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Forecasting of transportation-related energy demand and CO_2 emissions in Turkey with different machine learning algorithms

Ümit Ağbulut

Department of Mechanical Engineering, Faculty of Engineering, Düzce University, 81620, Düzce, Turkey

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ABSTRACT

Adverse impacts of the transportation sector on not only air quality but also economic growth of a country are nowadays well-noticed, particularly by developing countries. Today, the transportation sector is powered by burning the fossil-based fuels at more than 99% and approximately 6.5 million deaths annually occur due to air-pollution-related diseases worldwide. Therefore, knowledge of both energy demand and CO_2 emission of a country is a very significant issue in order to revise its future energy investments and policies. In this framework, three machine learning algorithms (deep learning (DL), support vector machine (SVM), and artificial neural network (ANN)) are used to forecast the transportation-based-CO_2 emission and energy demand in Turkey. The gross domestic product per capita (GDP), population, vehicle kilometer, and year are used as input parameters in the study. It is noticed that there is a very high correlation among year, economic indicators, population, vehicle kilometer, transportation-based energy demand, and CO_2 emissions. To present a better comparison, the results of these algorithms are discussed with six frequently used statistical metrics (R^2, RMSE, MAPE, MBE, rRMSE, and MABE). For all machine learning algorithms, R^2 values are varying between 0.8639 and 0.9235, and RMSE is smaller than 5×10^6 tons for CO_2 emission and 2 Mtoe for energy demand. According to the classifications in the literature, the forecast results are generally categorized as "excellent" for rRMSE metric ($<$10%), and “high prediction accuracy” for MAPE metric ($<$10%). On the other hand, with two mathematical models, future energy demand and CO_2 emission arising from the transportation sector in Turkey are forecasted by the year 2050. In the results, it is forecasted that the annual growth rate for transportation-related energy demand and CO_2 emission in Turkey cumulatively rise by 3.7% and 3.65%, respectively. Both energy demand and CO_2 emissions from the transportation sector in Turkey will increase nearly 3.4 times higher in the year 2050 than those of today. In conclusion, the paper clearly reports that the future energy investments of the country should be revised, and various policies, regulations, norms, restrictions, legislations, and challenges on both energy consumption and emission mitigation from the transportation sector should be established by the policy-makers.

1. Introduction

The transportation sector is an essential tool for many activities such as passenger mobility, and the supply of goods to be sustainable in daily life (Manoj Kumar and Dash, 2017; Onat et al., 2014). However, this sector has continued its sustainability by the burning of fossil-based fuels in the internal combustion engines (Santos et al., 2021). Unfortunately, these fuels are neither renewable nor clean energy sources (Tarhan and Çil, 2021). Furthermore, more than half of the world’s oil production is consumed in the transportation sector (Kodjak, 2015), leading to the rapid depletion of fossil reserves. Correspondingly, the fuel prices have gradually shown increments (Yaman et al., 2021). Actually, these increments in prices are not the only problem arising from the transportation sector that the world has today witnessed, but also as a result of such high consumption, this sector alone contributes to approximately a quarter of global anthropogenic carbon dioxide emissions(Kodjak, 2015; Touratier-Muller et al., 2019). Over the last decades, carbon footprint and energy consumption issues have been the main concerns for the policy-makers, because both the effect of the carbon footprint on human health and the effect of energy consumption on the national economic development of the governments as an obstacle has been more apparent in today’s World (Bakay and Ağbulut, 2021; Ahmed et al., 2020). In parallel to social and economic developments, the energy demand has increased all across the world. Correspondingly, the rapidly growing rate in population, technological developments, urbanization, and socioeconomic enhancement in Turkey as like in other countries

E-mail address: umitagbulut@duzce.edu.tr

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have cumulatively led to an increment in the energy demand for many sectors as well as an increment in global carbon emissions (Guleryuz, 2021; Turgut et al., 2021). Carbon emission also affects human health in two ways: directly and indirectly. First, when carbon emissions are inhaled in high dosages, they have direct effects on people's respiratory systems and can cause serious problems such as breathlessness, headache, dizziness, weakness, fatigue, and even delirium (Dong et al., 2021; Sánchez-Ccoyllo et al., 2007; Sechzer et al., 1960). Second, it affects people indirectly by causing important global problems such as global warming, climate change, and acid rains (Bakay and Ağbulut, 2021; Liu et al., 2020; Xu et al., 2015). All of these problems are of great significance to both environment and human beings, and it seems that the only way in reducing their impacts is to mitigate their release. Apart from carbon emissions, the transportation sector also releases other significant air pollutant emissions such as $PM_{2.5}$, PM_{10}, SO_2, N_2O, etc. (Colvile et al., 2001; Magazzino et al., 2020; Shrivastava et al., 2013). According to the report published by The Lancet in the year 2016, around 6.5 million deaths annually occur due to diseases caused by air pollution worldwide, and this is more than that from the combination of tuberculosis, AIDS/HIV, and road accidents (Lancet, 2016).

It is of great importance to nexus between energy consumption and air pollution, and to understand the mechanism behind both the consumption of energy and the triggers of air pollutants on regional and globe scale (He and Lin, 2019). It is accepted that fossil-based fuel consumption is the most serious leading source of air pollution worldwide (Bakay and Ağbulut, 2021; Yıldız et al., 2020). Nowadays, the primary energy demand of the world is met by burning fossil-based fuels at a respectable share of 85% (British Petrol, 2018). Numerically, global greenhouse gas emissions (GHGs) in the year 2016 are equal to nearly 50 billion tonnes CO_2-eq (Ritchie and Roser, 2017), while those of Turkey are equal to nearly 0.5 billion tonnes CO_2-eq in the same year (Turkstat, 2020). Among GHG emissions, the largest share belongs to CO_2 emissions in Turkey. Numerically, CO_2 emission in Turkey accounts for 69% of total GHG emissions in 1990, and this share reached 80.5% in the year 2018 (Bakay and Ağbulut, 2021). The transportation sector is one of the biggest contributors to GHG emissions with a rate of 23.2% for Turkey (Güzel and Alp, 2020; UNFCCC (United Nations Framework Convention on Climate Change) 2019). On the other hand, the share of the transportation sector on global GHG emissions is also equal to 14% (Pichs-Madruga et al., 2014). Accordingly, it is obviously seen that the GHG emissions arising from the transportation sector in Turkey is very higher than that of the world average. Therefore, it seems to be logical that the country should firstly focus on reducing the emissions from the transportation sector. However, this reduction in emissions cannot be expected to be cut with a sharp change in a short time. It is necessary to make plans for the short, medium, and long term in the country. With this viewpoint, it is of great importance for Turkey to know its transportation-based emission in the upcoming years and should revise its investments and plans, accordingly. Furthermore, with the reduction of the carbon footprint from the transportation sector, it will be also easier for a country like Turkey, which is a party to the Kyoto Protocol and the Paris Climate Agreement (Akyol and Uçar, 2021) to reach satisfactory levels in GHG emissions. In this framework, the GHG emissions arising from the energy-related sectors is at a strategic location for the governments. Energy-related sectors are the largest contributor of global and national greenhouse gas emissions with a ratio of 73% (Ritchie and Roser, 2017). Fig. 1 illustrates the shares of total final energy consumption (global) by sector both in the years 1971 in Fig. 1(a) and 2018 in Fig. 1(b), separately.

According to the World Energy Balances report published by International Energy Agency in the year 2020, the largest final energy consumption shares among the sectors belong to the industry with the rate of 38%, transportation with the rate of 28%, and residential with the rate of 21% in the year 2018 (World Energy Balances, 2020). In addition, final consumption increased from 4243 Mtoe to 9938 Mtoe from 1971 to 2018. In other words, energy consumption has soared 2.3 times between these years. It is foreseen that the world's energy needs will exponentially increase in the upcoming years. In particular, this increase will be more visible in those countries in which have higher economic growth rates (Choudhari et al., 2020).

Given that the growth change of the sectors in recent years, the change in total energy consumption growth has generally stagnated whilst the sharpest increment is noticed for the transportation sector with more than an increase of 20% (See Fig. 1). This increment is of great significance because the transportation sector nowadays burns fossil-based fuels, which are responsible for air pollution (Wei et al., 2021). Most of the transportation sector is supplied from liquid carbon-based fuels and highly contributes to greenhouse gas emissions and air quality (Huang et al., 2020). Numerically, the transportation sector accounts for 24.5% of the energy-related greenhouse gas emission in the year 2017 (IEA, 2017; Jilte et al., 2021; Yan et al., 2017). Actually, the vehicles have played a respectable role in the transportation network, and nearly all of them on the roads have been powered by internal combustion engines, which highly release greenhouse gas emissions into the atmosphere (Bakay and Ağbulut, 2021; Andersson and Börjesson, 2021; Ternel et al., 2021). In other words, the global transportation sector is currently powered by fossil-based fuels at the rate of more than 99% (Leach et al., 2020; Ağbulut et al., 2020; Kalghatgi et al., 2018), and liquid petroleum fuels account for 95 of this rate (Leach et al., 2020). Moreover, according to the report of the Australian Bureau of Statistics, 2.3, 2.7, and 1.6-kilogram greenhouse gas emissions are releasing into the atmosphere at the cases of separately burning only one liter of petrol, diesel, and liquefied petroleum gas in internal combustion engines, respectively (Australian Bureau of Statistics, 2020). It is clear that this dominant usage of fossil-based fuels in the transportation sector has caused an unsurprisingly increase in greenhouse gas emissions all around the world in the short and long run. Moreover, the number of vehicles on the roads is exponentially increasing day by day with the increment in the population as well as living standard all across the world (Afzal et al., 2019). Even statistics reveal that in the year 2050 there will be three times more vehicles in the world than that of today (Ahmadi, 2019).

