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PREDICTING TRAVEL-TIME RELIABILITY IN ROAD NETWORKS: A FITRNET-BASED APPROACH – A CASE STUDY OF ENGLAND

Summary. This Travel Time Reliability (TTR) is a crucial aspect of transportation planning and management. It affects individual decisions, scheduling, and productivity, and has significant financial implications for passengers and goods. Traffic congestion is a major factor impacting TTR, which can be classified as recurring (predictable) or non-recurring (unanticipated). Researchers have developed various definitions and measures for TTR and Planning Time Index (PTI) is one of these indexes. Proper communication of TTR is essential, and numerical measures like PTI are commonly used to convey this information to travelers. Machine Learning (ML) models, particularly neural networks, have become increasingly popular for TTR estimation due to their

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ability to handle complex relationships and high-dimensional data. This study proposes using Fitrnet, a feedforward fully connected neural network, for predicting TTR at a network level. While Fitrnet has been used in other fields of engineering, its application in TTR estimation is novel. The study uses a dataset from the UK government covering the Strategic Road Network from April 2015 to March 2021. Results show that a Fitrnet model with 5 hidden layers can accurately predict PTI, with MAPE values below 10% in most cases, demonstrating the effectiveness of Fitrnet for TTR prediction in smaller datasets. The study contributes to the growing body of research on TTR modeling by proposing a new approach using Fitrnet and applying it to a previously unused dataset.

Keywords: Travel Time Reliability (TTR), Fitrnet machine learning algorithm, England's Strategic Road Network (SRN), prediction accuracy

1. INTRODUCTION

Travel Time Reliability (TTR) is a fundamental component of transportation planning and management. Its significance stems from the impact on various aspects of transportation systems, particularly those influenced by temporal variations in travel time, also known as TTR. TTR affects individual decisions, scheduling, and productivity, and has significant financial implications for passengers and goods [1].

Studies have confirmed that traffic congestion is a critical factor that makes travel time unreliable. Traffic congestion can be classified as recurring and non-recurring congestion. Recurring congestion is predictable and often occurs when the demand for using a facility exceeds its capacity. On the other hand, non-recurring congestion temporarily reduces the capacity of transportation systems and is usually unexpected [2].

Researchers have used a wide range of definitions for TTR, but since it is out of the scope of this paper, they will be mentioned herein briefly. The first definition attempts were made by Polus and Schofer in 1979, defining operational consistency as reliability [3]. According to the Texas Transportation Institute, TTR is the dependability of travel time as measured across different times of day or from day to day [4]. Also, Shaw summarized three of the most frequently used reliability definitions in his study, and only one of them is mentioned herein: the variability between the expected travel time and the actual travel time [5]. Based on this definition, numerical measures were extracted to estimate TTR, including PTI and Travel Time Index (TTI). Further information on PTI, which is used as the measure of this study, will be provided in the subsequent paragraphs. According to Kuhn et al., PTI is defined as the ratio of the 95th percent peak period travel time to the free flow travel time. Also, TTI can be defined as the ratio of average travel time in peak hours to free-flow travel time. It should be noted that both the PTI and TTI are unitless measures [6].

Conveying (TTR) properly is as crucial as defining it, as accurate information transfer is necessary for travelers to comprehend it. To provide a reliable tool for communicating with TTR, experts suggested using numerical measures such as PTI, TTI, Buffer Index (BI), and so on. Detailed explanations of these measures are available in the "Lexicon for conveying travel time reliability information"[6] and "Incorporating reliability performance measures into operations and planning modeling tools" [7]. In this study, PTI is used for the sake of modeling. Numerous advantages, including the ability to be compared with TTI directly, capturing extreme variations, and its practical application have made this measure a valuable tool for modeling TTR [8].

TTR is a widespread concept in transportation, and researchers have considered its application in various aspects of their research. The first class of studies aims to estimate TTR in links or networks. TTR has also proved itself as an influential factor in the traffic assignment process [9], controlling and improving the performance of intersections [10], and route choice behavior [11]. While this study contributes to the body of research on TTR, it aligns with the growing interest in this area.

Today, accurate estimation of TTR has gained attention. Accurate forecasting of TTR is essential to both transportation authorities and road users. This importance served as a motivation for developing suitable tools that could be beneficial.

