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Forecasting CO₂ emissions due to Electricity power generation in Bahrain

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Abstract:

Global warming is one of the biggest challenges among the leaders and scientists from developed and developing countries. Rapid industrialization and urbanization have given the boost to the amount of greenhouse gases' emission. Carbon dioxide (CO₂) is a significant of greenhouse gases and is the major contributing factor for global warming. CO₂ emissions concentrations in the atmosphere have increased by 47% over the past 170 years due to human activities. As per Doha amendment of the Kyoto protocol in 2012, the target for maximum CO₂ emission per capita for Bahrain was set to 20.96 metric ton for 2020. However, the current amount of CO₂ emission per capita is 21.64 metric ton as of 2019. This research has applied multiple methods such as neural network time series nonlinear autoregressive, Gaussian Process Regression and Holt's methods for CO₂ emission forecasting. It attempts to forecast the CO₂ emission of Bahrain. These methods are evaluated for performance. Neural network model has the RMSE of merely 0.206 while the GPR-RQ model has RMSE of 1.0171 and Holt's method has RMSE of 1.4096. Therefore, it can be concluded that neural network time series nonlinear autoregressive model has performed better for forecasting the CO₂ emission of Bahrain.

Keywords: Neural Network; Time series forecasting; Gaussian Process Regression; Holt's method; CO₂ emission

1. Introduction

Climate change is one of the hot discussions around the global community due to the threat it poses to sustainable development (Destek and Sarkodie, 2019; Khalid et al., 2021). Urbanization and industrialization have given the economic growth to the world but also have caused climate change resulting in global warming. One of the major contributing factors for global warming is carbon dioxide (CO₂) emission along with other greenhouse gases. Although, CO₂ is a minor component of the atmosphere but it is very significant. There are several gases when they collect in the atmosphere, they prevent the solar radiation to bounce off the surface of the earth and absorb sunlight. As this radiation traps in the atmosphere because of these pollutant gases, it causes an increase in the temperature of the planet. This phenomenon is known as greenhouse effect. The gases causing greenhouse effect include CO₂, methane (CH₄), nitrous oxide (N₂O), chlorofluorocarbons (CFCs) and water vapor. Carbon dioxide is the significant greenhouse (heat-trapping) gas. There are several side effects of emission of greenhouse gases such as air pollution, global warming, etc (Yang et al. 2021; Usman et al. 2021). The poor air quality poses the high health risks of the citizens. There are direct consequences such as health and environment deterioration associated with these effects. Measuring the CO₂ emissions is an important factor in guiding the climate mitigation policies (Usman and Makhdum 2021).

CO₂ concentration in the atmosphere has increased by 47% over the past 170 years due to human activities (NASA 2020). Though, this level would have reached over a period of 20,000 years naturally (NASA 2020). The primary source of the CO₂ emission is the human activities such as combusting fossil fuels and deforestation. There are several other natural factors as well including volcanic eruptions and respirations. Almost 40% of the emitted CO₂ globally comes from the burning of fossil fuels to generate electricity (Qader, 2009; Usman and Jahanger 2021). Rapid industrialization is usually the driving factor for economic development (Intisar et al. 2020). However, the shift to industrialization causes an excessive consumption of natural resources. It also increases the demand of energy that is often produced by the combustion of the fossil fuels. Energy consumption have been directly associated with CO₂ emission by various researchers. Excessive consumption of natural resources and combustion of the fossil fuels cause severe threats to the environment such as water shortage, deforestation, and climate change (Dagar et al. 2021).

Forecasting models considers the historical data and trends to produce an estimation of the entity being forecasted. Though, the future human behaviour and actions impact a lot how accurate the estimations will be such as, if the future climate changes will depend on the commitments on the governmental policies related to climate and their impact on other policies such as in manufacturing, energy production and consumptions etc. There are a number of factors that may impact the climate. The global-mean temperature increment depends on the overall emission of the greenhouse gases. Therefore, the overall human behaviour and actions are responsible for the climate change and emission of the greenhouse gases. Fossil fuel combustion is one of the primary factors that introduce CO₂ into the atmosphere. Several research studies have investigated the relationship between CO₂ emission and energy consumption and several other indicators such as fossil fuels, oil and coal consumption, transportation, economic growth and financial investment, health expenditures, trade openness, energy use, and electricity consumption, etc.