During the past two decades, Turkey has experienced a rapid increase in the vehicle population due to the increments in human population and living standards. This trend in the increment direction will undoubtedly continue to increase in the upcoming years. This increment in the number of vehicles and the resulting in an increment in fuel consumption has also triggered the increment in energy demand and carbon dioxide (CO_2) emissions. To be honest, this has not only caused a noteworthy increase in greenhouse gasses of Turkey year by year but also adversely affects the economy of Turkey as a country that has a high dependency of nearly 75% of its total energy need (Gürel et al., 2020). Accordingly, Turkey has swiftly become one of the countries that suffer from both excessive energy consumption as well as air pollution in a short time. Therefore, some concrete steps should be taken by the decision-makers and policy-makers in the country. Both saving in the energy consumption and mitigating in the emissions for the country are an issue which should be taken into consideration together. While taking these steps, it is vital to know, and evaluate the historical data of the country and to understand the relationship among the elements, and forecast the future data so that the governments can revise their energy-consumption policy for the transportation sector in the future. Therefore, the studies

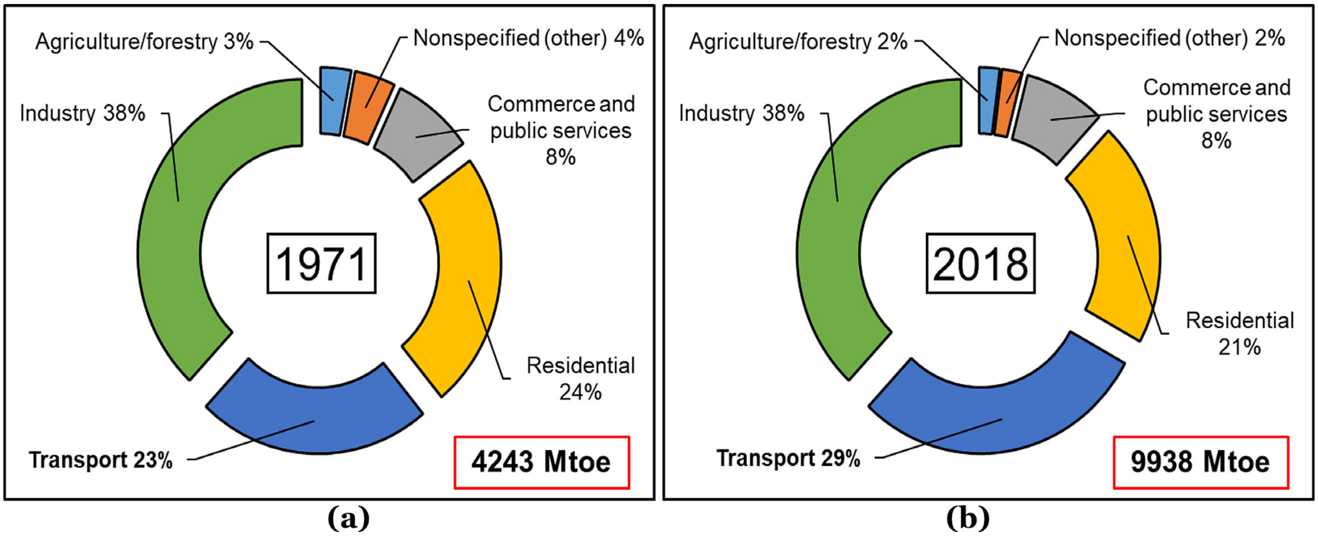

Fig. 1. Total final energy consumption by sector in the years (a) 1971 and (b) 2018 (The graphs drawn according to the data taken from the ref (World Energy Balances 2020).

on forecasting the energy-emission elements for a country is always a hot topic of interest to the researchers (Magazzino, 2016; Nguyen et al., 2021; Pao et al., 2012). Besides, in recent years, various policies, regulations, norms, restrictions, legislations, and challenges on both energy usage and emission mitigate issues have led to an accelerating increase in the popularity of these studies. That is why many researchers are dedicated to understanding the relations between the energy consumption and emission trends of the countries.

In the relevant literature, several methods including various algorithms, theories, and mathematical models have been studied for the tracking trends, modeling, and forecasting of CO_2 emissions, heretofore. In general, the studies regarding the forecasting of CO_2 emission and energy demand for Turkey and other countries have mainly focused on the overall energy consumption dataset of the relevant countries. Nevertheless, it is possible to find a few papers in CO_2 and/or another GHG emission forecasting of Turkey using the transportation dataset, but the number of those studies is very limited. Table 1 gives a comprehensive summary of the previous studies focusing on CO_2 and energy demand forecasting.

Table 2

As can be seen from the literature, various techniques have been frequently applied for accurately forecasting both the CO_2 emission and energy demand. The relevant papers have revealed that the population, vehicle kilometer, energy import and export, gross domestic product, oil price, passenger kilometer, annual vehicle kilometer, historical $CO_{2,}$ and historical energy trends have a strong correlation with energy demand and CO_2 emissions for the relevant regions and countries. To the best of the Author's knowledge, there is no study using deep learning and support vector machine algorithms in forecasting the transportation-based CO_2 emissions and/or energy demand for Turkey, heretofore. Besides, it is seen from the available literature that the studies have generally centered on forecasting either energy demand or CO_2 emission for a country. To fill this gap, this study aims to forecast transportation-based CO_2 emission and energy demand in Turkey by using deep learning (DL), support vector machine (SVM), artificial neural network, linear and exponential regression models. The dataset includes the GDP, human population, vehicle-kilometer, and year as input parameters, and also transportation energy consumption and transportation-based CO_2 emissions between the years 1970 and 2016 as output parameters. Firstly, to observe the performance success of the machine learning algorithms in terms of CO_2 emissions and energy demand forecasting, the dataset from 1970 to 2002 is used to train the algorithms, and then the last 14 years (2003–2016) are forecasted with three algorithms. Then some significant statistical metrics including R^2, RMSE, MAPE, MBE, rRMSE, and MABE are used to discuss the performance of the algorithms. At the second stage, two mathematical models depending on the year variable are created to forecast the future transportation based-CO_2 emission and energy demand in Turkey, and both outputs are forecasted by the year 2050.

The rest of the present paper is organized as follows: Section 2 gives the details on data collection and sources, the relation between input and output variables, descriptive statistics of the dataset, machine learning algorithms and their parameters, and mathematical models. Then, Section 3 defines the statistical benchmarks, formulas, description, and success criteria. Section 4 presents the results and discussion achieved from the algorithms and mathematical models, and the graphs are deeply discussed. The results are classified to show the success ability of the algorithms according to the classification used in the literature. Finally, the paper ends with the concluding remarks in Section 5. Additionally, main findings and some suggestions for future works and decision-makers on energy investments are shared in this section.

2. Methodology

In this section, detailed information about where the data is supplied from, machine learning algorithms, and mathematical models used is presented. The correlation between each element of the dataset is discussed in Section 2.1. Then the optimized machine learning parameters and the mathematical equations working behind the algorithms are shown in Section 2.2, and then the details of mathematical models is given in Section 2.3.

2.1. Data collection

The dataset used in this paper is including the gross domestic product per capita (GDP), population (million), vehicle kilometer, year, transportation energy consumption/demand (Mtoe), transportation-based carbon dioxide emission (CO_2) over the years. Among these, GDP, population, vehicle number, and year data are used as input parameters, and the remaining parts (energy

Table 1
A summary of the literature works regarding energy consumption and/or CO_2 emissions.

Ref, year	Model	Dataset	Region	Forecast	Input	Output	Statistical metrics
(Ayvaz et al., 2017)	GM,	1965 and 2014	Turkey	2015–2030	Energy-related	CO_2	MAPE, MSE, and RMSE
(Hamzacebi and Karakurt, 2015)	GM	1965–2012	Turkey	2013–2025	Energy-related	CO_2	MAE, MAPE, C C=error ratio
(Sun and Liu, 2016)	SVM, GM, and BPNN	1978–2008	China	2009–2012	major industries and residential consumption	CO_2	MAPE, MaxAPE, MdAPE, RMSE
(Lotfalipour et al., 2013)	ARIMA and GM	1965–2010	Iran	2011–2020	Previous CO_2 data	CO_2	RMSE,MAE, and MAPE
(Aydin, 2015)	Regression models	1971–2010	Turkey	2011–2025	GDP, Population, and energy consumption	CO_2	R^2
(Şahin, 2019)	GM	1995–2016	Turkey	2017–2025	Previous CO_2 data	CO_2	APE, MAPE
(Ozturk and Ozturk, 2018)	ARIMA	1970–2015	Turkey	2016–2040	Previous energy consumption data	Energy consumption	–
(Akcan et al., 2018)	ARIMA	1990–2013	Turkey	2014–2018	Different sectors	GHG emissions	ME, MAE, RMSE
(Sonmez et al., 2017)	ABC algorithm and regression models	1970–2013	Turkey	2014–2034	GDP, population, and annual vehicle-km	Transportation energy demand	R^2, RMS, MAE, MAPE, Std_AE, Std_APE
(Kankal and Uzlu, 2017)	ANN	1980–2012	Turkey	2013–2018	GDP, population, import, export	Energy demand	RMSE, MAE
(Beskirli et al., 2018)	Artificial Algae Algorithm (AAA) based regression	1979–2005	Turkey	2006–2025	GDP, import, export, and population	Energy demand	MRE
(Ünler, 2008)	Linear and quadratic regression	1979–2005	Turkey	Up to 2025	Population, GDP, import-export, and growth rate	Energy demand	R^2
(Kıran et al., 2012)	PSO and ABC based regression	1979–2006	Turkey	2007–2025	GDP, population, import, export	Energy demand	R^2
(Korkmaz and Akgüngör, 2018)	Flower pollination algorithm and mathematical models	1970–2016	Turkey	2017–2035	Annual Vehicle-km, GDP, and CO_2	Transportation energy demand	R^2, RMSE, MAE, MAPE, Std_AE, Std_APE
(Tutun et al., 2015)	Regressions and ANN	1975–2010	Turkey	2010–2020	Imports, exports, gross generation, transmitted energy	Energy demand	MAPE, RMSE, MSE, MAE, SSE (sum square error)
(Ofosu-Adarkwa, Xie and Javed, 2020)	GM	2005–2018	China	2018–2030	Cement industry	CO_2	MAPE, RMSE, MAE
(Çodur and Ünal, 2019)	ANN	1975–2016	Turkey	2017–2030	GDP, population, vehicle –km, oil price, passenger km, ton km	Transportation energy demand	AE, APE, R^2, RMSE, MAE, MAPE, MSE
(Toksarı, 2007)	Linear and quadratic regression	1979–2005	Turkey	Up to 2025	Population, GDP, import and export	Energy demand	R^2
Present paper	DL, ANN, SVM, mathematical models	1970–2016	Turkey	Up to 2050	GDP, population, vehicle –km, year	Transportation related energy demand and CO_2	$R^{2,}$, RMSE, MAPE, MBE, rRMSE, and MABE.

Table 2
Input parameters, data source, and the influences on the output parameters.

Label	Source	Pre-selection influencing factors?
GDP	WorldBank	There is a high correlation between GDP-energy consumption and GDP-CO_2 emissions depending on the energy consumption amount. Any change in GDP highly influences future energy and emission trends.
Population	WorldBank	As the population increases, the demand for any country undoubtedly increases. Correspondingly, the emission level is directly affected therein.
*Vehicle kilometer	Turkish Statistical Institute (TurkStat)	This value depends on the vehicle number registered to the traffic in the country. As this value annually increases, it is understood that both energy consumption and carbon footprints from the transportation sector will increase.
Year	–	As the years pass, it is foreseen that there will be an increase in all kinds of energy demand and emission for the countries from the historical data.

* Passenger cars, minibusses, buses, small trucks, trucks (tankers and road tractors are also included), and motorcycles are included. It is calculated by using administrative records compiled from odometers of vehicles inspection stations.

Table 3
Descriptive statistics of the dataset.