Single distribution modeling techniques were among the first and the most widely used methods for predicting TTR [9]. Researchers utilized Normal, Lognormal, Gamma, Burr, and Generalized Extreme Value (GEV) distributions to address the problem of TTR estimation. Lomax and Margiotta followed a normal distribution as a part of their modeling approach [12]. Also, lognormal distribution was utilized by Emam and Al-Deek in modeling TTR of I-4 corridor in, Florida, US [13]. In a study conducted by Polus, an inference was made about the application of Gamma distribution in modeling TTR [14]. In a work published by Taylor, the practical use of Burr distribution in modeling TTR was evaluated [15]. Finally, Generalized Extreme Value (GEV) could prove itself as a promising tool for modeling TTR in the publication of Zhang et al. [16]. Due to multimodal distribution of travel time, which is a consequence of traffic congestion in urban transportation systems, single distribution models failed to represent a promising performance; hence, mixture distribution models were introduced. Mixture models comprise a weighted combination of single distribution models. Guo et al. proposed a multi-state approach for modeling TTR. They utilized discrete travel time states to report and forecast reliability based on probabilities between these states [17]. On the other hand, Rahmani et al. developed a non-parametric approach. Their methodology could estimate route travel time distributions from low-frequency floating car data [18]. Finally, Chen et al. developed a copula-based approach to estimate TTR on urban arterials by considering the dependence structure between segments of a road for better estimation of travel time distributions [19].

The ability of regression models to predict continuous variables, along with simplicity, efficiency, interpretability, and generalizability have made them a popular tool for modeling [20]. Researchers in the field of TTR modeling have also used it widely. Elefteriadou and Cuy collected data on a roadway in Philadelphia and used congestion, weather conditions, work zones, and crashes as independent variables, to estimate a linear regression model for predicting TTR [21]. Charlotte and Sandra presented innovative regression-based explanatory models for understanding variability in road travel times, aiming to incorporate reliability benefits into transport projects [22]. Kwon et al. developed their empirical modeling approach for predicting TTR along freeway sections by considering five key components: incidents, weather, work zones, special events, and inadequate base capacity or bottlenecks. Their method leveraged quantile regression [23]. Also, Zheng et al. focused on a corridor in China and developed a linear regression model to explain the relationship between travel time and its reliability, standard deviation, skewness, and other relevant traffic characteristics [24].

Whereas regression models have benefits, ML methods are often preferred over regression models for many reasons, including handling nonlinear relationships, high-dimensional data, robustness to outliers, and feature interactions and importance. Gradually, Machine Learning (ML) models became practical and were used as reliable tools in various fields of transportation engineering, including TTR estimation. Since this study utilizes Fitrnet, a feedforward fully connected neural network for regression, studies with ML as their methodology will be further analyzed. Table 1 describes studies that have used ML techniques as their methodology. The relevant data is too detailed and complicated to be described thoroughly in a table, so the interested reader is referred to cited articles for further information.

It should be noted that the number of studies that focus on Travel Time Prediction (TTP) is much more than articles considering TTR estimation. It is thought that TTP and TTR imply the same concept, whereas they represent two distinct concepts in transportation engineering. In better words, they are related, but TTP offers an estimate of the required time for a trip from point A to point B, whereas TTR prediction estimates how consistent those travel times are.

This study focuses on developing a Fitrnet method for predicting TTR at a network level. To the best of our knowledge, Fitrnet has been used in only 43 studies in Google Scholar, primarily in other fields of engineering. Its usage in traffic and transportation engineering has been limited, with only one study focusing on the electrification of transportation, and was not previously used for TTR estimation. Table 2 will provide information on studies that have utilized Fitrnet as their methodology and highlights their scope.

