Artificial Intelligence Based Modelling for Predicting CO_2 Emission for Climate Change Mitigation in Saudi Arabia

Sultan Alamri[1], Shahnawaz Khan[2]
College of Computing and Informatics, Saudi Electronic University
Saudi Arabia[1]
School of ICT, Bahrain Polytechnic
Isa Town, Bahrain[2]

***Abstract*—Climate change (such as global warming) causes the barrier in the attaining sustainable development goals. Emission of greenhouse gases (primarily carbon dioxide CO_2 emission) are the root cause of global warming. This research analyses and investigates the emission of CO_2 and attempts to develop an optimal model to forecast the CO_2 emission. Several machine learning and statistical modeling techniques have been implemented and evaluated to explore the patterns and trends of CO_2 emissions to develop an optimal model for forecasting future CO_2 emissions. The implemented methods include such as Exponential Smoothing, Transformers, Temporal Convolutional Network (TCN), and neural basis expansion analysis for interpretable time series. The data for training these models have been collected and synthesized from various sources using a web crawler. The performance of these models has been evaluated using various performance measurement metrices such as RMSE, R2 score, MAE, MAPE and OPE. The N-BEATS model demonstrated an overall better performance for forecasting CO_2 emission in Saudi Arabia in comparison to the other models. In addition, this paper also provides recommendations and strategies for mitigating the climate change (by reducing CO_2 emission).**

Keywords*—Exponential smoothing; transformers; temporal convolutional network; neural basis expansion analysis; climate change

I. Introduction

The United Nations (UN) has proposed several climate friendly actions for the governments while developing the post-pandemic recovery plans. Governments, all over the globe, are aiming to tackle the climate-crisis for changing the course of carbon dioxide (CO_2) emission trajectory to net-zero, to create a more sustainable and safer future for their citizens. But why there is so much attention given to CO_2 emission? CO_2 is a greenhouse gas. Greenhouse gases traps the heat in the atmosphere and radiates it back in all directions including towards the surface of earth [1]; hence, causing an increase in the global temperature (climate change). There are multiple sources (such as fossil fuels extraction and consumption, wildfires, volcanic eruptions and other similar natural processes, etc.) that generate carbon dioxide. Among these sources, fossil fuels are the major contributing factor of CO_2 emission.

The Kingdom of Saudi Arabia (KSA) presented its first national review report on sustainable development goals (SDGs) to UN High-Level political forum in 2018 [2]. The presented review is the first attempt by the KSA to conduct a comprehensive and systematic review of the status. Climate action is one of the 17 SDGs agenda set by the UN. As the UN member state, Kingdom of Saudi Arabia has adopted the sustainable development goals under its vision 2030. There have been several great initiatives and indicators that has exemplified the enthusiasm of the Kingdom of Saudi Arabia in achieving these goals as indicated from the first voluntary national review report [2][3]. The review suggests that the KSA has made great efforts in numerous areas; however, there are several bottlenecks that place the KSA in a challenging position to achieve its 2030 vision. Based on the review report, the major challenges include data availability, efficient measures and methods for SDG-related statistics collection and dissemination, more effective and better coordination techniques among the non-government and government institutions to avoid effort duplication, enriching and enhancing the existing institutional frameworks, so on and, so forth. Therefore, more profound interventions are essential to move forward. One of the areas of concern among these challenges is emission of greenhouse gases.

Climate change is one of the major hurdles in attaining the sustainable development goals [4][5]. Rapid industrialization and urbanization have given the unexpected economic growth but the world has to pay the price in the shape of climate change. Due to the unprecedented utilization of fossil fuel in energy generation and consumption, the emission of greenhouse gases (primarily CO_2) has increased exponentially. Greenhouse gases gather in the atmosphere, absorb sunlight, and avert the solar radiations to reflect back from the earth surface. Thus, the radiations are entrapped in the atmosphere. The entrapped radiations become the reason to increase the temperature of the plane and thus, causing global warming. This procedure is referred to as greenhouse effect. The gases that cause greenhouse effect include carbon dioxide (CO_2), nitrous oxide (N2O), chlorofluorocarbons (CFCs), methane (CH4), and water vapor. Though, among these gases, CO_2 is the primary contributor to greenhouse effect. However, human interventions and activities have increased the CO_2 concentration significantly (by 47%) in the atmosphere in the past 170 years. This increment in CO_2 concentration would have taken a period of over 20,000 years naturally [6]. Therefore, to mitigate the climate change, an efficient technique is required that can measure the emission of greenhouse gases and can provide an insight for the future emission trends so that an effective climate change mitigation solution can be developed and put into action.