Label	Year	Vehicle kilometer	GDP (US$)	Population	Energy Cons. (Mtoe)	CO_2 (10^6 ton)
Median	1993	42.33	4375.17	56,605,264	10.75	34.12
Standard error	2	4.49	567.19	1,916,035.6	0.86	2.23
Standard deviation	13.71	30.76	3888.46	13,135,678.4	5.87	15.27
Kurtosis	−1.20	−0.09	−0.52	−1.15	0.31	−0.20
Skewness	0.00	0.91	1.00	0.02	0.95	0.62
Range	46	113.19	12,159.38	44,945,421	22.67	57.12
Minimum	1970	6.48	455.10	34,876,303	3.21	11.50
Maximum	2016	119.67	12,614.48	79,821,724	25.88	68.62
Observation	47	47	47	47	47	47

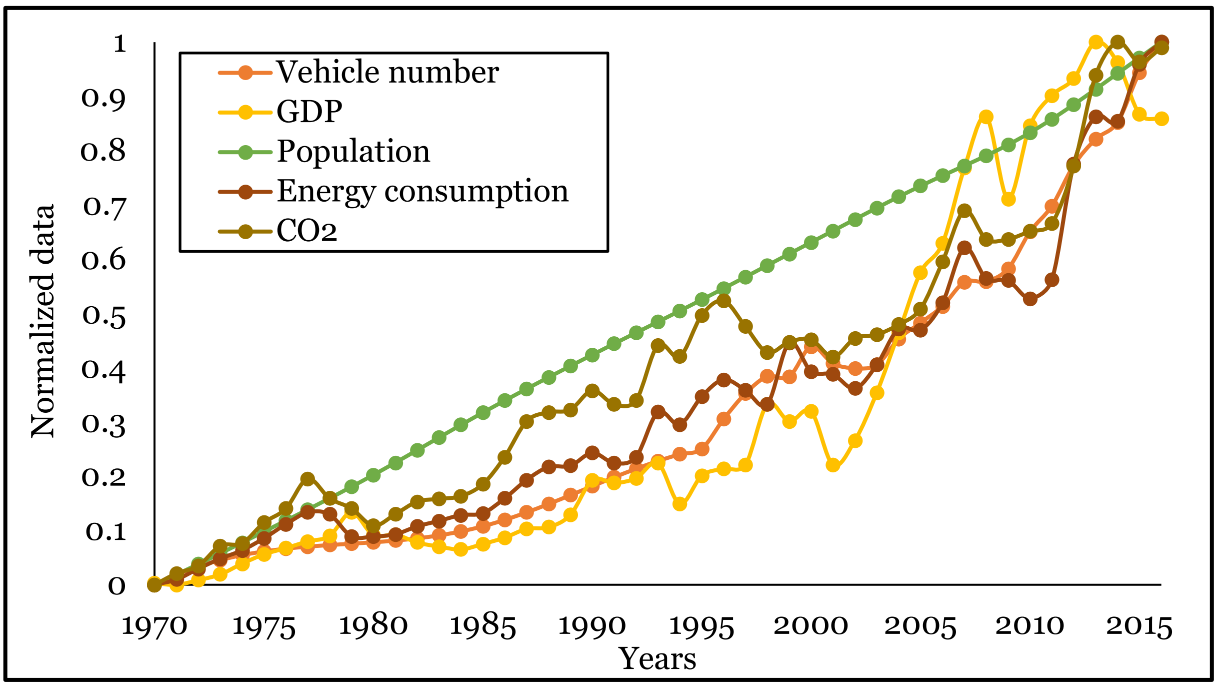

Fig. 2. Normalized input and output parameters.

consumption and CO_2 emission from the transportation sector) is also used as output data. Additionally, the dataset covers the years 1970–2016. The GDP, CO_2, population, and transportation-based energy consumption data were supplied from the World-Bank (WorldBank, 2020). The vehicle kilometer data was taken from the Turkish Statistical Institute (TurkStat 2021d) and the Turkish General Directorate of Highways (TGDH, 2020).

The descriptive statistics of the dataset used in this study are given in detail in Table 3.

Given that the differences between the magnitude scales of each parameter, it is not meant to give the data on a graph. Therefore, it is a better way to convert each parameter into a scaled form. Accordingly, each parameter was converted to a normalized form ranging from 0 to 1 in this paper. Eq. (1) shows how the actual data is converted into normalized data.

$$X_{1(\text{normalized})} = \frac{X_1 - X_{1(\text{min})}}{X_{1(\text{max})} - X_{1(\text{min})}} \tag{1}$$

Where X_1 refers to the actual data, and $X_{1(\text{min})}$ is the minimum value among all X_1 values in the dataset. Similarly, $X_{1(\text{max})}$ represents the maximum X_1 value among all X_1 values in the dataset. Accordingly, $X_{1(\text{normalized})}$ shows the normalized X_1 value, and changes between 0 and 1. In Fig. 2, each attribute including input and output parameters can be seen as the normalized form.

As can be seen from the figure, each parameter has an increment trend over the years, even if they have exhibited some down and ups trends for some period of history. To provide the relation between the output and input parameters, Table 4 gives the correlation value of each input parameter against each output parameter.

As can be seen in Table 4, the correlation values are changing from 0.8993 to 0.9997. It is possible to rank the relation between the input and output parameters based on the correlation coefficients. Accordingly, the correlation coefficient can be interpreted as follows according to the literature works (Bakay and Ağbulut, 2021; Hidecker et al., 2012; Swinscow and Campbell, 2002).

- $|r| \geq 0.8$ very strong relationship;
- $0.6 \leq |r| < 0.8$ strong relationship;
- $0.4 \leq |r| < 0.6$ moderate relationship;
- $0.2 \leq |r| < 0.4$ weak relationship;
- $|r| < 0.2$ very weak relationship.

Based on this classification, it can be concluded that there is a very strong relationship between each input and output parameter. Accordingly, these inputs are used to train the machine learning algorithms for the prediction of transportation based CO_2 emission and transportation based energy demand in Turkey.

Table 4
Correlation values of variables according to each other.

Label	Years	Vehicle km	GDP	Pop	Energy cons.	CO_2
Years	1	–	–	–	–	–
Vehicle km	0.9467	1	–	–	–	–
GDP	0.9006	0.9535	1	–	–	–
Pop	0.9997	0.9498	0.8993	1	–	–
Energy cons.	0.9412	0.9864	0.9336	0.9456	1	–
CO_2	0.9565	0.9864	0.9207	0.96	0.9856	1

Input parameters: Years, vehicle km, GDP, Pop, and Output parameters: Energy cons., and CO_2.

2.2. Machine learning algorithms

Machine learning is a frequently used method of artificial intelligence (AI) where classification, regression, and decision processes are able to be applied in different areas from health to engineering (Senturk and Bakay, 2021; Alpaydın, 2020; Akour et al., 2021; Quiroz et al., 2021). Machine learning algorithms ensure very satisfying accuracy capability. In the present research, three machine learning algorithms –artificial neural network (ANN), support vector machine (SVM), and deep learning (DL)– are studied by using RapidMiner Studio Version 9.5 in the prediction of transportation based energy consumption and CO_2 emissions.

2.2.1. Artificial neural network (ANN) algorithm

Artificial neural networks (ANN) are probably the most extensively used algorithm among the artificial intelligence (AI) algorithms and inspired by biological neural networks in the brain and imitating them by simplifying Zhelavskaya et al., 2018). This algorithm basically simulates the biological nervous system works. Just like in a biological system, it first tries to learn the systems, and then generalizes the results. It has a huge ability to predict non-linear and complex systems; therefore, frequently used in many fields. In the present investigation, multilayered feed-forward neural networks named multilayer perceptron (MLP herein) was utilized. As it is well known, the backpropagation algorithm was a commonly used method of training MLP. It technically works by approaching the complex nexus between input and output data and tuning the weight values in the MLP. General output and error functions of MLP are stated as in Eqs. (2) and ((3) (de Ramón-Fernández et al., 2020; Saber et al., 2019).

$$y_i = f\left(\sum_{i,j=1}^{L,M} \left(w_{ij}.x_i\right)\right) \tag{2}$$

$$E = \frac{1}{N}\sum_{i=1}^{N} (D_i - y_i)^2 \tag{3}$$

Where x_i and w_{ij} refer to the input data, and a weight value, respectively. Additionally, f() gives the activation function, and y_i and D_i are the net output, and the estimated output value, respectively.

A backpropagation algorithm generally consists of two stages named training and testing, and also its topology consists of three layers named input layer, hidden layer, and output layer. The structure of the model in this study is achieved when the input, output and hidden layers are 4–15–1 for CO_2 prediction, and 4–28–1 for energy-demand prediction. Other important parameters such as training cycle, learning rate, and momentum are obtained to be 250, 0.1, and 0.9, respectively for both outputs. The structure of ANN modeled in this study is illustrated in Fig. 3.

2.2.2. Support vector machine (SVM) algorithm

Support vector machine algorithm is a supervised learning technique and it is able to apply for regression and classification problems. SVM was firstly introduced (Boser et al., 1992) in the year 1992. Then, it has an accelerating interest for the researcher in various fields thanks to its highly effectiveness and feasibility as a machine learning technique used for classification and regression. However, there are some significant advantages for the SVM algorithm in comparison with other machine learning algorithms. SVM works according to the statistical learning theory and principles of minimizing structural risk. Accordingly, it shows an attempt to pull back the error upper bound in the generalization rather than pulling back the error in the local training stage. This is the most obvious feature that distinguishes the SVM algorithm from other learning-based machine algorithms (Chen et al., 2013a; Vapnik, 2013).

A hyperplane, which created by SVM, is determined for the linear functions f as like in Eq. (4) when a set of data points are given as $P = \{(x_i, d_i)\}_i^n$. Herein, n is the observation, x_i and d_i are input vector and output variables, respectively. The core aim is to seek a function f(x) as close as possible to all points (Wen and Cao, 2020).

$$f(x) = \omega\varphi(x) + b \tag{4}$$

Where b is the bias and ω is the target function weight vector. In the same equation, $\varphi(x)$ refers to a high-dimensional space feature. It is non-linearly mapped from x which is low dimensional space (Wen and Cao, 2020).