Tab. 1

Summary of conducted studies in TTR estimation

Author(s)	Type of network/Link	Methodology
Zhang et al. [25]	Interstate segments in Virginia	Quantile regression
Zhang and Chen [26]	Interstates 71 and 75 in Kentucky	Decision tree and Quantile regression
Zhang et al. [27]	Interstate segments in Virginia	Quantile regression Random Forest Regression
Babiceanu and Lahiri [28]	Interstate segments in Virginia	Classification and Regression Trees
Wu et al. [29]	Urban arterial in Texas	Feedforward Neural Network
Zhao et al. [30]	Interstate segments in Virginia	Quantile Random Forests (QRF) Generalized Random Forests (GRF)
Li et al. [31]	Urban road network in China	Long Short-Term Memory (LSTM) Quantile Regression

Tab. 2

Summary of some of the studies utilizing Fitrnet as their modeling tool

Author(s)	Field of study	Author(s)	Field of study
Sennefelder et al. [32]	Electrification of transportation	Oh et al. [33]	Applied thermal engineering
Shahbazi et al. [34]	Thermal modeling	Cousins et al. [35]	Bioenergy

As such, this paper adds the following to the previous body of research on TTR:

- Proposes Fitrnet approach to analyze TTR at the network level

Also, it is worth noting that the dataset utilized in this study has been used six times previously. In Table 3, a summary of these studies is provided. None of them were related to modeling TTR.

Tab. 3

Summary of studies utilizing the dataset of this study

Author(s)	Focus of study	Methodology
De Gan et al. [36]	Air pollution	Accurate simulation of traffic-related air pollution
Hadjidemetriou et al. [37]	Transport planning	Adaptive policy pathways used in flood-risk planning
Greenhalgh et al. [38]	Urban Planning	Temporal and statistical analysis, GIS
O'Garra& Fouquet [39]	Ecological economics	Regression analysis
Gorbunov et al. [40]	Travel time	Statistical analysis
Oakley [41]	Transport infrastructure	Analytical report/ No methodologies

As Table 3 suggests, none of the previous studies utilizing this dataset has focused on predicting TTR, so it is the first time this data is being used for this purpose.

The remainder of this paper is organized as follows: Section 2 introduces the methods, including the dataset used in model development and the technique employed to predict TTR. Section 3 analyzes results relevant to network-level predictions. Finally, Section 4 concludes the paper.

2. METHODS

It is acknowledged that using ML, and especially neural networks, is well-documented in transportation engineering. It should be noted that the specific use of Fitrnet has not been mentioned either in TTR prediction or other transportation-related studies.

The Fitrnet function is used to establish a feed-forward neural network. This kind of network is structured in layers, with each layer consisting of several neurons or nodes. Data in this network flows from the input layer straight to the output layer, without any circular paths, which is why it's referred to as 'feed-forward'.

The most appropriate reference that provides information about the Fitrnet is the official documentation of MATLAB. This document can be accessed via MathWorks' website[6]. In the Fitrnet, there is a connection between network input, which is known as predictor data, and the first layer of the neural network, which is fully connected. Also, there are connections between subsequent layers and previous layers. Those as mentioned earlier, fully connected layers take the input and multiply them by a weight matrix. In the next step, a bias vector is added. Each fully connected layer, except for the last one, is followed by an activation

[6] https://www.mathworks.com/help/stats/fitrnet.html

function. Finally, predicted response values, which are the final fully connected layers, produce the network's output.

To better realize how Fitrnet works, each part is broken down to represent its basic usage. First, the model should be initialized. The next step is the optimization of hyperparameters, which is optional and is out of the scope of this article (a brief explanation about all of them is mentioned). Then, the neural network has to be trained. This process is vital, as the network learns to generalize input-output mapping without memorization. Cross-validation can also be performed during the training process. After training the model, its performance should be evaluated using the loss function. This function could be either Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), or other proper measures. It should be noted that RMSE measures the average difference between values predicted by a model and the actual values, whereas MAPE measures the average magnitude of error produced by a model, Finally, the trained model is used to make predictions on new data. As explained, the steps for developing a Fitrnet model are similar to those for other machine learning models, with the primary difference being the unique structure of the Fitrnet model itself.