The emission of greenhouse gases does not only causes global warming but also has several other effects such as air pollution, so on and, so forth. The poor quality of air causes various health risks to the citizens. Therefore, there several direct and indirect consequences of GHG emission such as environment deterioration, health deterioration, etc. A research study [7] illustrates that almost 40% of global CO_2 emission is contributed by the electricity generation by combustion of the fossil fuels. However, there are several other natural factors that contribute to GHG emission such as respirations, and volcanic eruptions. Although, the modern industrialization shift has resulted in excessive combustion of the fossil fuels and consumption of natural resources. It also leads to several other major environmental challenges such as climate change, deforestation and water shortage. Effective measurement, analysis and forecasting techniques of GHG emission will guide in identifying the key factors and emission sources that will affect the climate change mitigation policies.

This paper has been organized into six sections. The next discusses the related work in this regard. Section three states the problem statement, research importance and objectives. Section four describes the data and methodologies. It also describes the proposed system framework and the methodologies which have been implemented for developing an effective forecasting model. Section five illustrates the results of different forecasting models, provide performance analysis, and suggest CO_2 emission mitigation strategies. Section six concludes the research paper and provides the future research direction for mitigating climate change.

II. Literature Review

Climate change is one of the most defining global issues of this century. United Nations has listed 17 SDGs in its 2030 agenda. Climate action is one of the sustainable development goals among others such as sustainable cities and communities, affordable and clean energy, responsible consumption and productions, etc. The United Nations 2030 agenda encompasses primarily five pillars such as Planet, People, Peace, Prosperity, and Partnership. The 17 SDGs incorporate these five pillars. As a member state of United Nations, Kingdom of Saudi Arabia (KSA) has adopted sustainable development goals. In the past few years, the KSA has already implemented numerous polices under the Vision 2030, these policies align with the United Nations 2030 agenda. The ongoing 2030 vision has demonstrated progress in several indicators to achieve the sustainable development goals and to become a welcoming economy for visitors, workers and investors. Saudi Arabia has proved its commitment in achieving sustainable development goals and is enthusiastic in recognizing the importance to address these global challenges.

Swift urbanization and unprecedented industrialization have raised the issue of global warming and climate change around the world. The UN have been setting goals to curb the drastic effects of climate change for its member states. In turn, all the member states have been implementing different policies and taking actions to accomplish their goals for sustainable development. However, due to the high demand of energy for industrialization and urbanization, the ways of energy production and consumptions have not been efficient in lowering the GHG emission levels. As a result, the level of GHG emission have been increasing around the world and causing global warming. The Kingdom of Saudi Arabia is no exception to this. Despite the numerous efforts made by the concerned authorities, the KSA still has to go far to meet is target level of GHG emission. As per the first voluntary national review report [2], the KSA has to cut down its annual carbon dioxide emission as much as 130 million tonnes by 2030.

The Kingdom of Saudi Arabia has placed several policies and strategies to meet its requirement. However, due to the increased power (energy) demand by industrialization and population growth, over 80% of the overall energy demand is fulfilled by using the fossil fuels for energy generation (Amran et al, 2020). Energy generation using fossil fuels is directly linked with CO_2 emission. Thus, an ambitious target for the KSA is to switch to alternative sources of power sources such as nuclear power, green energy [8] or renewable energy sources [9], etc. Climate change does not only cause increment in atmospheric temperature but also accounts of huge financial loses. It has costed around 130 million dollars in 2018 only and almost USD one billion from 1980-2010 (Al-Bassam et al., 2014). Climate's hyper aridity and the sensitive ecosystem place the KSA at a certain climate change risk [10]. In some areas of the KSA, a very high temperature (52°C) has been recorded which is negatively influenced by various human activities and vehicle emission [3].

The government of Saudi Arabia is addressing several challenges for climate change mitigation and adapting measures to restraint the social and diverse economic impacts on the country. Some of these efforts include King Abdulaziz public transport project, conservation measures for water and electricity [11], urban planning scheme [10], research on environment [12], and many more. Although, despite the significant efforts made by the government, per capita CO_2 emission in the Kingdom is still amongst the highest in the world [13]. Therefore, solid strategies, measures and plans are required to put into action for climate change mitigation and economic diversification such as promoting the social responsibilities of corporations for safeguarding the environment.

