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The impact of COVID-19 on rail travel demand: Case study of Iran

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As a result of the outbreak of COVID-19, the demand for rail travel has decreased. It is not reasonable to compare the rail travel demand during the pandemic year with previous years in order to examine this decrease. The travel demand forecast for the pandemic year should be compared with the actual demand for the pandemic year. In this study, the effect of the COVID-19 pandemic on passenger demand for Iranian railways has been investigated. Using seasonal data from 2011 to 2018, the linear regression model, multilayer perceptron neural network, SARIMA, Holt-Winters, and a combination of them (the average result of other models) have been fitted. Rail travel demand for the year before the COVID-19 outbreak (normal conditions) is predicted, and the models' results are compared based on MAD, RMSE, and MAPE. Finally, using the superior model (the hybrid model), rail travel demand for the first year of the COVID-19 outbreak is forecast. Active population and employment have a positive relationship, and vehicles per capita have a negative relationship with rail travel demand. Also, the annual rail travel demand for the Iranian railways in the period of one year after the outbreak of COVID-19 compared to the forecast of the superior model has decreased by 73.12 percent, which is equal to 13.9 billion passenger kilometers.

1. Introduction

On December 31, 2019, reports of COVID-19 in China were released by the World Health Organization. These reports have identified cases such as pneumonia of unknown cause [1]. The disease spread rapidly around the world and affected all aspects of human life. The services provided by mass transit networks have been changed by the new limitations. With the outbreak of COVID-19, people's activities outside the home have declined, and the demand for transportation has fallen sharply [2]. During the COVID-19 pandemic, the transmission of the disease to remote areas became a significant concern due to the extensive reach of both rail and road transportation. As these modes of transportation encompass long-distance corridors, they played a crucial role in spreading the virus to distant regions. Consequently, it is imperative to conduct thorough research on the impact of both rail and road transportation in order to better understand and mitigate the transmission of the disease during such pandemics [2].

In Iran, as in many countries around the world, transportation demand has been affected by COVID-19, and one of the modes responsible for mass passenger transportation is rail transportation. In 2019, the Iranian Railways registered the statistics of carrying 14800 thousand passenger kilometers [3]. Examining

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changes in rail travel demand is important to understand the current situation. The results can help policymakers make decisions or make comparisons with other countries. To assess the impact of COVID-19 on rail travel demand, a travel demand forecast for the pandemic year is used and compared with actual demand. In the literature on rail travel demand forecasting, various methods are employed, broadly categorized into two groups: quantitative models and qualitative models. The quantitative category further divides into four main sub-sections [4]. Four sub-sections include time series models [5], econometric models [6, 7], artificial neural networks [8], and fuzzy models [9]. Quantitative methods have been widely used in the literature, and in addition to forecasting and studying travel demand, comparisons between different methods have been common [8]. The result of these comparisons can be considered the introduction of a superior model for use in future studies. According to the literature, superior methods are different in various studies [9-11]. Therefore, to find the best model in each study, a comparison must be made between different models. In this research, to achieve higher accuracy results and use the analytical advantages of models such as linear regression, five common models in the literature have been used. These models include multiple linear regression, multilayer perceptron neural networks, SARIMA time series, Holt-Winters time series, and hybrid models (simple average of the results of previous models). The models were calibrated to forecast rail travel demand in Iran in the year before the COVID-19 outbreak. Then, based on MAD, RMSE, and MAPE measures, the superior model was identified. Finally, using the superior model (the hybrid model), the effect of the prevalence of COVID-19 on the use of rail travel in the first four seasons of the pandemic was investigated.

This research consists of six sections. In the second section, the literature review is presented, and in the third section, the research method is introduced. After calibrating the models in the fourth section, the superior model is identified, and the impact of the COVID-19 pandemic on the demand for rail travel is reported. Finally, the conclusion is stated in the sixth section.