As per the British petroleum energy statistics (BP, 2020), carbon emission increased by 0.5% from energy use in 2018, it is lesser than the average growth of previous 10 years carbon emission from energy use that is 1.1% per year. However, due to the large number of extreme weather days in 2019, carbon emission rose and average growth of carbon emission of 2018 and 2019 become higher than its 10-years average (BP 2020). The countries that produce highest amount of CO₂ are China (28%), United States (15%), India (7%), Russia (5%) and Japan (3%) (UCSUSA 2020). One can argue that CO₂ emission is correlated to the economies or gross domestic product (GDP) of the countries. The rich countries produce high amount of CO₂ while poor countries produce low amount of the CO₂. However, this is not the case; several rich countries have managed to reduce the CO₂ emission such as the UK, Spain, France, Italy, and many others. Bahrain stands at 6th position in CO₂ emission per capita globally and 3rd in the Gulf Cooperation Council (GCC) countries (Knoema 2020). The following Figure 1a and Figure 1b illustrate CO₂ emission per capita of GCC countries.

Figure 1a: CO₂ emission per Capita of GCC countries

Figure 1b: Periodic CO₂ emission per Capita of GCC countries

Accurate CO₂ emission measurement is a challenging task due to several reasons and types of emissions. Reliable measurements are a prerequisite in more accurate analysis and forecasting CO₂ emission. However, CO₂ emission caused by the transportation is one of the most challenging tasks in accurate measurement of CO₂ emission due to involvement of multiple traffic parameters. Therefore, most of the models and methods of CO₂ emission measurement from various sectors provide approximate values as 100% accuracy is not difficult to achieve. The amount of carbon dioxide emission was measured 35.4 million tonnes for Bahrain in 2019 while it was 32.9 million tonnes in 2018. There has been an increase of 7.68% which is much higher than that of the average annual growth of CO₂ emission globally. As per Doha amendment of the Kyoto protocol (UN 1997) in 2012, the baseline year for the countries was set to 1990 and the target for maximum CO₂ emission per capita for Bahrain was set 20.96 metric ton for 2020. The current amount of CO₂ emission per capita is 21.64 metric ton as of

105 2019. The trend comparison of CO₂ emission per Capita for all GCC countries is reported in
106 Table 1.

107 Table 1: Periodic CO₂ emission per Capita of GCC countries

Location	1970	1980	1990	2000	2010	2019
Bahrain	13.93	20.92	24.17	26.73	23.24	21.64
Saudi Arabia	8.06	19.25	10.60	12.73	17.44	18.00
United Arab Emirates	82.54	39.45	30.60	28.01	20.78	22.99
Kuwait	51.34	23.62	15.53	26.75	28.77	23.29
Qatar	134.39	65.18	35.69	53.59	39.23	38.82
Oman	10.13	11.16	8.60	11.17	17.26	18.55

108 This research considers the CO₂ emission data from 1933 to 2019. The data has been
109 collected from multiple sources such as from Statistical Review of World Energy report (BP
110 2020) and from the organization by the name Our World in Data (World Bank 2020). The
111 Figure 2 illustrates the CO₂ emission data of Bahrain from 1933 to 2019. It is evident from
112 the CO₂ emission time series data that there is an upward trend in the series in twenty-first
113 century and in the later part of twentieth century. The series also shows that there is the
114 leveling off at around 1950 and then the series shows another sharp upward trend at around
115 1970. Several researchers have examined the relationships between CO₂ emission and
116 renewable energy. It has been observed that renewable energy negatively impacts the CO₂
117 emission and other environmental hazards. As based on these observations, it is possible to
118 forecast the CO₂ emission using statistical and other forecasting techniques. However, it is a
119 question of interest that whether the overall trend of CO₂ emission is natural or due to some
120 human-made interventions.

Figure 2: CO₂ emission of Bahrain (1933 to 2019).