This research will utilize the data collected from past to analyze the trends and will employ forecasting and/or prediction models in estimating the CO_2 emission (because it is the major constituents amongst GHG). As the future human activities and behavior will have a substantial impact on the accuracy of the estimations, therefore, this research has also attempted to provide the guidelines in developing the effective climate change mitigation pathways and policies. Several machine learning, statistical and mathematical modelling techniques have been employed for the development of an effective forecasting model. As the amount of the GHG emission data available [14] [15] from all the possible resources is limited, therefore, this research has employed the techniques that perform well under the limited data. Finding an appropriate time series forecasting method has been a significant challenge amongst the community of researchers. Finding a prediction or forecasting technique that can perform well on the known and unknown data is a challenging task. When the historical data available is in low quantity, prediction or forecasting techniques performs well on the training data and produce results with minimal error rate, while on the unseen data the results are usually disastrous [16] [17]. This research has implemented several machine learning, statistical and mathematical modelling techniques for simulating the CO_2 emission in the Kingdom of Saudi Arabia. These findings will play a substantial role in developing the climate change mitigation policies and strategies for Saudi Arabia.

The literature review illustrates that Saudi Arabia has to cut down its annual carbon dioxide emissions by 130 million tonnes by 2030, but it does not provide information on the country's current emissions levels. Several efforts have been made by the Saudi Arabian government to address climate change. However, it has also been observed that there are need for solid strategies, measures, and plans for climate change mitigation and economic diversification. It has also been observed that machine learning, statistical and mathematical modeling techniques have been used for forecasting CO_2 emissions in Saudi Arabia, but it does not provide information on the data sources or the accuracy of the models used.

III. Research Importance and Objectives

The GHG emission in Saudi Arabia has increased almost 200% in the past three decades. Per capita GHG emission is the second highest in Saudi Arabia amongst the G20 countries. Kingdom of Saudi Arabia would require to reduce its CO_2 emission below 389 Mt by 2030 as its commitment to UN's sustainable goals and to achieve it vision 2030 goals. Ambient air pollution (a resultant of emission) poses higher health risks (such as stroke, heart disease, lung cancer, and chronic respiratory diseases) in Saudi Arabia as compared to other G20 countries. Kingdom of Saudi Arabia loses almost SAR 859m (~USD 229m) because of extreme weather events and is vulnerable to climate change. The Saudi Arabia has a target to reduce emission equivalent to 130 million tonnes per year. To address and achieve the above targets and issues, an effective estimation technique and guidelines are required which this research study aims to address. This research synthesizes the findings from literature to recognize the opportunities for potential estimate emission reduction and intervention. It implements several machine learning, statistical and mathematical modelling techniques for simulating the emission of greenhouse gases (specifically CO_2) in the Kingdom. It will also aim to address the issue of accuracy in the synthesized data by verifying it from multiple sources as described in the next section. As there is a need for solid strategies, measures, and plans for climate change mitigation and economic diversification, therefore, this research also provides suggested strategies and policies that can be utilized along with the forecasting model to mitigate the climate change.

IV. Materials and Methods

This section examines the data collection, and forecasting methodologies used in this paper. This section is organized into three subsections which are dataset, proposed system framework, and forecasting methodologies utilized in this research. The dataset subsection describes the data collection and data pre-processing. The proposed system framework subsection describes the research design, and the forecasting methodologies subsection describes the different forecasting methods implemented in this research study.

A. Dataset

For this research study, CO_2 emission data (as CO_2 is the major greenhouse gas) has been collected available in the public domain. Some major sources of the data that have been considered are World Bank [13], BP [14], and our world in data [15]. This research utilizes the complete emission data obtained from all these sources by converting to one scale and synthesizing it. The figure (see Fig. 1) illustrates the synthesized data.

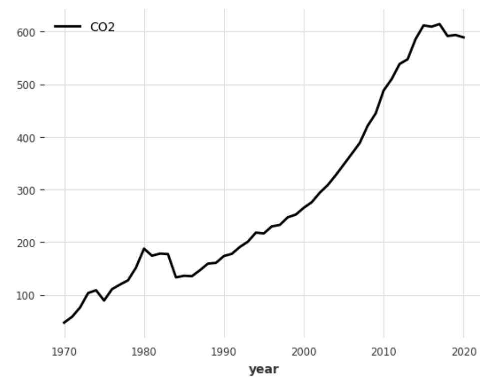

Fig. 1. Year-wise CO_2 emission in Saudi Arabia.