2. Literature Review

The global spread of the COVID-19 virus significantly altered the daily activities of people worldwide. As the demand for transportation is inherently derived from these activities, the reduction in external engagements led to a notable decrease in transportation demand. This decline, however, varied across different travel modes and countries. In this article, the reduction in demand for rail transport in a developing country has been investigated. Many studies have investigated the effect of COVID-19 on traveling by rail, among which the research of Tardivo et al. [12] can be mentioned. In their study, by considering various aspects of the effect of COVID-19 on transportation systems, such as environmental effects, health effects, and changes in the supply chain, they emphasized the need for a new model to increase the flexibility of railways in future health emergencies. To this end, it identifies the five "R": resilience, return, re-imagination, reform, and research as essential steps to increase railways' ability to face future crises. Some other articles have investigated the decrease in travel demand due to the spread of COVID-19.

Xin et al. [13] investigated the daily trip demand reduction of urban rail transport in 22 cities from Asia, Europe, and the United States using the Synthetic Control Method (SCM). The results of this research show that the decrease in demand for urban rail transportation is related to the intensity and duration of quarantines and social restrictions. Some other researchers have investigated the factors affecting passengers' use of rail transportation. In this case, one can refer to the study by Tan et al.[14]. They calibrated the logistic regression model related to the use of rail transportation using a sample of 559 numbers. Their research model is based on three factors: personal attributes, travel attributes, and perceptions of COVID-19. Based on the results of Tan et al.'s research, occupation, commuting vehicle before the outbreak of COVID-19, walking time from residence to the nearest subway station, probability of infection in a private car, and probability of infection in public transportation are effective in determining the choice of rail travel method.

Although in the above articles, the impact of COVID-19 on the rail transportation system and the public transportation system has been investigated, some articles have investigated the effect of transportation systems on the spread of COVID-19. Zhu and Guo [15] investigated the role of high-speed rail and air transportation in the spread of COVID-19 in China. Their analysis, employing a random-effects panel data model and a Difference-in-Differences in Reverse (DDR) model, indicates that the connectivity of high-speed rail transportation and air transportation with Wuhan is associated with an increase in the average number of confirmed COVID-19 cases. Specifically, the study finds that high-speed rail transportation contributes to a 25.4% rise, while air transportation is associated with a 21.2% increase in confirmed COVID-19 cases. Also, Li et al. [16] have used China's high-speed railway network to assess and predict the regional risk of COVID-19.

It should be noted that the effect of COVID-19 on transportation systems is different in all countries around the world. In one category, developing countries and developed countries have had different conditions for COVID-19. In developing countries, the lack of transportation systems and the low level of technology have created different conditions [17]. Some studies have investigated the effects of COVID-19 on developing countries. It should be noted that these studies are very importantbecause developing countries have more complex issues than developed countries and Iran, as a developing country, is not an exception. Various researchers in Iran have investigated the effect of COVID-19 on the rail transportation system. Maljaee and Khadem Sameni [18] have studied the factors affecting the use of the subway in Tehran by students during the outbreak of the COVID-19 disease. Their results show that gender, education level, and being the only child in the family have the most significant impact on using a private car. Also, Aghabayk et al. [19] have studied behavioral changes and changes in the perception of crowding among Tehran subway passengers due to maintaining social distance from people. Some other studies have investigated the effect of COVID-19 on intercity railways. Mahpour and Naeini [20] have studied the effect of COVID-19 on Iran's rail transportation system. In their article, like many other reports around the world, they calculated the impact of COVID-19 on railways based on the difference in the number of passengers transported during the outbreak of COVID-19 and the previous year of the COVID-19 pandemic (normal conditions). There are better methods than this, as the actual demand for rail travel in the year of the outbreak of COVID-19 and the forecasted demand should be compared. In general, most past research has examined the impact of COVID-19 on urban transportation systems. This study examines the effects of COVID-19 on the intercity rail transportation demand of a developing country with the correct measurement method.

3. Methodology

The study area in this study is the Iranian Railway Network. In 2019, the total length of Iran's railway network was 14779 km [3]. With this rail network, Iran is ranked 67th in rail network density and 52nd in rail transportation efficiency among 141 countries [21].