As it can be seen from Eq. (4), it is highly similar to the linear regression model. To estimate w and b, the regression problem above is firstly converted into a minimization problem of the regularized risk function which gives the model complexity and the empirical error under ε-insensitive loss. This can be written in the following Eqs. (5-6) (Nabipour et al., 2020; Helaleh and Alizadeh, 2016; Amar and Zeraibi, 2018).

$$\text{Minimize}\frac{1}{2}w^2 + C\sum_{i=1}^{n}\left(\xi_i - \xi_i^*\right) \tag{5}$$

$$Subject\ to \begin{cases} d_i - w\varphi(x) + b_i \le \varepsilon + \xi_i \\ w\varphi(x) + b_i - d_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0, i = 1, \ldots .l \end{cases} \tag{6}$$

Herein, $\frac{1}{2}\mathbf{w}^2$ refers regularization term. ε and C represent the loss function and regularization constant ($\mathbf{C} > 0$). $\boldsymbol{\xi_i}$ and $\boldsymbol{\xi_i^*}$ show the variables of positive slack which lower and upper excess deviation, respectively. Applying the LaGrange multipliers and optimality constraints, a general function can be stated as in Eq. (7) (Mohammadi et al., 2015).

$$\mathbf{f}\left(\mathbf{x}, \mathbf{a_i a_i^*}\right) = \sum_{\mathbf{i=1}}^{\mathbf{n}} \left(\mathbf{a_i} - \mathbf{a_i^*}\right)\mathbf{K}(\mathbf{x}, \mathbf{x_i}) + \mathbf{b} \tag{7}$$

In this equation, $\mathbf{a_i}$ and $\mathbf{a_i^*}$ are LaGrange multipliers, and the kernel function $\mathbf{K}(\cdot,\cdot)$ is written according to Mercer condition as follows (Chen et al., 2013a, b):

$$\mathbf{K}(\mathbf{x}, \mathbf{x_i}) = \boldsymbol{\varphi}(\mathbf{x_i})\boldsymbol{\varphi}\left(\mathbf{x_j}\right) \tag{8}$$

The combined effect of the kernel function, $\mathbf{C}$, and $\boldsymbol{\varepsilon}$ parameters to achieve high accuracy as well as high performance for SVM

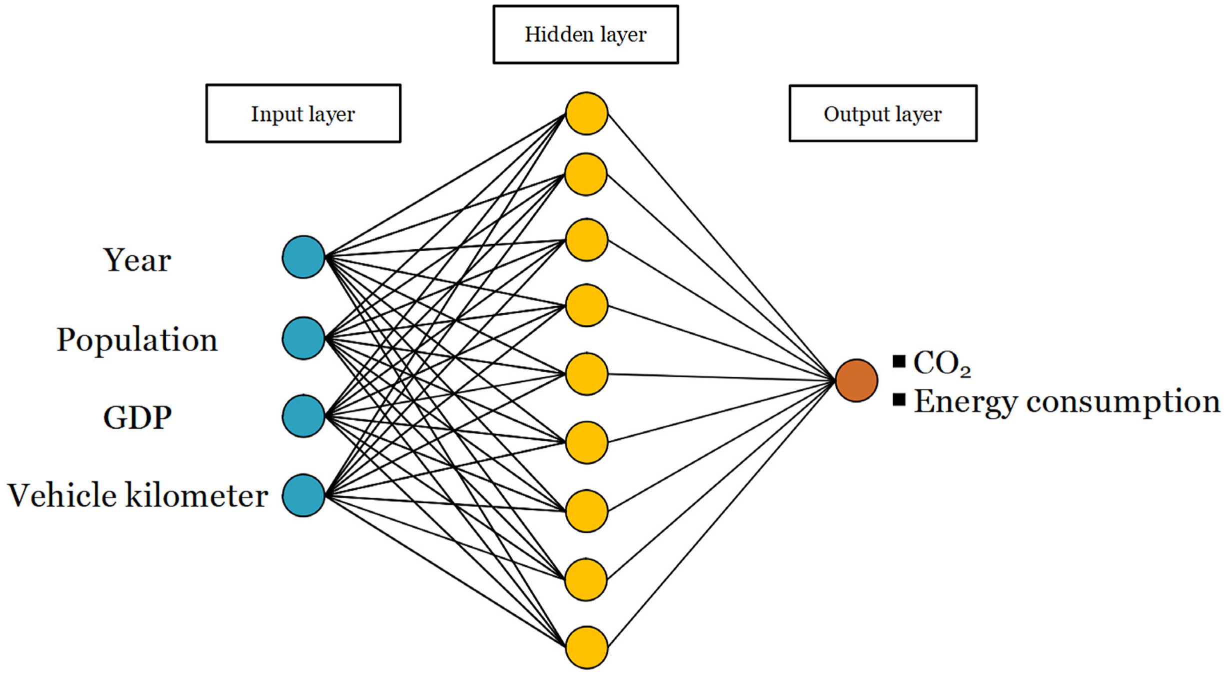

Fig. 3. A schematic view of ANN architecture.

algorithm are vital and thereby must be properly selected. In this paper, these parameters are selected by using the grid search technique. Accordingly, the best results are noticed for CO_2-prediction when kernel function type was dot, kernel cache was 220, C was equal to 0.166, convergence was equal to 1.75, iterations 100,000, L positive and negative parameters are equal to 4.4357 and 0.31, respectively, and ε was equal to 0. Then, the best results were noticed for the prediction of energy-consumption when the kernel function type dot, kernel cache was 120, C was equal to 8, converengence was equal to 0.025, iterations 100,000, both L positive and negative was equal to 0.9, and ε was equal to 0.62.

2.2.3. Deep learning algorithm

Deep learning (DL) algorithm is a new form of ML algorithms, and it needs relatively large datasets in bringing a solution to the complex problems on which the learning stage can take place in a semi-supervised (Najafabadi et al., 2015), supervised (Miyato et al., 2018) or unsupervised (Chen et al., 2018). Technically, it is derived from ANN. Therefore, hidden layer size, activation function, epsilon, and epochs number are significance metrics that highly influence the learning stage and accuracy of the labels (Bakay and Ağbulut, 2021). More importantly, deep learning algorithm has the ability to automatically extract features from the dataset (Ağbulut et al., 2021; Kivrak et al., 2021; Lin et al., 2017; Mei et al., 2017). In the present paper, the best results were noticed for CO_2-prediction when the activation function is rectifier, epochs number is equal to 45.9, and epsilon 10,100. On the other hand, the best results were also noticed for energy-demand prediction when the activation function is rectifier, epochs number is equal to 28.7, and epsilon is 10,100. Additionally, the layers are selected 50 × 50 for both prediction layers.

2.3. Mathematical models

To make a future forecasting for transportation-related CO_2 emission and energy consumption in Turkey, two mathematical models named linear and exponential regression which are frequently used in the literature are developed based on the change of the year. Accordingly, the data between 1970 and 2003 was used to create the equations.

In this section, it is aimed to forecast the transportation based CO_2 emissions and transportation based energy demand in Turkey considering only year variables. For this aim, the following mathematical linear and logarithmic regression equations are developed to forecast the future CO_2 and energy demand response of Turkey. Accordingly, the following equations give the mathematical formula for future CO_2 and energy demand based on the year in Turkey.

$$\textbf{Model I\_CO}_2 = 0.8981\mathbf{y} - 1757.2 \tag{9}$$

$$\textbf{Model II\_CO}_2 = \; = 9\mathbf{E} - 31\mathbf{e}0.0364\mathbf{y} \tag{10}$$

$$\textbf{Model I\_Energy\_demand} = 0.2886\mathbf{y} - 565.54 \tag{11}$$

$$\textbf{Model II\_ Energy\_demand} = \; = 6\mathbf{E} - 34\mathbf{e}0.0395\mathbf{y} \tag{12}$$

Where y refers to the year, and Model I_CO_2 and Model II_CO_2 give the linear and logarithmic regression equations, respectively. Similarly, Model I_Energy_demand and Model II_energy demand give the linear and logarithmic regression equation, respectively. These equations are created by using the CO_2 data between the years 1970 and 2016. Their performance successes are evaluated on two significant metrics: R^2 and RMSE.

3. Statistical benchmarks

The present paper deeply discusses the performance success of the forecasting results obtained from the machine learning algorithms with six statistical metrics which are highly used in the literature. These metrics are determination coefficient (R^2), root mean square error (RMSE), mean absolute percentage error (MAPE), mean bias error (MBE), relative root mean square error (rRMSE), and mean absolute bias error (MABE). Table 5 summarizes the descriptions, performance criteria, and equations of these metrics.

Table 5
Equation, description, and evaluation of metrics.

Metrics	Equation	Description	Performance Criteria	Equation number
R^2	$1-\frac{\sum(y_i-x_i)^2}{\sum(x_i-\bar{x}_i)^2}$	R^2 is undoubtedly the frequently used metric in measuring the performance success of the prediction results. It gives a clue on how well the trends of the model results is able to track the trends of actual data (Gouda et al., 2019; Quej et al., 2016).	R^2 changes from zero to 1, and the bigger R^2 values are desirable (Ağbulut, et al., 2021).	13
RMSE	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-x_i)^2}$	RMSE is reasonable in discussing short-term testing results (Ağbulut et al., 2021; Fan et al., 2019a). RMSE is based on the sample standard deviation of the differences between the prediction values and actual values. It presents a measure of accuracy for the prediction values.	RMSE takes the values from zero to ∞, and the small RMSE values are desirable (Bakay and Ağbulut, 2021; Zang et al., 2020).	14
MAPE,%	$\frac{1}{n}\sum_{i=1}^{n}\left\|\frac{x_i-y_i}{x_i}\right\|\times 100$	MAPE is one of the most frequently used metrics owing to its advantages of scale-independency and interpretability (Kim and Kim, 2016). It is a statistical benchmark on how accurately a prediction model is. It discusses the size of the errors as a percentage. (Ticknor, 2013; Zang et al., 2020).	A smaller MAPE value is desirable for the prediction results (Ağbulut, et al., 2021).	15
MBE	$\frac{1}{n}\sum_{i=1}^{n}(y_i-x_i)$	This is a commonly discussed metric particularly in evaluating the results of the long-term performance for predictor results (Manju and Sandeep, 2019; Chakraborty and Elzarka, 2018).	The best value is zero for MBE. As the MBE value gets close to zero, the result is approaching the fitting one. If the sign of MBE metric is negative, it means the average of the prediction results is bigger than the actual ones. If the sign of MBE metric is positive, it means the average of the prediction results is smaller than the actual ones (Alzahrani et al., 2017; Fan et al., 2018).	16
rRMSE,%	$\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-x_i)^2}}{\bar{x}_i}\times 100$	rRMSE is achieved by dividing RMSE value to mean actual value.	This metric result changes between 0 and 100%. As the metric result gets close to zero, it comes close to desirable results (Bakay and Ağbulut, 2021; Chen et al., 2013a, b).	17
MABE	$\frac{1}{n}\sum_{i=1}^{n}\|x_i-y_i\|$	The MABE presents the absolute value of bias errors (Quej et al., 2016).	MABE takes the values from zero to ∞, and the smaller the value of MABE, the more successful results for the relevant model would be (Hu et al., 2010).	18

In Table 5, $\mathbf{y_i}$ and $\mathbf{x_i}$ are forecasted and measured data, respectively; $\underline{\mathbf{x_i}}$ is the mean of measured data; n is the number of observations.

4. Result and discussion

It is planned to give the result and discussion section within four sub-sections. Firstly, a general discussion of the transportation based energy demand and CO_2 emission over the years is handled and the possible reason behind the increment in both outputs will be discussed in Section 4.1. Then the forecasting results of CO_2 and energy demand will be explained with six statistical metrics for three machine learning algorithms in Section 4.2, and Section 4.3, respectively. Finally, the future forecasting of Turkey's energy demand and CO_2 emissions arising from the transportation sector is performed by the year 2050 according to two mathematical models.