B. Proposed System Framework

A quantitative analysis has been conducted on the data collected from all the sources to investigate the patterns and trends. This research explores and implements several forecasting techniques such as Exponential Smoothing, Transformers, Temporal Convolutional Network (TCN), neural basis expansion analysis for interpretable time series, and Fast Fourier Transform Forecasting. The following figure (see Fig. 2) illustrates the proposed system framework.

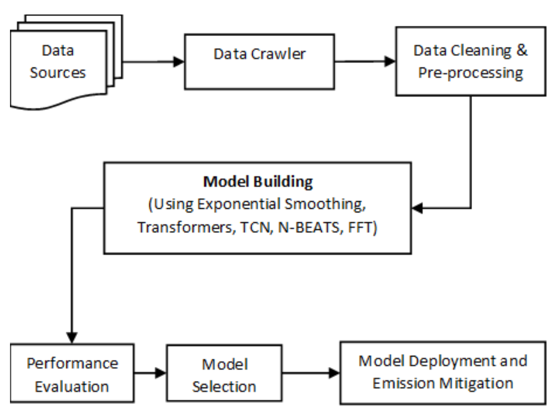

Fig. 2. Proposed system framework.

The study implements an automated data crawler to extract data from various sources [18]. The collected data is processed for any abnormalities and missing values and cleaned. The data is scaled to have the same unit. The next module implements multiple machine learning and statistical modelling techniques. All the developed models are evaluated for their performance. The best performing model is selected as the forecasting model and used to forecast emission by 2030. The findings from the quantitative analysis and literature study have been used in developing the proposed strategies for CO_2 emission mitigation and to achieve sustainable development goals, and Saudi Vision 2030.

C. *Model Building*

For developing an effective model for predicting CO_2 emission in Saudi Arabia, this research has investigated multiple approaches for forecasting. The forecasting results obtained from of some of the approaches like Fast Fourier Transform Forecasting Model (FFT) very were discouraging. However, there are several techniques which have performed very well and have promising forecasting results [19] [20]. These techniques include approaches such as Exponential Smoothing, Transformers, Temporal Convolutional Network (TCN), and neural basis expansion analysis for interpretable time series (N-BEATS). This segment analyzes the forecasting techniques implemented in this research paper.

1) Exponential smoothing: Exponential smoothing is a statistical forecasting method used for time series analysis and predicting the values of a time-series variable based on its historic data points. Exponential smoothing was first proposed 1950s by three different researchers: Charles C. Holt, Peter W. Winters, and Robert G. Brown [21] [22] [23]. Each of them developed a slightly different version but based on the same fundamental concept. This method is based on the assumption that the time-series pattern can be modeled by a weighted average of the historical observations. In exponential smoothing, usually recent events or observations are granted more weights than the older observations. However, by varying the values of the smoothing parameter, more weight can be shifted to the older observations. The following equation illustrates the exponential smoothing for predicting the future values based on the historical observations:

$$F_{t+1} = \alpha\, A_t + (1 - \alpha)F_t \tag{1}$$

Where, F_{t+1} is the predicted time-step value for the next step, F_t is the predicated value for the current period and A_t is the actual observation value of the time series at time step t. The term α represents the smoothing parameter, and the values of the parameter varies between 0 and 1 that determines the weight allotted to the current observation. Keeping the α value larger, more weight is shifted to the most recent observations. One of the criteria for applying exponential smoothing is its level of persistence of forecasted values with the historic observations. However, it is not very resistance to the irregularities or sudden changes in the time-series data. The implementation in this paper is based on the simplified version present in [24].

2) Transformers: Transformers are a type of neural network having self-attention mechanism [25]. Self-attention allows to process different parts of the input sequence while processing each element. Self-attention computes the attention weight between all the pairs of the input values in the time-series. This mechanism aids in determining the importance of each observation. The transformer implementation for this research study, applies self-attention in two processes. One is to extract the intra-dependencies within the output and within the input vectors which is also known as self-attention. The second is to draw the inter-dependencies within the output and within the input vectors which is also known as encoder-decoder attention. The attention mechanism grants the transformers the ability to grab the long-range dependencies efficiently. The transformer also includes a component called multi-head attention which allows the transformers suitable for parallel processing of the multiple components of the input sequence.