With the onset of the COVID-19 pandemic, there has been a substantial decline in the demand for rail travel in Iran. It is crucial to assess the magnitude of this decline. To accurately gauge this reduction, a direct comparison between travel demand in the pandemic year and the preceding year might not be appropriate. This is because travel demand typically follows a trend over the years, and the impact of the pandemic disrupts this established pattern. To assess the extent to which the pandemic has affected rail travel demand, it is necessary to revert to the year before the pandemic. Conducting a forecast for the upcoming year at this point allows for a meaningful comparison between the model's projections and the actual demand, providing insights into the pandemic's impact on rail travel. In this study, a linear regression model, multilayer perceptron neural network, SARIMA time series and Holt-Winters time series were calibrated using quarterly data from April 2011 to December 2018. According to the literature, building a hybrid model (the mean of the results of different models) usually produces better results [22]. Therefore, it has been used in this research. To determine the variables used in the regression model and neural network model, common factors affecting rail travel demand in the literature have been studied. After identifying the variables and calibrating the models, to ensure the use of the superior model, the accuracy of the five models in predicting rail travel demand for the period January 2019 to January 2020 was examined. Based on MAD, RMSE, and MAPE measures, the best model has been identified. Finally, the first year of the pandemic is forecasted using the superior model. By comparing the model results with real demand, the impact of the pandemic on rail travel demand has been determined. An overview of the study methodology is shown in Figure 1.

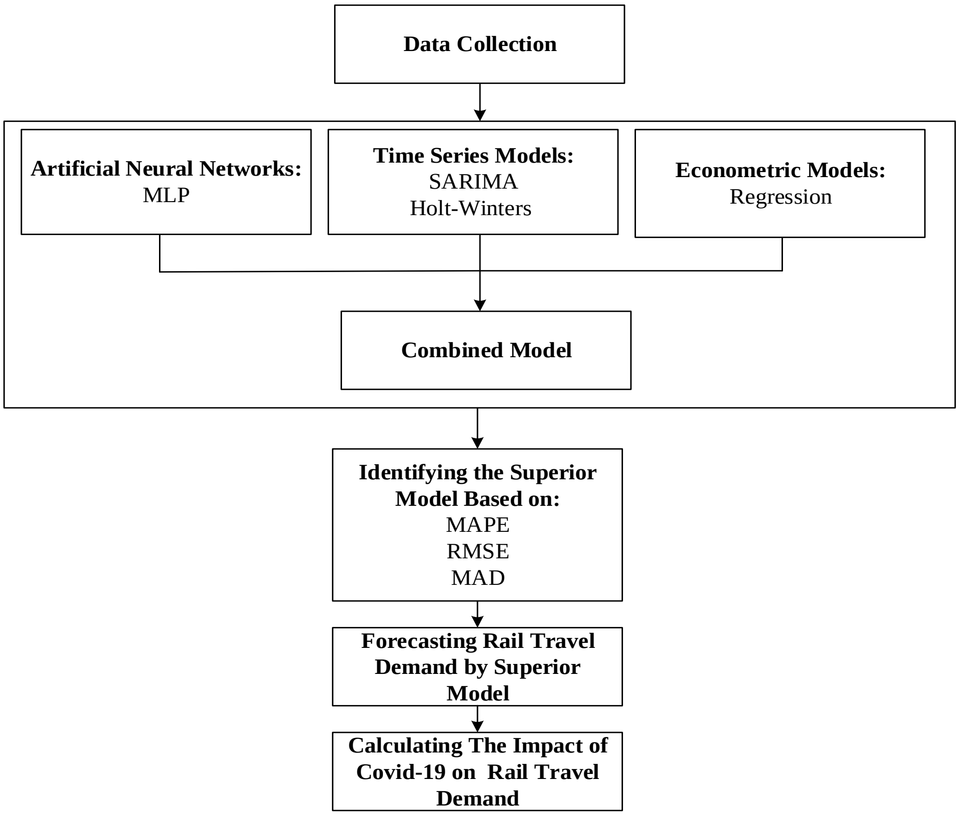

Figure 1. Methodology summary diagram.