The hyperparameters of Fitrnet in MATLAB are as follows:

- Layer size: The size of the layer dictates the quantity of fully interconnected layers within the neural network. Fitrnet adjusts the size of each layer within a range of 1 to 300. Typically, Fitrnet optimizes across three fully interconnected layers, not including the last fully interconnected layer.
- Activation: This hyperparameter determines the activation function for every fully connected layer in the neural network, except for the last one. The Fitrnet method optimizes over a set that includes 'relu', 'tanh', 'sigmoid', and 'none'. The role of an activation function is to add non-linearity to the model, which enables it to identify and learn more intricate patterns in the data.
- Lambda: This hyperparameter, known as Lambda, influences the intensity of the regularization component in the loss function. Regularization is a method employed to avoid overfitting by incorporating a penalty term into the loss function. The Lambda hyperparameter is responsible for setting the size of this penalty term. Fitrnet fine-tunes Lambda across a continuous range from 1e-5 to 1e5.
- Standardize: The "Standardize" hyperparameter is a boolean value that determines if the predictor data should be standardized. When set to true, it adjusts each numeric predictor variable based on its respective column mean and standard deviation, effectively centering and scaling them. This process of standardization ensures that the model is not affected by the different scales used for the predictor measurements.
- Layer weights initializer: The layer weights initializer is a hyperparameter that decides the method used to set the weights for each fully connected layer. Fitrnet adjusts the layer weights initializer among the options 'glorot' and 'he'. The 'glorot' initializer selects from a uniform distribution with a mean of zero and a variance of $\frac{2}{I+O}$, where I represents the input size and O is the output size of the layer. On the other hand, the 'he' initializer selects from a normal distribution with a mean of zero and a variance of $\frac{2}{I}$, where I is the input size of the layer.
- Layer biases initializer: The layer biases initializer is a hyperparameter that sets the starting values for the biases in every fully connected layer. The Fitrnet algorithm adjusts the layer biases initializer among the options 'zeros' and 'ones'. When 'zeros' are selected, the initial

bias for each fully connected layer is set to 0. If 'ones' is selected, the initial bias for each fully connected layer is set to 1.

Fitrnet has some benefits, including but not limited to flexibility in model architecture, standardization of predictors, automatic initialization of weights and biases, and so on. For further information on the application of Fitrnet, the interested reader is referred to the studies mentioned in Table 2.

The utilized dataset of this study includes data on TTR and is accessible through statistical datasets of the United Kingdom (UK) government[7] . Table 4 describes the utilized data, and Figure 1 depicts the distribution of the Strategic Road Network of England[8].

Tab. 4

Description of utilized data in this study, PTI, average speed, and average delay

Variable	Number	Mean	SD	Min	Q1	Median	Q3	Max
PTI	72	1.62	0.14	1.22	1.62	1.67	1.69	1.78

Before going through the results section, a concise overview of the dataset is necessary. The data and statistics of road congestion and travel times on the Strategic Road Network (SRN) and local 'A' roads can be accessed publicly, including statistics released by the UK government related to road congestion and reliability. The utilized database of this study consists of a continuous variable, the TTR metric (PTI). The aggregation level of records is monthly, spanning from April 2015 to March 2021. PTI represents reliability. To calculate PTI, according to [6], the 95th percentile of travel time should be divided into free-flow travel time. Free-flow travel times are based on speed limits for individual road sections. The calculated PTI is on the Strategic Road Network (SRN) level. To do so, the average of PTI across individual road sections was calculated, weighting by traffic flows for each section. Moreover, only car travel time observations were used for calculating PTI.

The behavior of the variable is shown in Figure 2. The vertical axis labels the values of the variables and the horizontal axis, labeled “Index”, starts from 0 indicating April 2015 to 72 indicating March 2021 (one unit in the horizontal axis is equivalent to one month.

The process of creating a Fitrnet model for the database in MATLAB has been mentioned previously. It should be noted that the data is split into training and test sets, with 80% of data for training and 20% for testing.

[7] https://www.gov.uk/government/statistical-data-sets/average-speed-delay-and-reliability-of-travel-times-cgn
[8] The figure can be downloaded from: https://nationalhighways.co.uk/media/qe1cjb2b/nh-srn-simplified-map-2023.pdf (Crown copyright and database rights 2023 OS 100030649)