The implementation in this paper is based on [25] [26]. The input chunk length has been set to three and output chunk length has been set to one. The transformer has been trained two encoder and two decoder layers with 128-dimension feedforward neural network. The multi-head number has been set to eight. The rectified linear unit (ReLU) activation function [27] has been used. The model was trained with batch size of 8 and over 200 epochs.

3) Temporal convolutional network: Temporal Convolutional Network (TCN) have been designed to process sequences of data. The TCN architecture implemented for this study is based on the TCN architecture proposed in [28]. TCNs are based on convolutional neural network. TCN applies 1-dimensional convolutions along the time dimension of the input data. It enables the neural network to learn the features that are relevant to the temporal structure (such as patterns or trends) of the data. In order to learn long-range dependencies in the input time-series, convolutions skip some of the observations in the input time-series. To learn long-term trends or long-range dependencies in the input time-series, TCNs use dilated convolution [29]. TCNs also resolves the issue of vanishing gradients (which often occurs in deep neural networks) by the use of residual connections. Residual connections are the connections that bypasses one or more convolutional layers and allow information to flow more easily through the network. These features of TCN can grab the complicated temporal relationships amongst the output and input values. The fully connected layers are fed with the output of the convolutional layers to map the learned features to the target output. The convolutional layers are usually followed by dilated convolutional layers to grab long-term dependencies in the time-series data. The final output is a sequence of predicted values for the future time-steps. The entire network is optimized to minimize the forecasting error in contrast to traditional forecasting methods which often require separate steps for feature extraction and model fitting.

The TCN implementation in this research paper is based on the architecture proposed in [28]. The future prediction time-step has been set to one. The kernel size in the convolutional layers has been set to two. Three filters have been used in the convolutional layers. The dilation base has been set to two. The network has been trained over 150 epochs.

4) Neural basis expansion analysis for interpretable time series: Neural basis expansion analysis for interpretable time series (N-BEATS) is a machine learning technique that is used for modeling and analyzing time-series data [30]. N-BEATS uncovers the underlying relationships and patterns present in the data. N-BEATS offers two architectures such as generic and interpretable. This research study implements the generic architecture. As the name suggests, N-BEATS utilizes a basis function expansion for time-series representation. The basis function expansion is a linear combination (weighted sum) of a set of basis functions. These basis functions aim to map to the patterns or relationships expected to be present in the time-series data. The coefficients of the basis functions are the weights.

The N-BEATS implementation for this research study is based on the architecture presented in [30]. The future prediction time-step has been set to one. During the training using neural network, the weights are learned. The resulting model is utilized for forecasting future values of the time-series. The weights of the basic functions provide insight about the underlying dynamics of the time-series data. The presence of high weights for certain basic functions indicates the presence of certain periodic patterns in the time-series data. Though, for the implementation in this research study, no such insight has been observed. Neural network is fed with the time-series data to learn the weights of the basic functions. In the training process, neural network learns the weights and produces an approximate time-series that best fit on the given time-series. N-BEATS have the ability to capture complex nonlinear relationships present in the time-series data [31].

V. Results and Discussion

Time series forecasting problems aims to find a fitting model that can fit the time-stamped historical observations in order to predict the future time-stamped observations of the given data. Traditional approaches have been effective in describing and predicting the time series values such as exponential smoothing and autoregressive integrated moving average (ARIMA). While ARIMA models aspire to depict autocorrelation in the time series data, exponential smoothing targets to characterize seasonality and trend in the time series data. However, sometimes, traditional approaches do not effectively describe and fit the time series, especially when the time series data is more complicated. Therefore, often advanced methods such as transformers, neural basis expansion analysis for time series (N-BEATS) forecasting, and temporal convolutional networks (TCNs), are employed to deal with the complicated time series data. This research utilizes multiple methods such as exponential smoothing, transformers, N-BEATS and TCN for describing and predicting the CO_2 emission values in Saudi Arabia.

Initially, a descriptive analysis of the data has been conducted and the synthesized data is cleaned and pre-processed for any data error. Python has been used for the analysis and modelling. The data preprocessing has been used for converting the data to have same units for carbon emission of each year, finding and handling missing values etc. The forecasting methods discussed in the previous section have been implemented and are fed with the time-series data to learn the weights. In the training process, forecasting models learn the weights and produces an approximate time-series that best fit on the given time-series. The weights are learned by minimizing the variance between the predicted observations and actual observations of the given time-series data. The data is segregated into training and validation data. The figure (see Fig. 3) illustrates training data and validation data.