4. Method

4.1. Multiple linear regression

Regression models are at the core of econometrics [23]. Regression methods are widely used in transportation studies. These models are generally divided into two groups: linear and nonlinear. The most common of these models are multiple linear regression models. In this research, a linear regression model has been used and calibrated by SPSS software. The model used in this research is as follows:

$$D = -21.1 + 3.1POP - 27.6VPC + 3.1E \quad (1)$$

D: Rail travel demand (Passenger-kilometer).

PoP: Active population of the country (the count of individuals aged 15 to 64 who possess the capability to engage in employment or work activities).

VPC: Vehicles per capita (per 1000 people).

E: Employment.

The model's goodness of fit is presented in Table 1, revealing an R-square value of 0.715. This indicates that the independent variables accounted for 71.5% of the total variations in passenger demand on the Iranian railway.

Table 1. Goodness of fit value in regression model.

Model	R	R^2	$Adjusted\ R^2$	Std. Error
1	0.84	0.71	0.68	0.32

To ensure the validity of the regression model, it is necessary to examine multiple linear regression hypotheses. In this study, all hypotheses were tested, and the validity of the model was confirmed.

4.2. Multilayer perceptron neural network

The neural network is a machine learning method inspired by the human brain. Neural networks such as those in the human brain are made up of a number of neurons that act similarly to brain neurons [24]. In general, a biological neuron receives inputs, then combines them, and finally delivers an output. By connecting several neurons together, a neural network is formed. Each neural network unit connects to other units through a model called network topology. This network has an input layer, a hidden layer, and an output layer [24]. There are many types of neural networks, and various models are being added to them every day. Figure 2 shows an overview of a network.

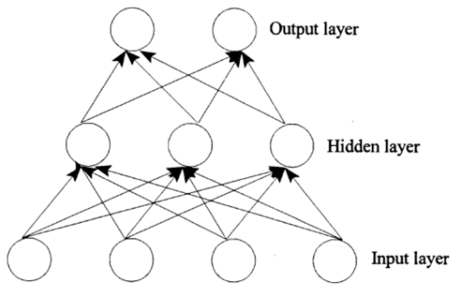

Figure 2. Artificial neural network layers [25].

The MLP neural network, a prominent model in the travel demand forecasting literature, has been employed in the current study. Through the utilization of MATLAB software, the optimal network has been identified based on achieving the lowest root mean square error (RMSE) and the highest R-square. Table 2 lists the RMSE and R-scores obtained from the neural network implementation for the three stages of training, validation, and testing. The neural network structure used in the present study is 1-3-9-3. This network has the best result using the Levenberg-Marquardt algorithm and the sigmoid transfer function. The data are randomly divided into three stages of training, validation, and testing and include 70%, 15%, and 15% of the data, respectively. The input variables of the neural network are similar to the input variables of the multiple linear regression model.

Table 2. Summary of neural network model steps.

Neural network type	Stages	R^2	$RMSE$
MLP	Training	0.9123	366.46
	Validation	0.9107	485.51
	Test	0.9040	380.54

4.3. SARIMA Model

Seasonal autoregressive integrated moving average models consist of several processes, which are as follows:

4.3.1. The Autoregressive Process, AR(p)

In the autoregressive process shown in Equation 2, the current value of the dependent variable (Y_t) is linearly equal to the weighted mean p of its previous value ($Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$) and a purely random factor process (such as white noise) with zero mean and constant variance [26].

$$Y_t = c + \phi_1 . Y_{t-1} + \phi_2 . Y_{t-2} + \cdots + \phi_p . Y_{t-p} + \varepsilon_t \quad (2)$$

$\phi_1, \phi_2, \dots, \phi_p$: Model parameters.

4.3.2. The Moving Average Process, MA(q)

In the moving average model shown in Equation 3, the current value of the dependent variable (Y_t) is linearly dependent on q, the current and past value of a random process (such as white noise) that has a mean of zero and a constant variance [26].

$$\mathrm{Y_t} = \mu + \varepsilon_t - \theta_1 . \varepsilon_{t-1} - \theta_2 . \varepsilon_{t-2} - \cdots - \theta_q . \varepsilon_{t-q} \quad (3)$$

μ: The mean of the time series.