4.1. General evaluation of transportation based-energy demand and CO_2 emission trends in Turkey

The variation of transportation based CO_2 emission and energy demand in Turkey is illustrated in Fig. 4 between the years 1970 and 2016. As can be seen from the figure, both variables have exhibited a nearly linear rising trend over the years. In general, the peak points of both outputs in a certain period are within similar years. For example, in the randomly selected years 1977, 1996, and 2007 marked on the curves of Fig. 4, it is more visible to notice the rising trends of both CO_2 emission and energy demand. Accordingly, there is a very strong relation between transportation based CO_2 emission and energy consumption and the correlation between these two outputs is equal to 0.9856 (See Table 4).

Transportation based energy demand was equal to 3.21 Mtoe in the year 1970 for Turkey whilst the CO_2 emissions arising from the transportation sector was equal to 11.50 $\times$ 10^6 ton in the same year. After that year, both items have generally increased over the years, and energy consumption reached 25.88 Mtoe and CO_2 emission also reached 68.02 $\times$ 10^6 ton in the year 2016 (WorldBank 2020). In other words, even if the relevant items drop in some years, the overall growth rate between 1970 and 2016 is annually found to be nearly 5% for energy demand and 4.2% for CO_2 emission. This increment in energy demand, as well as CO_2 emissions, can be associated with the rapidly growing population, socioeconomic development, and increasing living standards in Turkey. In the year 2019, Turkey's population is around 83 million and the working-age group (15–64 age group) covers more than 80% of the total population (Erat et al., 2021; TurkStat 2020a). Moreover, Turkey is a developing country. Given that the last 30 years, the country's average annual economic growth is around 3% and the country has the 18th largest economy in the world. In 2019, the national income per capita was around USD 8.811, while it is foreseen to increase this amount to USD 12.484 in 2023 (Erat et al., 2021; TurkStat 2020b). As expected, all these trigger an increment in the road motor number in the country. According to the data taken from TurkStat, the registered motor number was equal to 8.655.170 in the year 2002 (the oldest data in TurkStat), while it reached 24.144.857 in the year 2020 (TurkStat, 2021c). The registered motor number in Turkey is shown in Fig. 5 over the years.

Considering the data in the year 2002 as the beginning date, the growth rate in the registered road motor number in Turkey cumulatively increased by 179% in the year 2020. On the other hand, the annual growth rate of the registering motor number in Turkey is calculated to be approximately 9%. Accordingly, it seems that the motor number in the country will probably increase year

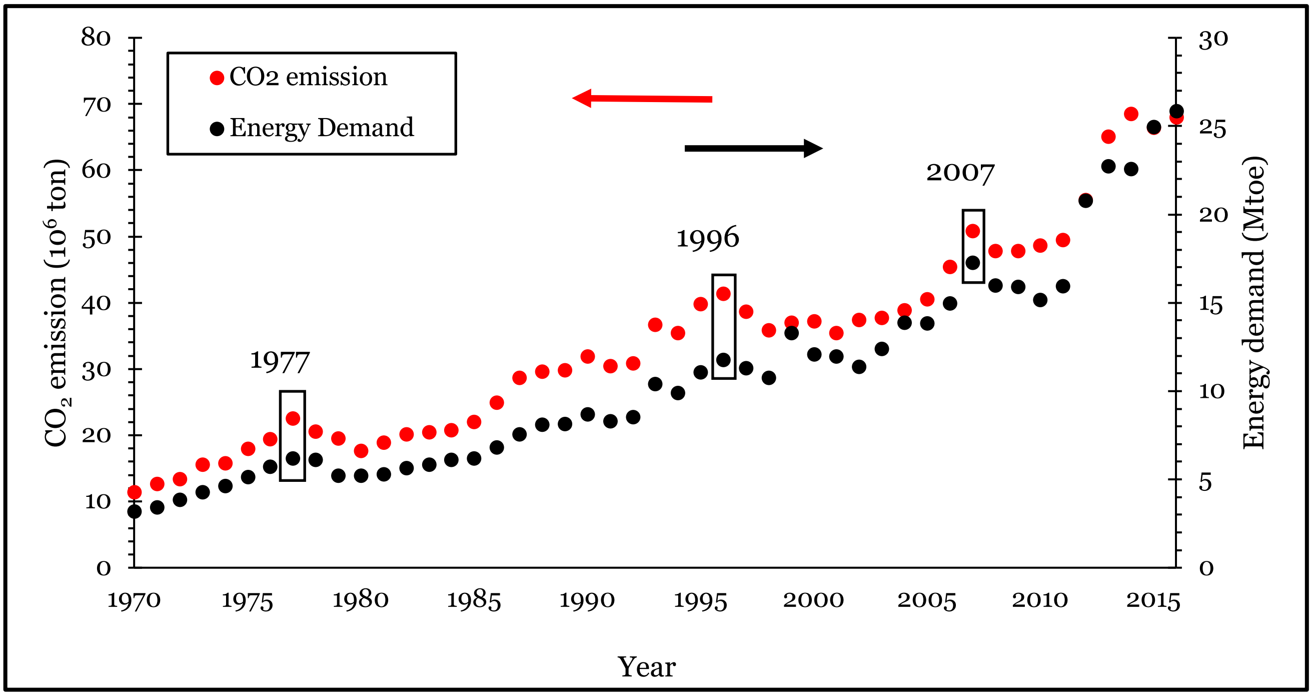

Fig. 4. Variation of transportation based CO_2 emission and energy demand between 1970 and 2016 in Turkey (The graph drawn according to the data taken from the ref (WorldBank, 2020).

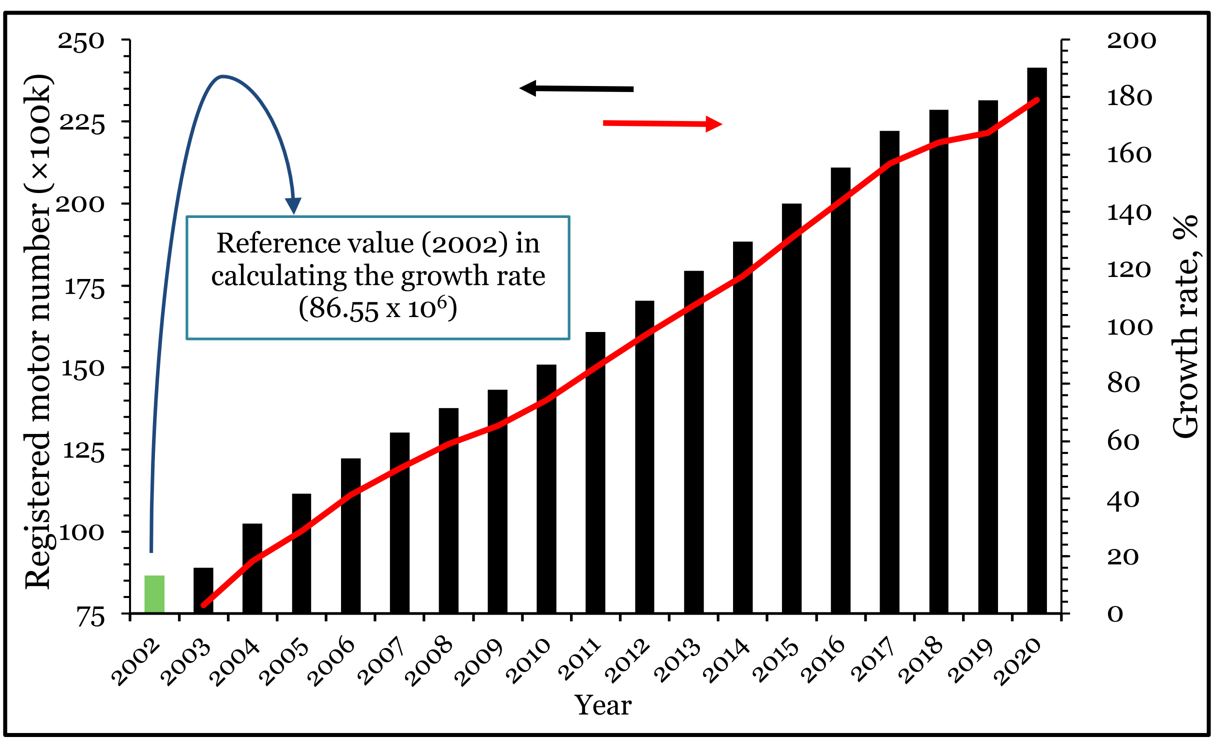

Fig. 5. The number of registered vehicles in Turkey and their growth rate between 2003 and 2020 (The graph drawn according to the data taken from the ref (TurkStat, 2021c).

by year. Turkey is a country that imports about 75% of the total primary energy demand (Gürel et al., 2020), and imports about 91 to 93% of its total petroleum demand (Solak, 2013). With the increase in the number of vehicles, the energy demand of the country from the transportation sector will undoubtedly increase. This case stands as an obstacle not only to the economic growth of the country but also brings environmental problems together. Another critical point is that approximately 3 kgs of CO_2 emissions are emitted into the atmosphere as a result of burning only 1 liter of diesel fuel or 1 liter of gasoline fuel in an internal combustion engine (Ağbulut et al., 2020; Kumar and Sharma, 2018). All these data prove the energy consumption from the transportation sector and its impact on both economy and environment should be taken seriously by the policy-makers and decision-makers for future in-

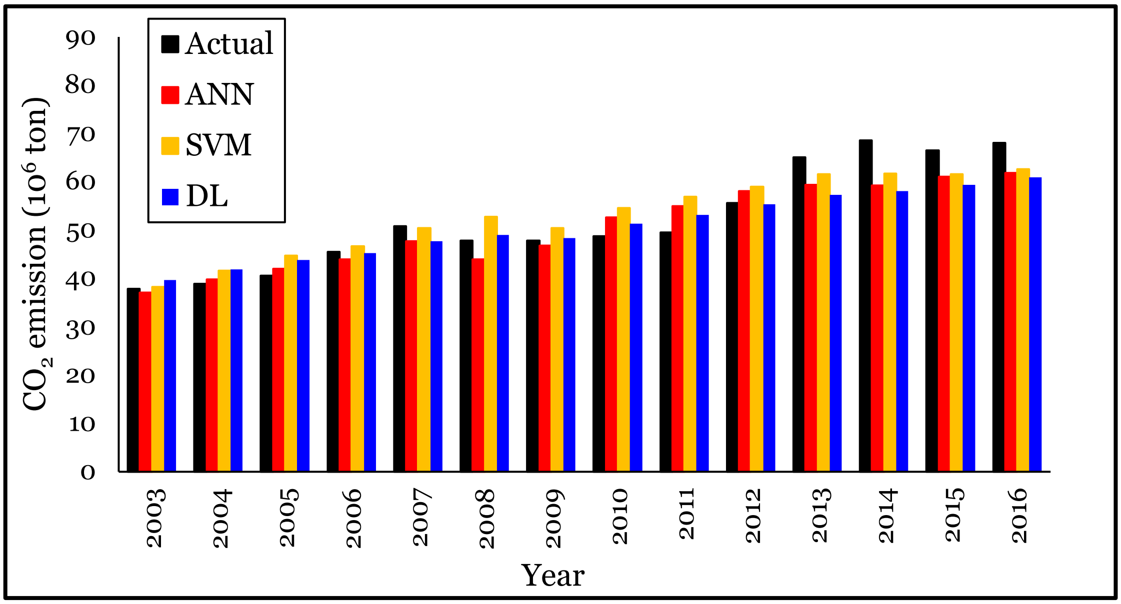

Fig. 6. Forecasting of transportation based CO_2 emission with respect to different machine learning algorithms.