However, the observations illustrate that on an average, there has been a decrease in CO₂ emission of Bahrain in last two decades. Though, as stated earlier that there has been an increase of 7.68% in 2019 in comparison to 2018, therefore, it is highly unlikely to meet its current target. However, the climate effect of corona virus pandemic might play an important role here, and the overall CO₂ may fall globally, not only in Bahrain and Bahrain might meet its target. An estimation of the CO₂ emission of Bahrain will play an important role in planning various economic and industrial developments for the next decade. Though, carbon capture and storage may be a key strategy to mitigate the CO₂ emission. However, it has several risks associated with it including the probability of leakage, measurement of economical, ecological, and social impacts, environmental perturbation strength assessment etc. This research employs multiple forecasting methods to predict the CO₂ emission in Bahrain for next decade. This research study is organized into five sections. Next section provides a brief literature review of CO₂ emission forecasting using different methods. Section three illustrates the methods used in this research for forecasting. Section four demonstrates and analyses the results obtain and last section concludes the research and provides future research direction.

2. Related Work

CO₂ emission analysis, planning and implementing various methodologies for decreasing the emission have been an important consideration for each of the participating countries after the Kyoto treaty (United Nation, 2020). The cost of the energy efficient policies that decreases the CO₂ emission is usually higher than the policies that do not consider CO₂ emission (Bye et al. 2018). CO₂ is a significant greenhouse gas and plays an important role in the global warming

and the climate change. Therefore, an estimation and analysis of CO₂ becomes more significant. Researchers around the world attempts to understand and analyses the factors responsible for CO₂ emission and strives to predict the amount of emission. Several methodologies have been employed by various researchers (Silva 2013) to predict the CO₂ emission and energy consumption. These methodologies include the usage of artificial neural network, support vector machine, ARIMA models, decision trees, Bayesian networks, and other statistical supervised machine learning algorithms. Neural network based approach is one of the most commonly used approach for forecasting CO₂ emission. Grey Model, computer based simulations, linear regression, multiple linear regression, logistic functions, Adaptive Neuro-Fuzzy Intelligent System, Autoregressive Integrated Moving Average, and Holt's methods are a few approaches which are used very often by various researchers in CO₂ emission forecasting.

There are several other approaches that are used considering various factors while forecasting. These approaches employ complex mathematical and sophisticated statistical techniques for forecasting. This research employs the Gaussian Process Regression Rational Quadratic Model, Holt's method and Non-linear autoregressive neural network. This section discusses the background of these methods in brief.

Gaussian Process (GP) based predictions, especially time series analysis, have been used since a very long time (Wiener 1949; Kolmogorov 1941). GP predictions have been commonly employed in geo-statistics (Journel and Huijbregts 1978; Matheron 1973). The application of Gaussian process in predication can be seen in various fields such as in meteorology (Daley 1991), in spatial prediction (Whittle 1963) and in spatial statistics (Ripley 1981; Cressie 1993), etc. Researchers realized that Gaussian process can be applied in the general regression context (O'Hagan 1978; Zhao et al. 2020). Early usage of GP in computer experiments (Sacks et al. 1989) discussed parameters optimization in the covariance function, choices of the input vector that provide most information. Williams and Rasmussen (1996) discussed the applications of GPs in machine learning and illustrates the optimization methods for the parameters in covariance function. Researchers have used Gaussian process regression for forecasting in a variety of fields such as rock fragmentation in surface mines, wind speed forecasting, dam displacement forecasting, stream flow forecasting, short-term photovoltaic power probability forecasting, and CO₂ emission forecasting, etc. Gaussian Process Regression Rational Quadratic Model is one of the methodologies used in this study to predict the CO₂ emission.