$\theta_1, \theta_2, \dots, \theta_q$: Model parameters.

4.3.3. The Autoregressive Moving Average Process, ARMA (p,q)

This model is a combination of the previous two models and has the characteristics of both of them. The general form of this model depends on its p past values and the q past values of white noise error terms, described in Equation 4 [26].

$$Y_t = c + \phi_1 . Y_{t-1} + \phi_2 . Y_{t-2} + \cdots + \phi_p . Y_{t-p} + \varepsilon_t - \theta_1 . \varepsilon_{t-1} - \theta_2 . \varepsilon_{t-2} - \cdots - \theta_q . \varepsilon_{t-q} \quad (4)$$

4.3.4. The Autoregressive Integrated Moving Average Process, ARIMA(p,d,q)

The “autoregressive” term of the ARMA model must be stationary; therefore, the stationarity of the time series should be checked before calibrating. If this condition is not met, a differentiation must be made. In the ARIMA model, d indicates the number of differences in the AR(p) term. In practice, d takes values of one or two [26].

4.3.5. Seasonal Autoregressive Integrated Moving Average Process, $\mathbf{SARIMA(p, d, q)(P, D, Q)}_m$

The last case under consideration is the seasonality of the time series. This type of model is displayed as $\mathrm{SARIMA(p, d, q)(P, D, Q)}_m$ that the added section is related to its seasonal features. In this model, m represents the number of periods in each season. For example, for seasonal and monthly data, the values of m are 4 and 12, respectively. The uppercase letters in the model correspond to autoregressive, differencing, and moving average terms for the seasonal parts [26].

In this study, the SARIMA model has been used to investigate the impact of the COVID-19 pandemic on Iran's rail travel demand. Seasonal passenger-kilometer data was used between April 2011 and December 2018, and the model was calibrated using Minitab software. The prerequisite for using the SARIMA model is the stationarity of the time series. The time series should be stationary in terms of variance and mean. To check the stationarity of time series, the stationarity of variance must first be checked; therefore, at first, it was investigated using the Cox-Box method. According to the result of this method ($\lambda = 1$), there is no need for transformation. To extend the stationarity of mean, the augmented Dickey-Fuller test (ADF) was used. Due to the significant level of augmented Dickey-Fuller test statistics, by performing two differentiations, the average time series becomes stationary.

The autocorrelation function (ACF) and partial autocorrelation function (PACF) have been used to identify the time series pattern. Among the significant calibrated models, the superior model was identified using the Akaike Information Criterion (AIC). Among the calibrated models, $SARIMA(1,2,0)(0,1,2)_4$ is introduced as the superior model. To check the validity of a model, the model hypotheses must be tested. Figures 3 and 4 show the normal plot and the histogram for the residuals of the model, respectively. In the probability graph, the points are approximately along a line, and the histogram is distributed as a normal graph; therefore, the residues have a normal distribution.

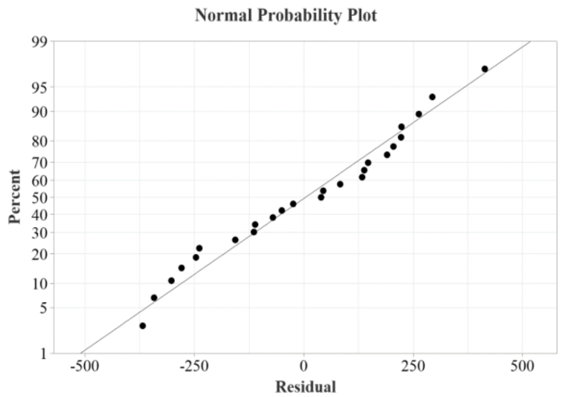

Figure 3. Normal plot of residuals.