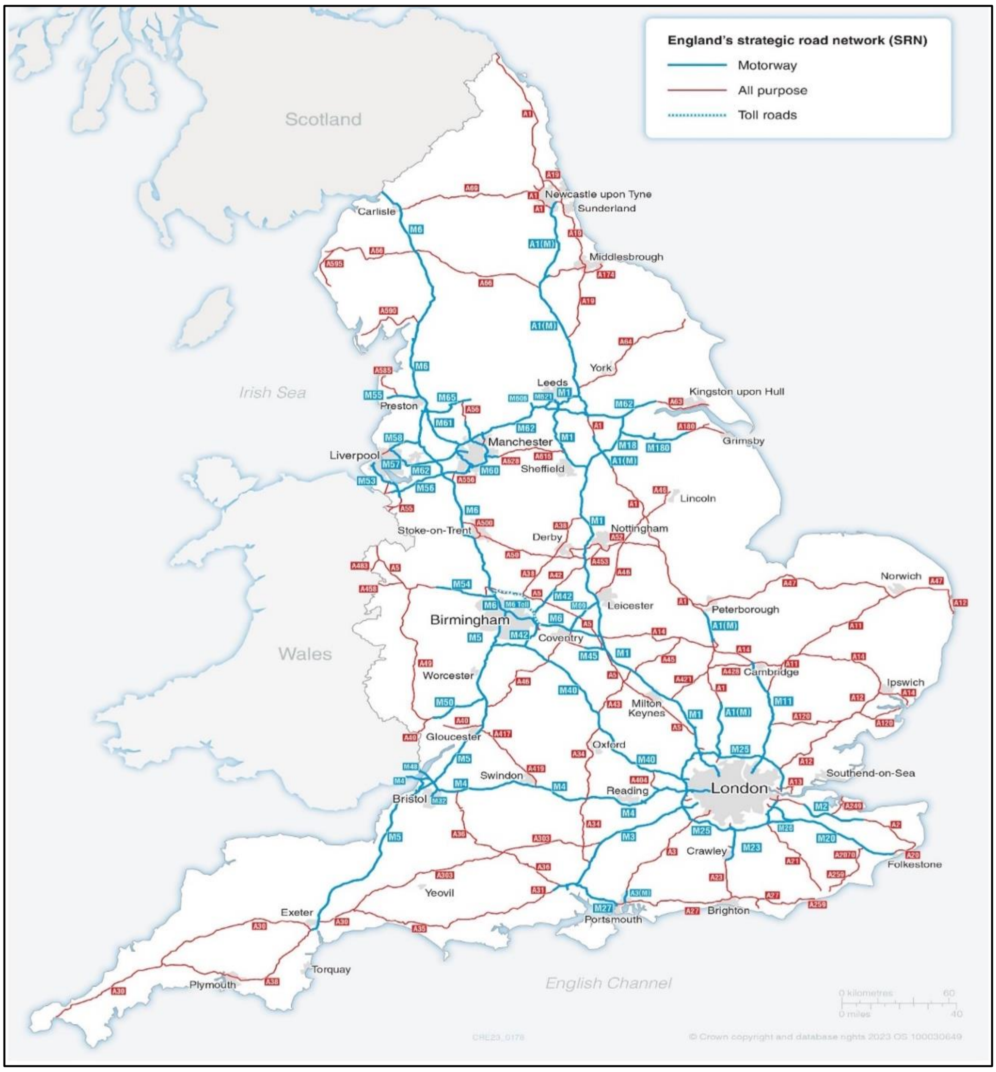


Fig. 1. Spatial distribution of the Strategic Road Network (SRN) across England

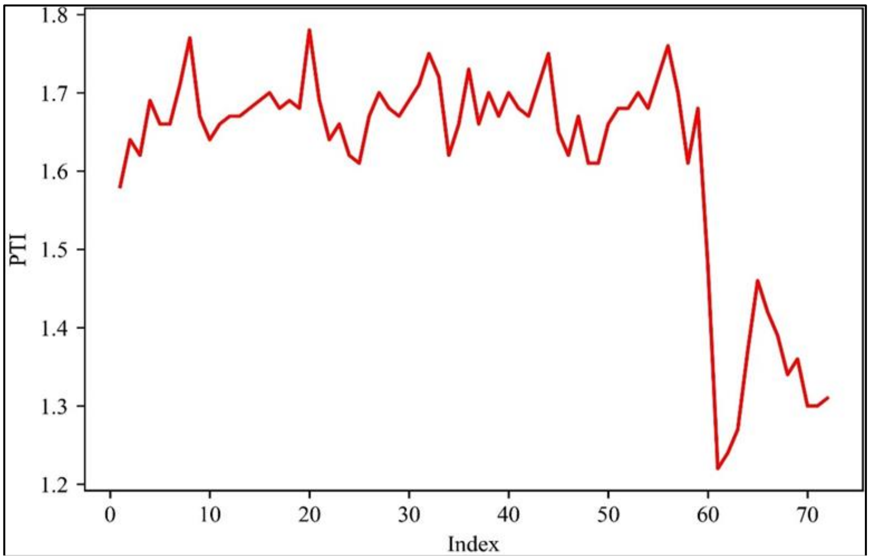


Fig. 2. Analyzing the behavior of PTI as a time series

3. RESULTS

In this section, the results of developing a Fitrnet model for the described dataset will be further discussed. First, the evaluation metric used to assess the performance of the proposed model is reported. This study uses MAPE to determine the model's performance.

To analyze and model the TTR data, the authors used different variants of the Fitrnet model to arrive at the best possible implementation results. The experimental results show that a feedforward neural network with 5 hidden layers is suitable for predicting PTI. The model was tested with different train dataset sizes (23, 30, and 37 elements) to predict the next 3 PTI elements. To show the stability and robustness of the method, a rolling time window with 5 elements is considered in all examples. The results are depicted in Figures 3, 4, and 5 for 23, 30, and 37 train dataset sizes respectively. In these plots, the blue points (blue lines) show actual data, the green points show simulated data and the red points show predicted data.