The origin of exponential smoothing can be traced back to World War II. Robert G Brown developed a tracking model to track the fire control information (Gass and Harris 2000). This

model was extended, and a general exponential smoothing method was developed (Brown 1959; 1963). Charles C. Holt developed a forecasting method similar to exponential smoothing in 1957, though it was published recently (Holt 2004a; 2004b). Winters applied the Holt's method to get empirical evidences and the results gained popularity as Holt-Winters forecasting method (Winters 1960). All variations of this method, to overcome the seasonality effect, have been developed by extending the winters' method (Winters 1960). There are several non-seasonal variations of this methods are additive trend (Holt, 1957), multiplicative trend (Pegels 1969), damped additive trend (Gardner and McKenzie, 1985) and damped multiplicative trend (Taylor 2003). Exponential smoothing method along with its several extensions has been utilized in different domain including CO₂ emission for estimating the future trends. Several researchers have used double exponential smoothing in developing a model for forecasting including in the field of environment pollution and ozone formation, etc. A research study (Choi et al. 2014) has used double exponential smoothing model for estimating the trend in CO₂ emission for U.S. transportation sector. Another research study that provides an estimation of CO₂ emission of Bahrain uses several methods including Holt-Winters method and neural time series forecasting (Tudor 2016).

Neural network-based prediction models have gained a lot of popularity in last couple of decades. There was an explosion of techniques used in artificial intelligence in eighties. Then, in the next decade, use of artificial neural networks was widely used in time series forecasting. In the recent years, the use of neural networks has increased multifold due to high increased in computational power. Neural network has been a reliable technique for prediction and forecasting in multiple domains. For example, multiple perceptron, due to their approximation property, were quickly adopted in time series forecasting besides being introduced as a technique to solve classification problems. There are several techniques available for time series forecasting and analysis, however, most of these methodologies assume a linear relationship among the variables. Linearity based methods does not perform well in the cases where the relationship among the variables is non-linear. Neural network-based model prediction models can perform well even if the relationship is non-linear. Non-linear autoregressive neural network for time series forecasting can overcome the non-linearity and has the potential to forecast with minimum prediction error (Benmouiza and Cheknane 2016; Hill et al. 1996). The use of neural network can be found in various domain such as machine translation (Khan and Usman, 2019; Shahnawaz and Mishra 2013; Bye et al. 2018), natural language processing (Khan et al. 2018), sentiment analysis (Astya 2017) and image processing (Bashir et al. 2017) etc. Neural network forecasting models have been implemented to predict

in several fields including the for CO₂ emission forecasting and air pollution estimation (Gallo et al. 2014), for forecasting the intensity of emission by some of the top CO₂ emitters (Acheampong and Boateng 2019) and CO₂ emission estimation (Zhao and Mao 2012; Sun and Huang 2020), for predicting humidity and room temperature (Mustafa raj et al. 2011), for predicting energy consumption (Ruiz et al. 2016; Usman and Hammar 2020).

3. Methodology

Time series analysis and forecasting are significant challenge for the researchers. Finding a forecasting method that can predict with minimum prediction error has been a major challenge. There are several complex mathematical and sophisticated statistical forecasting techniques available. This research paper implements Gaussian Process Regression Rational Quadratic Model, Neural Network Time Series Nonlinear Autoregressive and Holt's Method. This section illustrates the functioning of these methods in brief.

3.1 Gaussian Process Regression Rational Quadratic Model

In Gaussian process (GP), a subset of variables from any collection of random variables forms a joint Gaussian distribution (Williams and Rasmussen 2006). GPs have the potential to be employed for Bayesian supervised learning. In supervised machine learning, regression is a technique that concerns with the prediction of the future values of the continuous quantities. Gaussian Process Regression (GPR) models are nonparametric probabilistic models based on kernel with a multivariate distribution with a finite collection of random variables (Williams and Rasmussen 2006; MacKay 1998). GPR can perform well on small datasets. Over the past decade, the use of GPs has gain popularity in machine learning community. There are several types of kernel that can be used with GPR such as Rational Quadratic Covariance, Squared Exponential Covariance, Matern Class Covariance, Marginal Likelihood Gradient, etc. Based on experiments conducted, this study has found that rational quadratic performs relative better than the other kernels for CO₂ emission prediction. The algorithm for Gaussian Process Regression Rational Quadratic Model is outlined as following:

Step 1: Obtain the training dataset of n observations

$$Dataset = \{(x_i, y_i) \mid i = 1, 2, \dots, n\},$$

where x is the input vector of the *Dataset* dimension and y is the target or output variable.

Step 2: Begin with the standard linear regression model of the following form with Gaussian noise:

$$y = f(x) + \varepsilon, \text{ and } f(x) = x^T w$$

where w is weight vector (parameters) of the linear regression model.