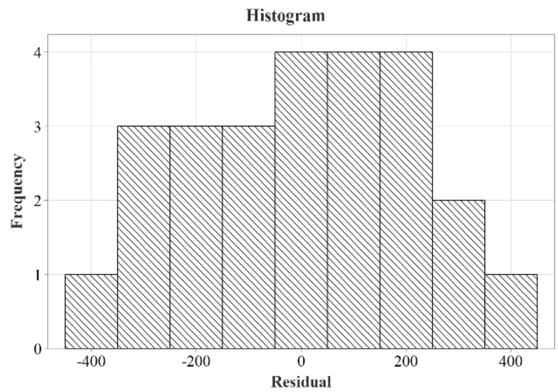

Figure 4. Histogram of Residual.

The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residues can be used to test the hypothesis of residual independence. Figures 5 and 6 show the autocorrelation function and partial autocorrelation function diagrams of the residues, respectively. Given that all autocorrelations are within the standard range, therefore, the hypothesis of independence of the residues can be accepted.

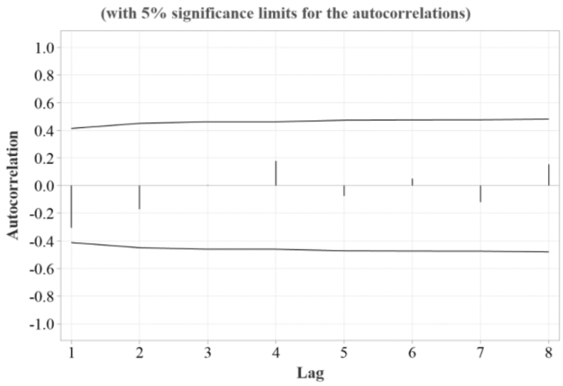

Figure 5. Autocorrelation function of residuals.

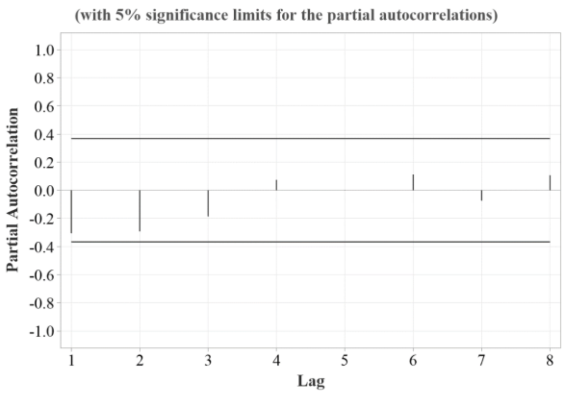

Figure 6. Partial autocorrelation function of residuals.

To test the homoscedasticity, the reader can refer to Figure 7. In this figure, the residuals are plotted against the fitted values, and no specific trend is observed in them; therefore, the homogeneity of variance is accepted. In Figure 8, the residuals are plotted against time, and this graph does not show a specific pattern; therefore, the residuals from the model fit are randomly distributed, which indicates that the model is well fitted.

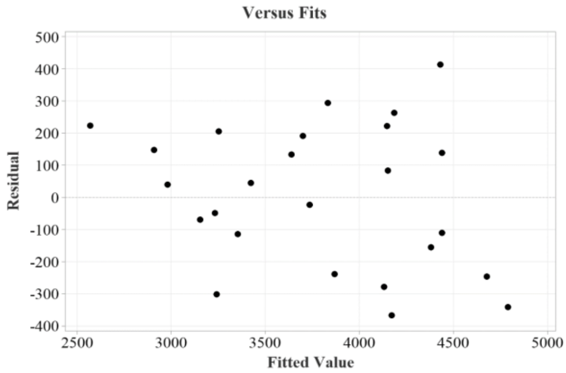

Figure 7. Residuals versus fits.

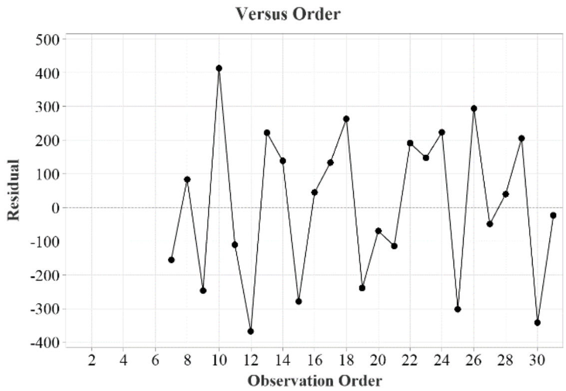

Figure 8. Residual versus order.