Table 6
Statistical metric results for transportation-based CO_2 emission forecasting in Turkey according to machine learning algorithms.

Response	Metrics	ANN	SVM	DL
CO_2	R^2	0.9088	0.8638	0.9116
	MBE, 10^6 ton	−1.4733	0.8276	−1.4441
	MABE, 10^6 ton	3.2427	3.8442	3.7103
	MAPE,%	8.57	7.24	9.81
	rRMSE,%	7.42	7.24	9.25
	RMSE, 10^6 ton	3.8774	4.4015	4.8307

Bold numbers refer to the best result of the relevant statistical metrics among three machine learning algorithms.

vestments, and concrete steps to be taken in the short, medium, and long run.

4.2. Forecasting of CO_2 emission with machine learning algorithms

Transportation based CO_2 emissions in Turkey are forecasted between the years 2003 and 2016 with three machine learning algorithms. Fig. 6 illustrates the actual and forecasted CO_2 emissions over the years.

As can be seen from the figure, the CO_2 emissions arising from the transportation sector in Turkey are gradually increasing year by year, and the actual CO_2 emission and forecasted ones are generally close to each other. Table 6 gives the numerical results of statistical metrics to make a better comparison among the algorithms.

Based on the calculated metric results, it is seen that R^2 value is varying from 0.8638 to 0.9116 for transportation based CO_2 emission. R^2 is the most frequently used metric in discussing the success of the forecasting results with respect to actual data, and it gives an idea of how the forecasting curves follow that of actual data. In particular, the difference between actual and forecasted data is getting bigger after the year 2013, and nearly all algorithms fail to capture the curves of the actual data after this year. As a consequence of this case, the values of R^2 metrics drop for all algorithms. Numerically, as can be seen from Table 6, the R^2 value of ANN and DL is very close to each other. DL algorithm exhibits a very satisfying result with 0.9116 in terms of R^2 metric for CO_2 emission, while SVM gives the worst R^2 result with 0.8638.

Another statistical metric handled in this study is the MBE metric. Numerical results of calculated MBE metric are very close to zero for each algorithm and this is a desirable case for MBE metric. In this aspect, the SVM algorithm has the best result of 0.8276 in terms of MBE metric, and then DL and ANN algorithms are closely followed for CO_2 emission forecast. As can be seen from Fig. 6, all algorithms forecast CO_2 emission data far below the actual values after the year 2013. On the other hand, after that year, SVM gives the highest forecast values for CO_2 emission among the three algorithms. It means that the relevant algorithm forecasts the CO_2 emission data to be higher than those of actual CO_2 emission, whilst ANN and DL predict smaller than those of actual CO_2 emission.

Based on the MABE results in Table 6, it is possible to say that there is not a significant difference among the algorithms. The value of MABE metric is 3.2427 for ANN, 3.8442 for SVM, and 3.7103 for DL algorithm. Accordingly, even if the best result is calculated for ANN algorithm, the difference among the MABE metric values of other algorithms is very smaller. Therefore, it is thought that it will be useful to discuss the results of other metrics in deciding the success of CO_2 prediction of algorithms. Another important metric discussed in this paper is MAPE. This metric gives the percentage error of the forecasting results. The previous studies suggested evaluating the success of the MAPE metric by classifying it in four ways. Accordingly,

- MAPE≤10%, then the prediction results can be classified as "high prediction accuracy".
- 10%<MAPE≤20%, then the prediction results can be classified as "Good prediction accuracy".
- 20%<MAPE≤50%, then the prediction results can be classified as "Reasonable prediction accuracy".
- MAPE>50%, then the prediction results can be classified as "Inaccurate prediction accuracy" (Bakay and Ağbulut, 2021; Emang et al., 2010).

Based on this commonly used classification in the literature, it is possible to say that the forecasting results for each algorithm can be categorized as "high prediction accuracy". In other words, the MAPE metrics in forecasting the transportation CO_2 emission are smaller than 10% for the three machine learning algorithms used in this study. The results of MAPE metric is calculated to be

8.57, 7.24, and 9.81% for ANN, SVM, and DL algorithms, respectively. Even though each algorithm gives a high forecasting accuracy in terms of MAPE metric, it is noticed that there are big differences between any two algorithms. It is understood that a more sensitive classification is needed to make a better comparison among the algorithms, and this classification in the literature should be more narrow.

Besides these metrics, rRMSE is also discussed in evaluating the success of the algorithms. This metric scales the magnitudes between 0 and 100. In the available literature, there is a commonly used classification for better understanding the performance of the algorithms based on the rRMSE results. Accordingly, the following classification gives a clue on how an algorithm presents the better result in terms of rRMSE metric. In this classification,

- rRMSE<10%, then the prediction results can be classified as "excellent".
- 10%<rRMSE<20%, then the prediction results can be classified as "good".
- 20%<rRMSE<30%, then the prediction results can be classified as "fair".
- rRMSE>30%, then the prediction results can be classified as "poor" (Ağbulut et al., 2021; Fan et al., 2019a, b; Heinemann et al., 2012; Tuncer et al., 2020).

As can be seen in Table 6, rRMSE value of ANN, SVM, and DL algorithms is 7.42, 7.24, and 9.25%, respectively. Based on the above classification, it is possible to say that the forecasting results of all algorithms can be classified as "excellent" considering the rRMSE metric. On the other hand, when rRMSE value gets to 0, then it means a better forecasting results for the relevant algorithm (Bakay and Ağbulut, 2021). Accordingly, the best forecasting result among the three algorithms is achieved within SVM algorithm according to rRMSE value as can be seen in Table 6. Then ANN closely followed to SVM algorithm in the forecasting of CO_2 emission according to rRMSE metric. In parallel to rRMSE metric, the result of RMSE metric is also calculated to be 3.8774 for ANN, 4.4015 for SVM, and 4.8307 for the DL algorithm. With the same logic, it is seen that ANN exhibits the best rRMSE metric result, and then SVM, and DL algorithms followed it, respectively. Given that the results of all statistical metrics together, the SVM algorithm is the best-fitting algorithm in the forecasting of transportation based-CO_2 emissions in Turkey. On the other hand, even though the DL algorithm gives the best R^2 value for CO_2 forecast among all algorithms, it fails according to other statistical metrics and it is the worst algorithm for CO_2 forecast among all algorithms.

To sum up, each statistical metric result for transportation based CO_2 emission is shown with a radar graph in Fig. 7. In this graph, each statistical metric was scaled in a certain range. For example, the relevant scale is equal to 0–1 for R2, 0–5 for RMSE, 0–15% for rRMSE, 0–15% for MAPE, 0–5 for MABE, and 0–3 for MBE. Given that all statistical metrics for CO_2 emission together, it is possible to say that each machine learning algorithm has presented very satisfying results in the forecasting of transportation based CO_2 emissions in Turkey. Of three machine learning algorithms, SVM, ANN, and DL algorithms have the best results three times, two times, and once, respectively.

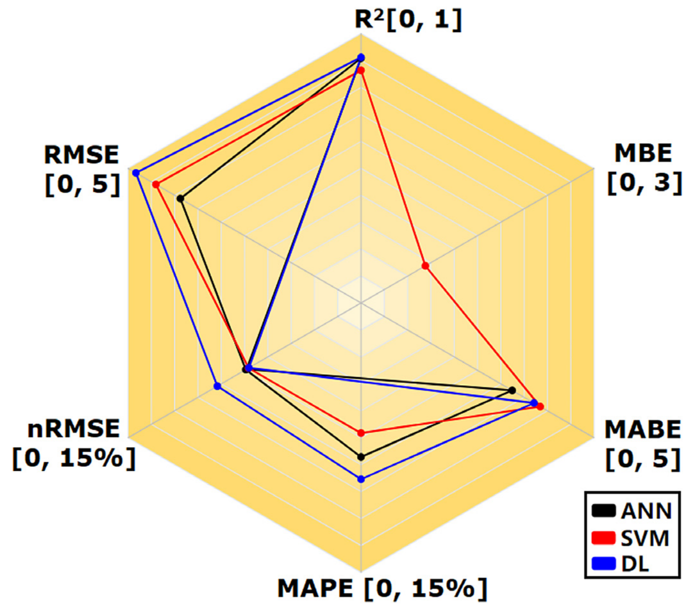

Fig. 7. A general view of the distribution of statistical metrics in a scaled radar graph for CO_2 emission.

Table 7
Statistical metric results for transportation based energy demand prediction in Turkey according to machine learning algorithms.

Response	Metrics	ANN	SVM	DL
ED	R^2	0.9235	0.8706	0.9019
	MBE, Mtoe	−0.3935	−0.3249	0.4275
	MABE, Mtoe	1.04	1.6105	1.5854
	MAPE,%	8.39	8.38	12.79
	rRMSE,%	8.38	11.05	9.996
	RMSE, Mtoe	1.2679	1.9923	1.8026

4.3. Forecasting of transportation based energy demand with machine learning algorithms

Transportation-based energy demand in Turkey is forecasted between the years 2003 and 2016 with three machine learning algorithms. Fig. 8 illustrates the actual and forecasted energy demand trend of Turkey over the years.

As can be seen from the figure, the actual energy demand arising from the transportation sector in Turkey is gradually increasing year by year, and the actual energy demand and forecasted ones are generally close to each other. Table 7 gives the numerical results of statistical metrics to make a better comparison among the algorithms.