Assuming that noise ε follows an identical independent Gaussian distribution having a variance of σ_n^2 and zero mean such as $\varepsilon \sim N(0, \sigma_n^2)$

The likelihood can be calculated as:

$p(y|f) = N(y|f, \sigma_n^2 I)$, where y is $[y_1, y_2, \dots, y_n]^T$, f is $[f(x_1), f(x_2), \dots, f(x_n)]$ and I is a unit matrix.

The target variable y_* or output is predicted for new input values x_* using the following joint distribution MacKay 1998; Bishop 2006).

$$\begin{bmatrix} y \\ y_* \end{bmatrix} = \begin{bmatrix} f \\ f_* \end{bmatrix} + \begin{bmatrix} \varepsilon \\ \varepsilon_* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K_y & k_* \\ k_*^T & k_{**} + \sigma_n^2 \end{bmatrix}\right)$$

Where $K_y = K + \sigma_n^2 I$, and $K = k(x_i + x_j)$, $f_* = f(x_*)$ is new input variable's latent function

Using the Gaussians conditioning rules (Bishop 2006), the predictive Gaussian distribution

$p(y_*|y)$ is computed using mean $m(x_*) = k_*^T K_y^{-1} y$ and covariance $\sigma^2(x_*) = k_{**} - k_*^T K_y^{-1} k_* + \sigma_n^2$

K_y^{-1} can be computed using the Cholesky decomposition (Williams and Rasmussen 2006).

Step 3: Use the Rational quadratic kernel

Using the Rational quadratic, the kernel is computed as

$$k(x_i, x_j|\theta) = \sigma_f^2 \left(1 + \frac{r^2}{2\alpha\sigma_l^2}\right)^{-\alpha}$$

Where r is the Euclidean distance computed as:

$r = \sqrt{(x_i - x_j)^T (x_i - x_j)}$, α is a positive scalar parameter and σ_l is standard deviation and σ_l is the characteristics length.

3.2 Neural Network Time Series Nonlinear Autoregressive

CO₂ emission is often subject to rapid transients and high variance; therefore, time series forecasting models have to overcome the non-linearity of the change in the emission.

According to a research study (Lapedes and Farber 1987), time series can be modeled using the following non-linear autoregressive model:

$$y(t) = h(y(t-1), y(t-2), \dots, y(t-d)) + \varepsilon(t).$$

In prediction, past values are used to predict the future values. Nonlinear autoregressive time series neural network is implemented using multilayer feed forward network with feedback connection (Lapedes, A., & Farber, R. (1987; L6pez et al. 2012). Figure 3 illustrates the topology of the nonlinear autoregressive neural network.

The model can be expressed as the following:

$$\hat{y}(t) = h(y(t-1), y(t-2), \dots, y(t-d)) + \varepsilon(t)$$

Where, the function h is unknown and the training aims to approximate the function h by adjusting the weights and bias. The term $\varepsilon(t)$ represents the error assuming that it is a random independent variables' sequence having zero mean and finite variance. The network uses feedback delays to learn from the past time series values. The parameter d represents the delay and can be tuned for the desired accuracy by trial and error method.

Figure 3: Nonlinear autoregressive neural network structure

There are several training algorithms that can be used for training the neural network such as Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient etc. Levenberg-Marquardt is the most commonly used algorithm. Scaled Conjugate Gradient algorithm uses gradient calculations that make it more memory efficient unlike the Jacobian calculations used by Levenberg-Marquardt and Bayesian Regularization training algorithms. However, Bayesian Regularization often attains better solutions for noisy and small problems. The neural network used in this study is an open loop network. Prediction using open loop network are often more efficient than the closed loop network. The open loop network allows the network to be fed with correct feedback inputs despite of training the network to produce the correct feedback outputs.