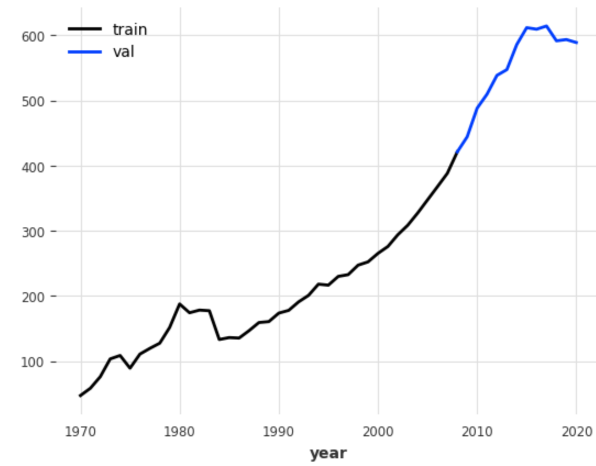

Fig. 3. Training and validation data.

The training, validation and prediction comparison for all the models implemented in this research study is illustrates in the following figures (see Fig. 4, 5, 6, and 7). The training, validation and prediction comparison for all the models implemented in this research study is illustrates in the following figure. The following figure 4 illustrates the training, validation and prediction of the CO_2 emission using the Exponential Smoothing model. All process has been represented using a different color as depicted via legends. The following Fig. 5 illustrates the training, validation and prediction of the CO_2 emission using the Transformers model.

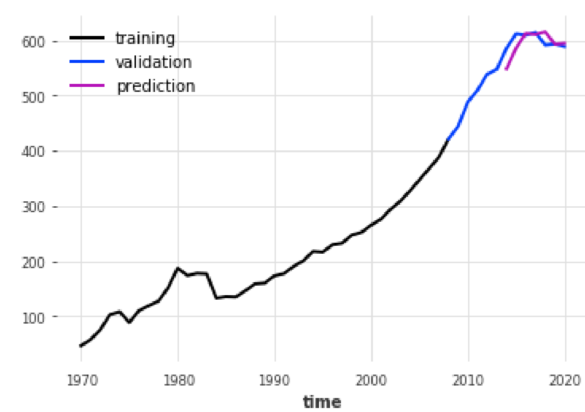

Fig. 4. Exponential smoothing

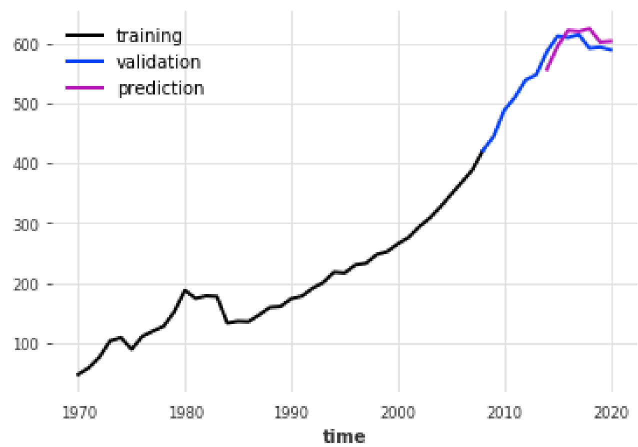

Fig. 5. Transformers.

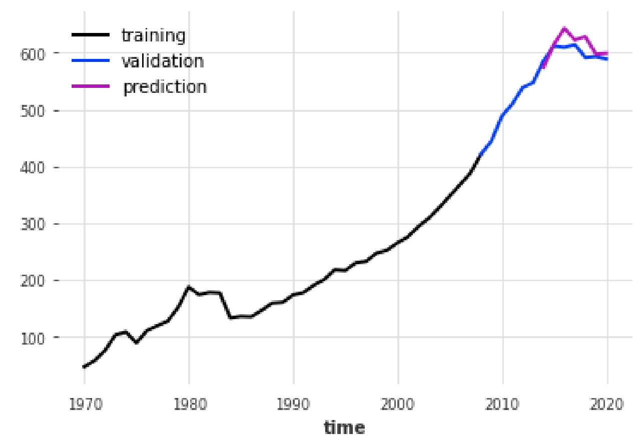

Fig. 6. N-BEATS.

