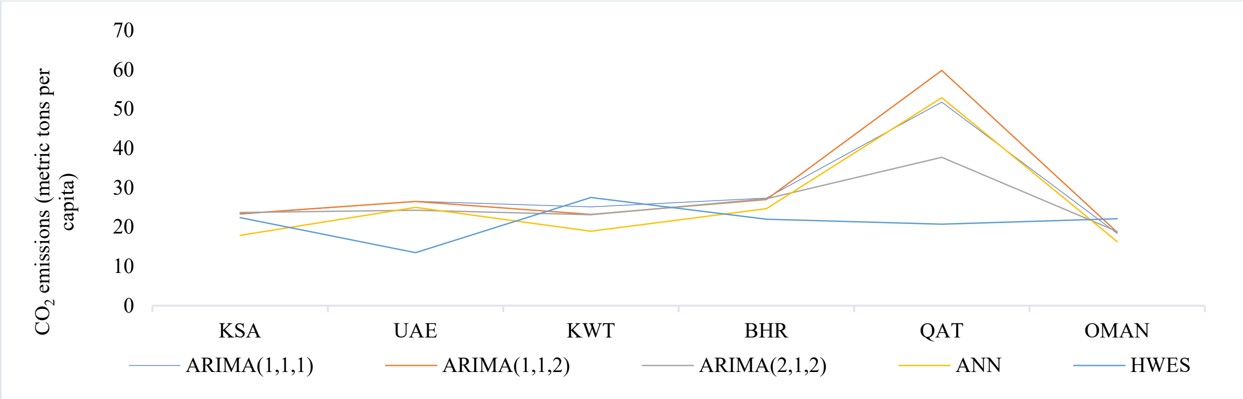

Figure 7. Best Predicted CO_2 Emissions (Metric Tons per Capita) – 2025

6. Conclusion

This study aims to project CO_2 emissions in the Gulf countries. Among various forecasting approaches, the Autoregressive Integrated Moving Average (ARIMA), Holt-Winters Exponential Smoothing (HWES), and Artificial Neural Network (ANN) models effectively capture diverse patterns in time series data, assuming a minimum of 50 observations is available. The analysis of accuracy metrics suggests that the ANN model is the most suitable choice for forecasting CO_2 emissions in Gulf countries for the year 2025.

The projected CO_2 emissions for 2025 are anticipated to vary when compared to the levels recorded in 2014. The findings indicate that it is essential for researchers to focus on models like ANN, ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (2,1,2), and Holt-Winters Exponential Smoothing when analyzing CO_2 emission time series data in this area. This study further emphasizes the efficacy of the ANN model when applied to these datasets. It is essential to acknowledge that ANN models typically require larger datasets, whereas ARIMA models can operate effectively with as few as 50 observations.

ANN, ARIMA, and HWES remain prominent forecasting techniques, recognized for their flexibility and reliability. This study utilized all three models, taking into account the structure and availability of the data. Future research should investigate more sophisticated techniques, including Support Vector Machine (SVM) regression and Polynomial Surface Fitting (PSF) models, to enhance predictive accuracy and identify more precise forecasting methodologies tailored to specific domains.

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