As can be seen in Table 7, R^2 value of ED is varying from 0.8706 to 0.9235. Accordingly, the best curve which sensitively follows the changes in the curves of recorded data is seen for the ANN algorithm. Even if the best R^2 value is calculated for the ANN algorithm with a value of 0.9235, DL and SVM algorithms also have very satisfied R^2 values with 0.8706 and 0.9019, respectively. Given that MBE metric for all algorithms together, the magnitude of this metric is very small and close to each other. Additionally, only the DL algorithm has the positive MBE value for ED forecast. That is only the DL algorithm forecasts the ED value higher than the actual data. In terms of MABE metric, the worst result is noticed for the SVM algorithm with a value of 1.61, whilst the ANN algorithm has the best MABE value of 1.04. On the other hand, the MAPE value of ANN and SVM algorithms in forecasting the energy demand is calculated to be nearly equal to each other as can be seen from Table 7. These two algorithms are classified as "high prediction accuracy" as they forecast the actual data with an error of less than 10% according to the classification mentioned above, while the DL algorithm exceeding the 10% limit is classified as "Good prediction" according to the same classification. Another classification is done for the rRMSE metric. Based on the classification for rRMSE, only the SVM algorithm exceeds 10% limit and is categorized as "good", even if the ANN and DL algorithms are very close to this limit, they are categorized as "excellent" according to the classification in rRMSE metric. However, these results clearly show that the statisti-

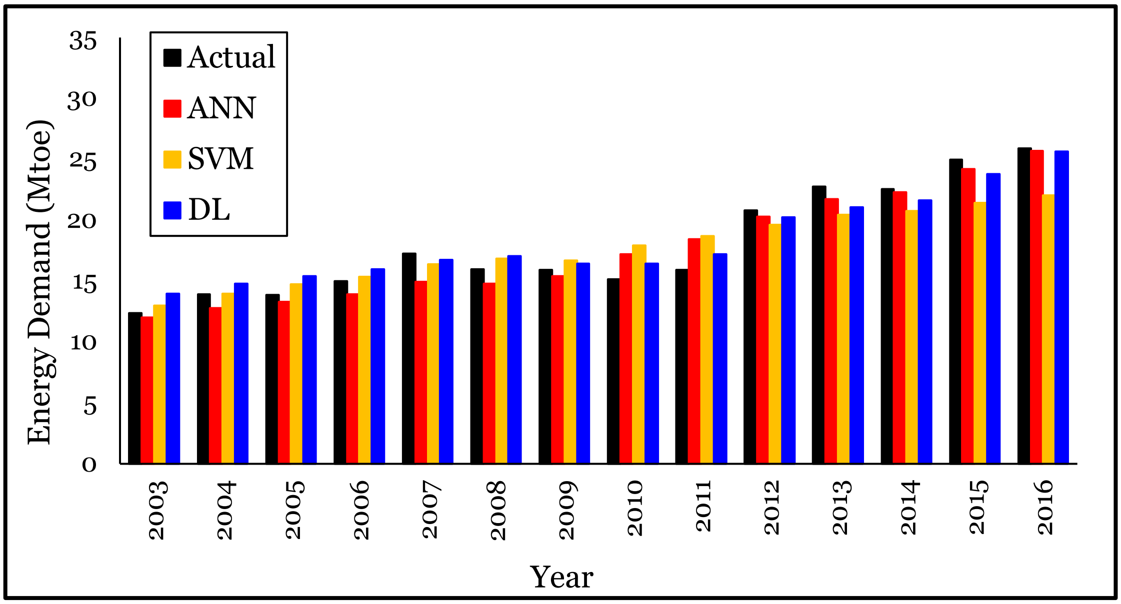

Fig. 8. Forecasting of transportation based energy demand with respect to different machine learning algorithms.

cal metrics consider different points in deciding the success of the predictors. Therefore, it is obviously seen the importance of interpreting multiple and different statistical metrics when discussing a predictor's performance success. On the other hand, the results revealed that the range of classifications used in the literature so far is quite large. For example, an algorithm with a value of 1% and an algorithm with a value of 9% in the comparison made for MAPE and rRMSE metrics are accepted as the same category in terms of performance success. This causes some confusion for the researchers in terms of performance discussion of the predictors. Therefore, it is crucial to discuss different statistical metrics. Accordingly, another statistical metric discussed in the present paper is RMSE. This metric is calculated to be smaller than 2 for all algorithms. Given that this metric for ED prediction, it is possible to say that the best RMSE value is seen for the ANN algorithm with the value of 1.2679 in predicting the ED response.

Each statistical metric result for both transportation related energy-demand is seen with a radar graph in Fig. 9. In this graph, each statistical metric is scaled in a certain range. For example, the relevant scale is equal to 0–1 for R^2, 0–5 Mtoe for RMSE, 0–15% for rRMSE, 0–15% for MAPE, 0–5 Mtoe for MABE, and 0–3 Mtoe for MBE in energy demand. Of the three machine learning algorithms, ANN and SVM algorithms have the best results four times and twice, respectively. On the other hand, the DL algorithm cannot fail to capture the best result for any statistical metric in the forecasting of transportation based energy demand in Turkey. and once, respectively. Given that all statistical metrics for CO_2 emission and energy demand in Fig. 7 and Fig. 9 together, it is possible to say that the machine learning algorithms have exhibited better forecasting results for energy demand in comparison that those of CO_2 forecast.

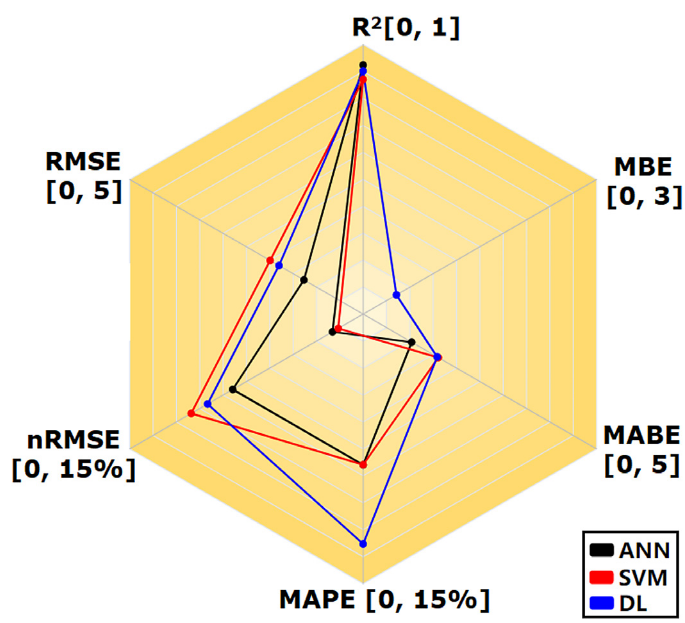

Fig. 9. A general view of the distribution of statistical metrics in a scaled radar graph for CO_2 emission.

4.4. Forecasting of future transportation based-CO_2 and –energy demand with mathematical models

Knowledge of future energy demand in a country is a very significant tool to be set a balance between demand and supply equilibrium. This knowledge is effectively used to plan and establish new energy investments by policy-makers, international agencies, and the respective governments (Sharma, 2018; Morales-Acevedo, 2014). Moreover, in today's world, it is easily understood a country's future CO_2 emission trends from its future energy investments. Therefore, future forecast studies for energy demand and emission portfolio are very attractive and always hot topics to researchers. Accordingly, in this study, two mathematical models are the developed basis on the year as in Eqs. (9)-12. Similar to machine learning algorithms, the energy demand and CO_2 emission data between the years 1970 and 2002 are used both for fitting the model and for creating mathematical equations. Then the models are tested with the data between the years 2003 and 2016. To observe the success of the models, R^2 and RMSE metrics are calculated using Equations 13 and 14, respectively according to the results in the testing stage of both models for transportation related CO_2 emission and energy demand in Turkey. The proposed models can be used to make predictions after considering that energy consumption and carbon emissions will not reach the inflection point

Table 8
Numerical results of R2 and RMSE metrics for developed mathematical models in the testing stage.

Output	CO_2				Energy demand			
Stage	Training		Testing		Training		Testing	
Metric	R^2	RMSE, 10^6 ton	R^2	RMSE, 10^6 ton	R^2	RMSE, Mtoe	R^2	RMSE, Mtoe
Model I	0.9133	2.63	0.8966	8.53	0.9285	0.7636	0.8508	4.87
Model II	0.9140	4.09	0.9075	3.95	0.9360	0.7322	0.8785	1.89

Table 9
Forecasted value of future transportation based-CO_2 and –energy demand with mathematical models.

Years	CO_2 (10^6 ton)		Energy demand (Mtoe)	
	Model I	Model II	Model I	Model II
2016*	68.02		25.88	
2017	54.27	69.12	16.57	23.93
2018	55.17	71.68	16.85	24.90
2019	56.06	74.34	17.14	25.90
2020	56.96	77.09	17.43	26.95
2021	57.86	79.95	17.72	28.03
2022	58.76	82.92	18.01	29.16
2023	59.66	85.99	18.30	30.34
2024	60.55	89.18	18.59	31.56
2025	61.45	92.48	18.88	32.83
2026	62.35	95.91	19.16	34.15
2027	63.25	99.47	19.45	35.53
2028	64.15	103.16	19.74	36.96
2029	65.04	106.98	20.03	38.45
2030	65.94	110.95	20.32	40.00
2031	66.84	115.06	20.61	41.61
2032	67.74	119.32	20.90	43.29
2033	68.64	123.75	21.18	45.03
2034	69.54	128.33	21.47	46.84
2035	70.43	133.09	21.76	48.73
2036	71.33	138.03	22.05	50.69
2037	72.23	143.14	22.34	52.74
2038	73.13	148.45	22.63	54.86
2039	74.03	153.95	22.92	57.07
2040	74.92	159.66	23.20	59.37
2041	75.82	165.58	23.49	61.76
2042	76.72	171.72	23.78	64.25
2043	77.62	178.08	24.07	66.84
2044	78.52	184.68	24.36	69.53
2045	79.41	191.53	24.65	72.34
2046	80.31	198.63	24.94	75.25
2047	81.21	205.99	25.22	78.28
2048	82.11	213.63	25.51	81.44
2049	83.01	221.55	25.80	84.72
2050	83.91	229.76	26.09	88.13

* represents data measured by government agencies.

in the forecast time period chosen in the study. The results of these significant statistical metrics are given in Table 8.

As can be seen in Table 8, the difference of metric results between the training and testing stage achieved from the mathematical models are close to each other for both outputs and within the acceptable limits. Statistically, it can be said that Model II is giving better results than Model I for both energy demand and CO_2 emissions. Accordingly, Table 8 gives the future transportation related CO_2 emission and energy demand of Turkey by the year 2050.

Table 9

Whilst the observed recent value for transportation-related energy demand in Turkey was equal to 25.88 Mtoe in the year 2016, it is forecasted to be 26.09 Mtoe with Model I, and 88.13 Mtoe with Model II for the year 2050. In other words, given that the historical transportation-related energy demand in Turkey, it continues to increase in the upcoming years. Based on the calculated data achieved from the mathematical models, it seems that the transportation related energy-demand for Turkey will increase by roundly 238% in the year 2050 according to that of the year 2016. Similarly, it is forecasted that the transportation related CO_2 emission will increase by roundly 241% in the year 2050. The future forecast trends of energy demand and CO_2 emissions in Turkey are illustrated in Figs. 10 and 11, respectively.