3.3 Holt's Method

Holt's forecasting method uses exponentially moving weighted average, using which flattens the random fluctuations. It puts a decreasing weight on the older data. Because of these properties of the Holt's method, it can perform well with minimum amount of data (Holt, 2004a; 2004b). The new average value or moving average is estimated by calculating the weighted average of the current value of the variable and the average value of the last period. Holt's method's capability of forecasting with minimum data combined with its flexibility

makes it a good candidate for predicting CO₂ emission. As the amount of CO₂ data is limited and fluctuations can be observed by simply plotting the data used for this research. If there may have trends of different kinds. There are three types of trends which are linear, exponential, and damped. A linear trend means an absolute equal value decrease or increase from one stage of time to another. An exponential trend illustrates a relative equal value decrease or increase from one period to another. A damped trend is a combination of the behaviour of exponential trend and linear trend.

The following three equations outline the method. The first equation is the forecasting equation, second equation is the level equation (for value smoothing) and third equation is for the trend. Forecasting model uses the trend and level equations to address trend and fluctuations. The equations are defined as following:

$$y_{t+h|t} = l_t + hb_t$$

Where, l_t is the series level at time t ; h is the forecast step and b_t is trend

$$l_t = \alpha y_t + (1 - \alpha)(l_{t-1} + b_{t-1})$$

Where, α is the smoothing parameter:

$$b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1}$$

where, β is the trend smoothing parameter such that $0 < \beta < 1$

Forecasting using linear method exhibits a constant decreasing or increasing trend. Empirical evidence suggests that using it results in over-forecasting (Gardner and McKenzie, 1985). The following set of equations illustrates the Holt's method using damped trend:

$$y_{t+h|t} = l_t + (\varphi + \varphi^2 + \dots \varphi^h)b_t$$

Where, l_t is the series level at time t ; h is the forecast step and b_t is trend and $0 < \varphi < 1$

$$l_t = \alpha y_t + (1 - \alpha)(l_{t-1} + \varphi b_{t-1})$$

$$b_t = \beta(l_t - l_{t-1}) + (1 - \beta)\varphi b_{t-1}$$

Where, α is the smoothing parameter and β is the trend smoothing parameter such that $0 < \beta < 1$

4. Implementation and Analysis of Results

This research study has used the CO₂ emission data collected from Global Change Data Lab's project 'Our World in Data' (World Bank (2020)). This project has a consolidated data for CO₂ emission from Carbon Dioxide Information Analysis Center (CDIAC) and Global Carbon Project. The data obtained is open source and contains the CO₂ emission data from 1933 to 2018 for Bahrain. The data for 2019 was taken from BP report (BP 2020). The amount of CO₂ emission is represented in million metric tons. This research study applies multiple methods and attempts to forecast the CO₂ emission of Bahrain. It also provides the comparison among

the forecasted amount by different methods. The implementation of the discussed methods has been done using various open-source Python libraries. GPR model was implemented using Rational Quadratic kernel function with 5-fold cross validation. The neural network created for predicting has 11 hidden layers and the number of delays was kept 2. The network was trained with 3 different algorithms that are Bayesian regularization, Levenberg-Marquardt and Scaled conjugate gradient. By using trial and error approach with the mentioned algorithms and network configurations, the best accuracy was obtained using Bayesian algorithm. This experiment implemented multiple approaches of Holt's method such as exponential smoothing trend, Holt's linear trend and Adaptive damped trend. 'Estimated' method has been used for initializing with the value of 0.11 with 0.9 smoothing level and 0.1 smoothing trend. The following figure 4 illustrates the responses predicted by the Gaussian Process Regression Rational Quadratic (GPR-RQ) Model. As mentioned in the previous section, this research has employed the rational quadratic kernel for training the Gaussian Process Regression model. The horizontal axis represents the year and vertical axis represents the amount of CO₂ emission.

Figure 4: GPR-RQ Model Response Plot

The figure 5 above represents the plot for actual amount of the CO₂ emission and the predicted amount. The diagonal line in figure 5 represents a prefect prediction in which predicted values are same as the actual values. As observed from the figure, almost all the points are lie on or nearby the perfect prediction. Training using GPR-RQ model achieved a root mean square error of 1.0171.

Figure 5: GPR-RQ Model Predicted vs. Actual Response Plot

Figure 6 training and responses of the trained neural network model. After trial and error method for initial weight initialization, the best accuracy was obtained using Bayesian algorithm among the three tested algorithms. The root means squared error obtained using neural network method was 0.206.