4.3. Holt-Winters time series and combined model

The Holt-Winters time series is based on three smoothing equations. One equation is for the time series level, one equation is for the trend, and another equation is for the seasonality of the time series. The difference between the Holt-Winters method and the Holt method is in the existence of the seasonal equation. These models are generally divided into multiplicative and non-multiplicative categories [27]. If the data of a time series contains a value of zero or a negative value, the multiplication model does not apply [27]. In this research, the multiplicative Holt-Winters time series model has been calibrated to predict and forecast rail travel demand using Minitab software.

In addition to the above, a plenty of research has been done in the literature to determine hybrid models (hybrid models mean the combination of different models to achieve more accurate results), and several methods in this field have been proposed. However, the average of the forecasts performed best or almost best in many studies [22]. Therefore, in this study, by taking a simple average of four results, a combination of prediction models has been used.

4. Estimation results

4.1. Comparison of models

To identify the superior model, the error rates of the models in forecasting rail travel demand have been compared. Table 3 shows the calculated errors for the linear regression model, neural network, the SARIMA model, the Holt-Winters model, and the combined model used to forecast the rail travel demand in the first year of the COVID-19 outbreak. According to the outcomes presented in Table 3, the combined model exhibits superior performance compared to other calibrated models in the study. Consequently, it is selected for further investigation to assess the impact of the COVID-19 pandemic on rail travel demand. Among other models, the SARIMA model had the most errors. The radar diagram in Figure 9 illustrates the error rates of different research models. An error in this figure is the difference between the model's forecast and actual rail travel demand. The combined model has the lowest error in January to March and July to September, according to this figure. In addition, the MLP model has the smallest forecast error from April to June and October to December. MLP and Combined models each have the lowest error in two time periods, but the Combined model has the lowest error overall. Therefore, it is used as a model for examining COVID-19's impact. The forecasting performance of the combined model is shown in Figure 10. There is a small error in this model, but it has been able to forecast the changes in rail travel demand.

Table 3. Model errors in the forecasting stage.

Model	MAPE	MAD	RMSE
Linear regression	6	241.11	255.49
Neural network	5.60	245.89	377.03
SARIMA	11.89	474.16	583.43
Holt-Winters	6.08	233.94	240.77
Combined model	4.53	171.15	215.48

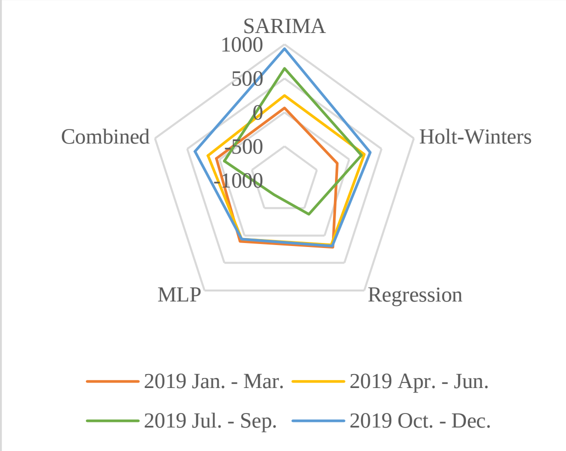

Figure 9. Radar plot of models' error.

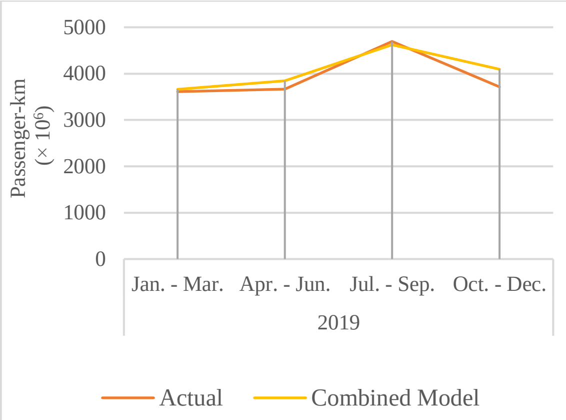

Figure 10. Performance of rail travel demand forecasting models.