As can be seen from Fig. 9 and Fig. 10, the transportation related energy demand and CO_2 emission in Turkey will reach 88.1 Mtoe and 229.8×10^6 ton in 2050, respectively. Moreover, the annum growth rate in energy demand is cumulatively increasing between 0.3% and 3.7% for Model I and Model II, respectively. On the other hand, the annum growth rate in CO_2 emission is cumulatively increasing between 0.7% and 3.65%, respectively. Accordingly, these outputs clearly demonstrate that the transportation sector will probably remain as an obstacle not only to the economic growth of the country but also brings environmental problems in the upcoming days. Considering the high external energy dependency of Turkey, some concrete steps should be taken by the decision-makers, and the energy policy to be planned in the country should be revised, accordingly. For a country like Turkey that imports approximately 75% of its energy needs (Gürel et al., 2020), to sustain the economic development, it is clear that energy consumption should be reduced, and more efficient utilization of the resources should be seriously required (Uzar and Eyuboglu, 2019).

5. Conclusion

This paper aims to forecast both transportation-related CO_2 emissions and energy demand for Turkey. In the forecasting of these outputs, three machine learning algorithms (artificial neural network, support vector machine, and deep learning) are initially used. In the training of the machine learning algorithms, gross domestic product per capita (GDP), population, vehicle kilometer, and year were selected. Six statistical metrics are discussed on the performance success of the algorithms in the forecast. Then two mathematical models are fitted depending on the years. Transportation-related CO_2 emissions and energy demand in Turkey are forecasted by the year 2050 with these mathematical models. Accordingly, the following bullets can be drawn based on the present research.

- It is observed that there has a strong correlation among the economic indicators, population, vehicle kilometer, transportation-related energy consumption, and CO_2 emission.
- Given that all metrics together, ANN and SVM algorithms have come to the fore in forecasting CO_2 emissions and energy demand from the transportation sector, and the DL algorithm is generally the worst result among the three algorithms. Nevertheless, the results demonstrate that each machine learning algorithm has presented very satisfied results in forecasting CO_2 emission and energy-demand outputs.
- Based on the widely used classification in the literature, all algorithms have been categorized as “excellent” in the forecasting of both energy demand and CO_2 emission in terms of rRMSE metric except for SVM in the energy demand ($rRMSE_{svm\text{-}ed}$=11.05%).

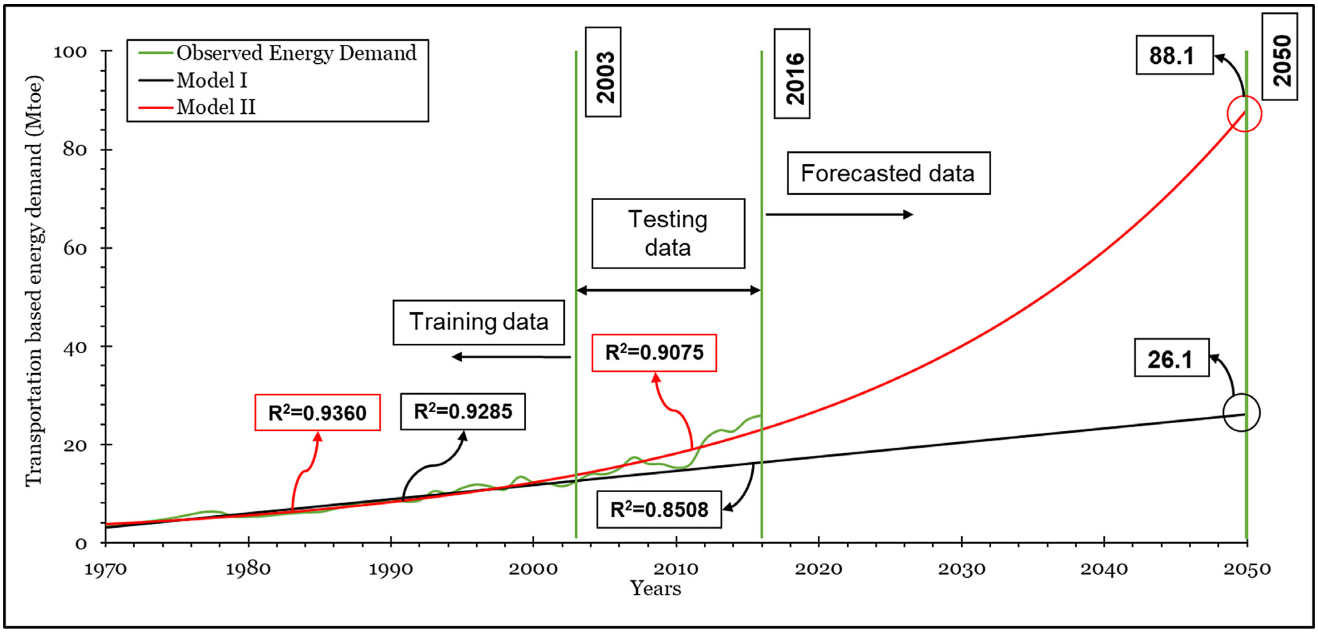

Fig. 10. Future forecast trend of transportation based energy demand in Turkey.

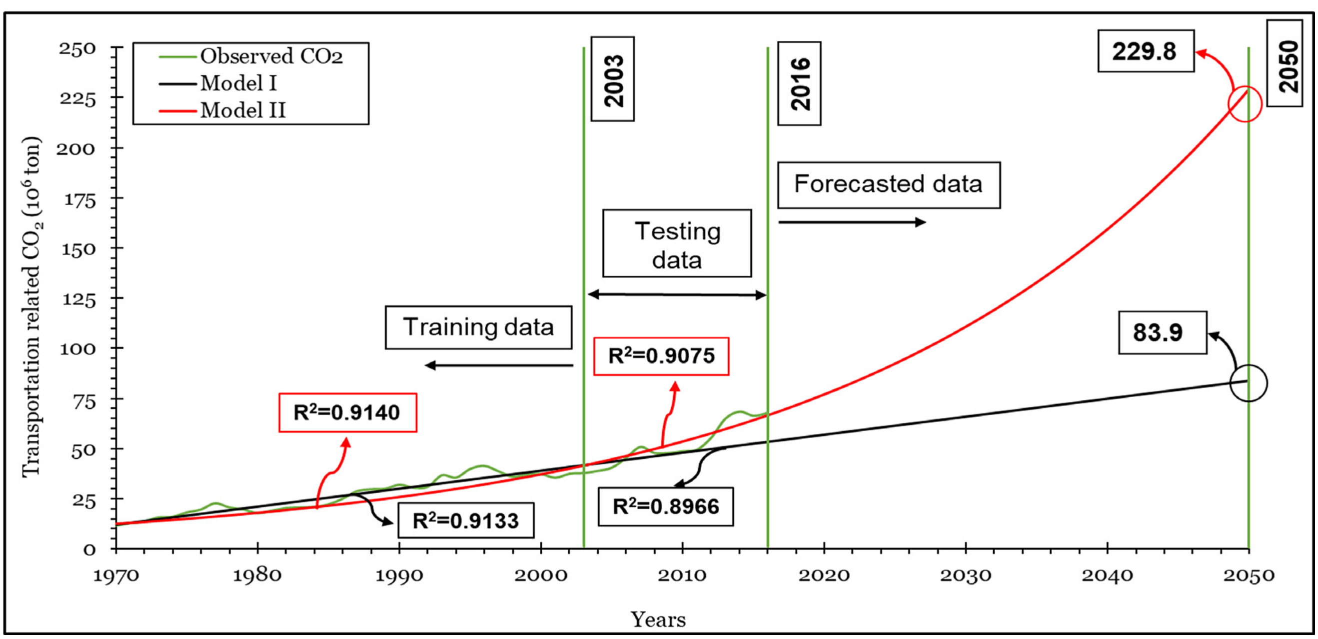

Fig. 11. Future forecast of transportation based CO_2 emission in Turkey.

- According to the classification for MAPE metric in the literature, all algorithms have showed “high prediction accuracy” for both CO_2 emission and energy demand except for the DL algorithm in the energy-demand ($MAPE_{DL\text{-}ed}$=12.79%).
- The overall annum growth rate in both energy demand and CO_2 emission is calculated to be approximately 3.65% by the year 2050. In a comparison of those of nowadays, it is forecasted that the transportation-related energy consumption and CO_2 emission will increase roundly 3.4 times in the year 2050. To sustain the acceleration in economic development for Turkey in recent years, it is obvious that the decision-makers should highly revise the energy policy. Otherwise, the energy issue for Turkey will continue to stay as the biggest obstacle in economic development and a respectable trigger for CO_2 emissions.
- Mathematical models can be easily used for the future energy demand and CO_2 emission forecasts from the transportation sector by the researcher. Statistically, it is seen that Model II exhibits better results in the testing stage.

To sum up, machine learning algorithms used in this paper have presented very satisfying forecasting results for both CO_2 emission and energy demand arising from the transportation sector in Turkey. Additionally, the future forecasting of CO_2 emission and energy demand results achieved from mathematical models revealed that some serious attempts should be taken by the policy-makers and decision-makers in the near future so that the growth rate of increments in both items can be damped.

6. Potential solutions to reduce the environmental impact and energy consumption from the transportation sector worldwide

Based on achieved results from the present paper, it is clear that sustainable development will undoubtedly face momentous threats in the upcoming days due to the increments of both energy demand and CO_2 emissions. Therefore, it is strongly recommended that various policies, regulations, norms, restrictions, and legislations can be imposed by the governments to mitigate GHG emissions and to reduce fossil-fuel consumption from the transportation sector. Besides, increasing taxes for environmentally polluting uses may also be a deterrent in the short term. In addition, carbon taxes, cap-and-trade systems, carbon offsets, carbon caps, and eco-friendly technology norms can be implemented by the governments. However, perhaps the most important thing is to provide education about the factors that cause environmental pollution and to increase community awareness in society. In today's world, the most accepted ways to reduce the energy consumption, as well as CO_2 emissions from the transportation sector, are loose to improve engine efficiency, to introduce low-carbon fuels, and to reduce the transportation miles traveled (Andress et al., 2011; Stanton, 2013). Furthermore, implementing the free bus policies by urban planners and policymakers may be useful on national fuel consumption as well as carbon footprint in the country. Additionally, these ways should be supported by a rapid transition to electric vehicles. However, the issue to be considered at this point is that the power plants that feed the charging stations of electric vehicles are fed with renewable resources. Otherwise, even if carbon emissions from the transportation sector reduce, the amount of carbon emissions from the energy production sector will undoubtedly increase. Today, after electric vehicles enter the market, their selling costs should be competitive with conventional internal combustion vehicles. For this, many countries encourage the public to buy electric vehicles by applying various regulations and tax changes. These and similar applications need to be increased even more. However, in order to commonly use electric vehicles, the infrastructure in the cities must be prepared in a short time (many charging stations, and fast charging, etc.). Nevertheless, it seems that it will take a long time to completely get rid of the use of liquid fuel in the transport sector. In this case, it will also be significant for governments to encourage the public to use alternative low-carbon fuels in order to mitigate the carbon footprints at least until the use of electric vehicles becomes widespread. Finally, it should not be forgotten that global challenges need global steps and efforts.

Declaration of competing Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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