Figure 6: Prediction by Neural Network Time Series Nonlinear Autoregressive Using Bayesian Regularization

The following Figure 7 represents the training and responses of the forecasting model using exponential smoothing trend, Holt's linear trend and Adaptive damped trend. The model was trained to observe the effects of different trends over forecasting accuracy. Experimented were performed with several different values for smoothing parameter and trend smoothing parameters. It was observed that among the three trends, exponential smoothing trend, Holt's

linear trend and Adaptive damped trend, Holt's linear trend has outperformed the other two. The best accuracy was obtained using $\alpha = 0.9$ and $\beta = 0.1$ for Holt's linear trends. The root means squared error obtained using Holt's method was 1.4096.

Figure 7: Prediction using Holt's method

The following Table 2 illustrates the performance comparison for the CO₂ emission prediction models. This research compares the performances of the applied forecasting methods by evaluating their accuracy with regards to root mean square errors. RMSE is always a positive value. As the predicted values are small (maximum around 35) therefore, a small root mean square error (RMSE) amounts to a large quantity. Smaller values of RMSE will lead to higher accuracy. As summarized, the accuracy of neural network time series nonlinear autoregressive is much higher than the Gaussian Process Regression model and the Holt's methods. Neural network model has the RMSE of merely 0.206 while the GPR-RQ model has RMSE of 1.0171 and Holt's method has RMSE of 1.4096. Therefore, it can be concluded that neural network time series nonlinear autoregressive has performed better for forecasting the CO₂ emission of Bahrain. The following Table 3 illustrates the CO₂ emission data forecast till 2025. The forecasted values have been predicted using neural network time series nonlinear autoregressive model. As among all the tested methods for predicting CO₂ emission, neural network model has illustrated the better performance. The lower the RMSE value, the more accurate the results are. The root mean square error for CO₂ emission prediction has been achieved minimum among the tested methods. The achieved RMSE value is almost 5 times smaller than the other methods. Therefore, the neural network time series nonlinear

autoregressive model for predicting the CO₂ emission of Bahrain has shown the best performance among the methods tested.

Table 2: Performance Comparison for forecasting model

Method	Root Mean Square Error
Neural Network Time Series Nonlinear Autoregressive	0.206
Gaussian Process Regression Rational Quadratic Model	1.0171
Holt's forecasting method	1.4096

Table 3: CO₂ emission data forecast till 2025 for Bahrain

Year	Predicted CO ₂ emission
2020	34.602373
2021	35.393697
2022	36.199162
2023	37.018644
2024	37.623421
2025	38.414745

5. Conclusion and Future Work

Among all the greenhouse gasses, Carbon dioxide (CO₂) is the major contributor for global warming. CO₂ is also known as heat trapping gas. It traps the solar radiations in the earth's atmosphere that might have bounced off if the atmosphere was not polluted with CO₂ and other greenhouse gases. CO₂ is the primary factor for global warming, and it must be curbed or reduced. An international treaty was signed known as Kyoto protocol that extends Climate Change framework by United Nations to put a restrain on global warming. In 2012, as per Doha amendment, baseline year and the target for CO₂ were set for several countries including Bahrain. However, as per the CO₂ emission data of 2019, Bahrain is lagging behind its target. Bahrain should consider CO₂ emission as one of the key factors while developing policies related to energy consumption, production and CO₂ emissions. Carbon capture and storage can be considered as one of the strategies for CO₂ emission mitigation. However, it comes with several associated risks such as leakage probability, measurement of economical, ecological, and social impacts, environmental perturbation strength assessment etc. This research attempts to find suitable forecasting model for CO₂ emission. Three methods were implemented and evaluated. Neural network model has achieved an RMSE of 0.206 while the GPR-RQ model

has an RMSE of 1.0171 and Holt's method has an RMSE of 1.4096. Therefore, it can be concluded that neural network time series nonlinear autoregressive model has performed better for forecasting the CO₂ emission of Bahrain. Researchers are working in the direction of investing the impact of different sector and their proportion in overall CO₂ emission of Bahrain and predicting the sector-wise contribution.

Ethics declarations

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Availability of data and materials: The datasets used and/or analyzed during the current study are variability from the corresponding author on reasonable request.

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