5.1. The impact of the COVID-19 pandemic on rail travel demand

By comparing the forecast of the superior model with real demand, the impact of COVID-19 on rail travel demand has been identified. Table 4 shows the actual passenger kilometers transported and the result of the forecast model in the first year of the COVID-19 outbreak. Demand for rail travel fell the most between April and June 2020. The reasons for these conditions are the proper observance of various health protocols and quarantines in Iran. In general, it can be said that the demand for rail travel in the year after the outbreak of COVID-19 has decreased by 73.12 percent, which is equal to 13.9 billion passenger kilometers.

Table 4. Impact of COVID-19 on railway travel demand in the first year of the pandemic.

Date range	Actual passenger-kilometer (thousand)	Combined model (thousands)	Demand decrease (%)
April to June 2020	468956	4429427.72	89.41
July to September 2020	1244523	5165826.18	75.90
October to December 2020	1424937	4721099.20	69.81
January to March 2021	1969695	4688432.34	57.98

4. Conclusion

This study examines the impact of COVID-19 on the demand for rail travel in Iran. By comparing the actual demand and the predicted demand, the extent of the impact of COVID-19 has been determined. A comparison of the demand for the year of the pandemic and the previous year, which has been done in other articles, is not accurate. Due to the fact that the demand for rail travel does not remain the same for two years in the absence of a pandemic, In this study, five different models, including linear regression, multilayer perceptron neural networks, SARIMA, Holt-Winters, and a combination of them (the average result of other models), were used. The effect of COVID-19 was examined using the superior model (combined model). The results of this study can be divided into two categories: model interpretations and pandemic study results. In the first part, the literature was reviewed to identify factors affecting rail travel demand. In choosing the variables and modeling rail travel demand in Iran's railways, it should be noted that the conditions of this system are different from those of other rail lines in the world. For example, in previous studies, there has always been a positive relationship between rail travel demand and the total network length. However, it is different in Iran. In other words, there is an irrational inverse relationship between the length of the rail network and travel demand in Iran. That is, as the length of the railway increases, the demand for travel decreases, and as the length of the railway decreases, the demand for travel increases. The reason for this can be considered the construction of rail infrastructure without demand in Iran. The presence of such factors has made travel demand modeling for Iran's railways deviate from the norm, which researchers should pay attention to in future studies. Based on the results of this research, the two factors of the country's active population and employment can increase the demand for rail travel. That is, as the active population of the country increases, the demand for rail travel also increases, and as employment increases, people use the train more. On the other hand, it should be noted that with the increase in vehicles per capita, people use the rail less. Because of the increase in vehicles per capita, people will likely use private cars. These results are consistent with the findings of previous studies. To increase rail travel in Iran, attention can be given to the parameters of the linear regression model. In the part related to the impact of the pandemic, the forecast results show that the demand for rail travel in Iran in the first year of the pandemic has decreased by 73.12% compared to the model prediction, equivalent to 13.9 billion passenger kilometers. This effect has decreased over time, reaching 89% in the first quarter of the pandemic first year, 76% in the second quarter, 70% in the third quarter, and 58% in the fourth quarter.

Future research should identify the factors affecting the sharp decrease in rail travel demand from the perspective of passengers. This is done by examining changes in railway passengers' behavior in order to maintain railway efficiency during future crises. In previous studies, high-speed railways have received considerable attention. In order to determine the effectiveness of non-high-speed railways and high-speed railways against COVID-19, it is recommended that a comparative study be conducted. High-speed railways are not available in many countries around the world. Therefore, comparative research can be useful in policymaking and resource allocation, especially in developing countries. Furthermore, it is recommended to extend this research to encompass other modes of travel, aiming to discern the distinctive behaviors of each mode in response to COVID-19. As technology evolves, future research endeavors can benefit from more precise methodologies, particularly if access to big data becomes available.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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