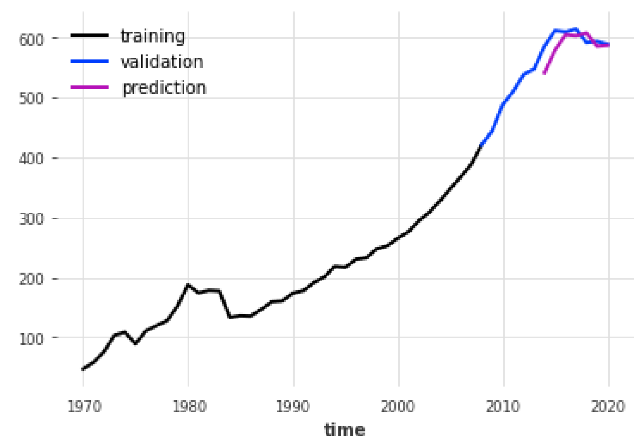

Fig. 7. TCN.

The above Fig. 6 illustrates the training, validation and prediction of the CO_2 emission using the TCN model. All process has been represented using a different color as depicted via legends. The above Fig. 7 illustrates the training, validation and prediction of the CO_2 emission using the N-BEATS model.

A. Performance

1) Mean absolute error: Mean Absolute Error is also commonly known as MAE is a performance measurement metric which is used to evaluate the performance of a prediction or forecasting models. It measures the average absolute difference of the forecasted data point and the actual data point value, and is expressed in the units of the data. MAE represents the average amount of the errors in the predicted observations, without considering their direction. Therefore, it is capable to handle both positive and negative errors, and it is resistant to the outliers present in the time-series. The formula for calculating MAE is as follows:

$$MAE = (1/t) * \Sigma|a - \hat{y}| \quad (2)$$

Where, t is the total number of data points, v is the actual value and ŷ is the predicted value.

2) Mean absolute percentage error: Mean Absolute Percentage Error is commonly known as MAPE. It is a performance measurement metric which is used to evaluate the performance of a forecasting model. It calculates the average percentage difference of the actual time series values and the forecasted values. The formula for calculating MAPE is as follows:

$$MAPE = (1/t) * \Sigma(|(a - \hat{y})/y|) * 100\% \quad (3)$$

Where, t is the total number of time-series data points, a is the actual time-series data-points and ŷ is the forecasted time-series data-points.

3) R2 score: Coefficient of Determination is also known as R2 Score. It measures the proportion of the variability in the data. The R2 score is calculated as follows:

$$R2 = 1 - (SS\_res \,/\, SS\_tot) \quad (4)$$

Where, SS_res is the sum of the squared residuals, and SS_tot is the total sum of squares.

4) Root mean squared error: Root Mean Squared Error (commonly referred as RMSE) is a widely used performance metric. It measures the average magnitude of the errors in the predictions, taking into account both the direction and the magnitude of the errors. The formula for calculating RMSE is as follows:

$$RMSE = sqrt((1/t) * \Sigma(a - \hat{y})^{\wedge}2) \quad (5)$$

Where, t is the total number of points in the time series data, a is the actual value of the time-series step and ŷ is the forecasted time-series value.

5) Overall percentage error: Overall Percentage Error (OPE) performance metric is used to measure the percentage difference between the actual time-series data values and the forecasted data values, averaged over all the data points. The OPE is expressed as a percentage. The formula for calculating OPE is as follows:

$$OPE = (1/t) * \Sigma(abs((a - \hat{y})/a) * 100) \quad (6)$$

Where, t is the total number of data points, a is the actual data point of the time-series and ŷ is the forecasted data-point.

All the models have been evaluated using the above performance measurement metrices. The following table (see Table I) demonstrates the comparative analysis of the different models. In the present research study, transformer model has performed worse. The study has tried parameter tuning in several ways but the forecasting results could not improve. R2 score achieved is 0.112, MAE score is 55.89, MAPE score is 9.97, RMSE score is 56.10, and OPE score is 9.9. The next model is Exponential Smoothing which has achieved an R2 score of 0.209, an MAE score of 36.87, an MAPE score of 6.43, an RMSE score of 46.90, and an OPE score of 1.413. The TCN and N-BEATS models have performed comparatively well. The R2 score for TCN model is 0.21, MAE score is 14.23, MAPE score is 2.39, RMSE score is 19.58, and OPE score is 0.82. Similarly, the N-BEATS model has achieved an R2 score of 0.7, an MAE score of 14.36, an MAPE score of 2.36, an RMSE score of 19.32, and an OPE score of 0.91.

TABLE I. PERFORMANCE MEASUREMENT FOR VARIOUS FORECATING MODELS

Performance Metric → Model ↓	**R2 Score**	**MAE**	**MAPE**	**RMSE**	**OPE**
Transformers	0.112	55.89	9.97	56.1	9.9
Exponential Smoothing	0.209	36.87	6.43	46.90	1.413
TCN	0.21	14.23	2.39	19.58	0.82
N-BEATS	0.7	14.36	2.36	19.32	0.91

The TCN and N-BEATS model have performed in almost similar fashion; however, the R2 score for N-BEATS model is much higher than the TCN model. A higher value (close to 1) of R2 score and lower values of the other metrices represents a high performing model. As it has been observed based on the performance measurement metrices the overall performance of N-BEATS model for forecasting CO_2 emission in Saudi Arabia is better in comparison to the other models.

However, the main limitation of these results is the limited amount of the sample dataset.

B. Proposed Strategies

Saudi Arabia is one of the top oil producing countries in the world and one of the major carbon dioxide (CO_2) emitters. Therefore, it is crucial to develop effective CO_2 emission mitigation strategies to achieve its vision 2030 goals. This subsection proposes a number of emission mitigation strategies as following:

- Carbon capture and storage: Due to being an oil-based economy, the country has a large number of power plants, refineries, and other industrial process that produces CO_2. Investing and implementing carbon capture and storage technologies will help in capturing CO_2 from various sources and the stored CO_2 can utilized for enhanced oil recovery or stored in underground geological formations.
- Green hydrogen: The fossil fuels can be replaced by green hydrogen as a cleaner alternative in transportation and industry.
- Promoting renewable energy sources: The kingdom has a vast land area that is not being used for any purpose and has a high potential to harness renewable energy such as wind power and solar energy. The country has already started investing in these sources of energy and plans to generate 58.7 GW of renewable energy by 2030, which will contribute significantly to reducing its CO_2 emissions. Encouraging its residents and citizens to utilize renewable energy sources and providing facilities and availability for energy generation from renewable energy sources such as using solar panels will contribute to reduce CO_2 emission.
- Reforestation and afforestation: Forests are natural CO_2 sequester. Planting trees and creating new forests will aid in mitigating CO_2 emissions.
- Energy efficiency: Improving energy efficiency in buildings, industry, and transportation can significantly reduce CO_2 emissions.
- Carbon Tax: A carbon tax or cap-and-trade system can provide an economic incentive for reducing CO_2 emissions.

By implementing proposed CO_2 emission mitigation strategies, the kingdom can reduce its CO_2 emission and contribute to global efforts to combat climate change.

VI. CONCLUSION

Accomplishing the KSA's goals of vision 2030 require to take actions against climate change. Adopting an apt method for prediction the CO_2 emission will assist in developing the policies for climate change mitigation. Emission analysis from various industries will aid in recognizing the areas of having alarming level of emissions and thus will be to focus the specific industry to put a rein on its emission [32] [33]. Analyzing the emission trends and forecasting the emission levels will provide the future directions of achieving sustainable development goals of the Kingdom as a member state of United Nation. The findings suggest that effective policy measures and technological interventions can help to minimize the negative impacts of climate change on sustainable development goals and achieving the vision 2030. Overall, the paper contributes to the growing body of research on climate change and its implications for sustainable development.

This research has implemented several machine learning and statistical methods include such as Exponential Smoothing, Transformers, Temporal Convolutional Network (TCN), and neural basis expansion analysis for interpretable time series. The data for training these models have been collected and synthesized from various sources using a web crawler. The performance of these models has been evaluated using various performance measurement metrices such as RMSE, R2 score, MAE, MAPE and OPE. The results indicate that the TCN and N-BEATS models perform similarly, with the N-BEATS model achieving a higher R2 score. The N-BEATS model has demonstrated strong predictive power with an R2 score of 0.7, an MAE score of 14.36, an MAPE score of 2.36, an RMSE score of 19.32, and an OPE score of 0.91. Overall, N-BEATS model, in particular, shows promise for achieving accurate and interpretable predictions. Further research could explore the applicability of these techniques in other domains and investigate approaches for enhancing model performance.

ACKNOWLEDGMENT

The authors extend their appreciation to the Deanship of Scientific Research at Saudi Electronic University for funding this research work through the project number (8111).

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