In Figure 3, the subfigure 3-D-8 does not generate acceptable results, while other subfigures are approximately acceptable. The related errors are given in Table 5. The related values of MAPE for Figures 4 and 5 are given in Tables 6 and 7 respectively. A comparison between Table 3 to Table 5 shows that considering a large enough training dataset, the proposed model can predict PTI accurately. Based on our experiments, the considered training dataset size (37) is appropriate. Increasing the training dataset size is not suggested, since overfitting may occur. In Figure 5, the subfigures 50-D-2 and 50-D-3 confirm that overfitting does not occur, while increasing the number of points affects the error and can bring about overfitting.

Tab. 5

The MAPE for predicting the next three PTIs where 23 elements are used for training

Subfigure (30)	D-1	D-2	D-3	D-4	D-5	D-6	D-7	D-8	D-9	D-10
MAPE (%)	2.78	2.61	3.86	2.38	2.66	1.14	5.23	27.95	11.10	3.96

Tab. 6

The MAPE for predicting the next three PTIs where 30 elements are used for training

Subfigure (40)	D-1	D-2	D-3	D-4	D-5	D-6	D-7	D-8
MAPE (%)	4.39	4.84	1.83	1.94	2.60	3.43	8.98	2.75

Tab. 7

The MAPE for predicting the next three PTIs where 37 elements are used for training

Subfigure (50)	D-1	D-2	D-3	D-4	D-5	D-6
MAPE (%)	1.57	3.42	1.60	0.54	4.63	8.23

To assess the performance of Fitrnet, the authors propose a set of numerical rages to interpret MAPE as follows:

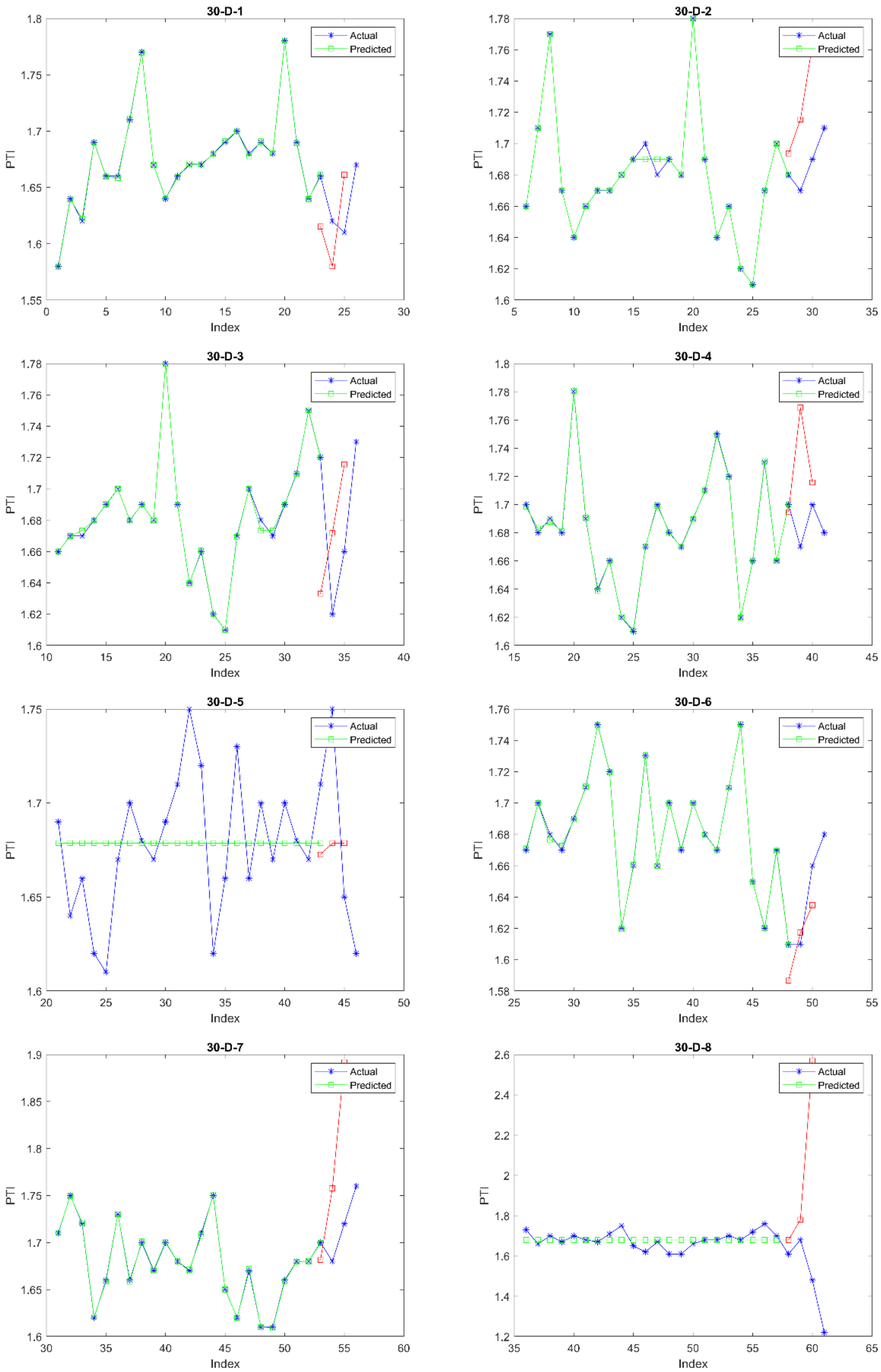
- 0% < MAPE < 10%: It is widely considered a highly precise prediction method. In numerous sectors, a MAPE value below 10% is often seen as a sign of a strong and reliable model.
- 10% ≤ MAPE < 20%: This range is normally noticed as satisfactory and suitable for the majority of practical prediction models, particularly in situations where a certain degree of fluctuation is anticipated.
- 20% ≤ MAPE < 5%: This range might be acceptable depending on the situation, but it suggests a certain degree of inaccuracy and implies that the forecasting method could potentially be enhanced.

Based on the values of Table 5 to Table 7, only in two scenarios (out of 24 scenarios), the MAPE value exceeded 10, in 30-D-8 and 30-D-9. In the other 22 cases, the MAPE values are below 10%, showing a highly precise and accurate prediction. This confirms that Fitrnet is a perfect tool for predicting the reliability of travel time in small datasets.

4. CONCLUSION AND DISCUSSION

TTR is an important aspect of transportation planning and decision-making, and precise prediction of TTR can support effective transportation planning, route optimization, and traffic management. Because of their ability to model complicated, non-linear connections and handle massive, high-dimensional datasets, many Machine Learning (ML) algorithms have been widely employed to forecast TTR. Various ML models have been employed for this purpose, but Fitrnet had not been employed for this purpose by any earlier study, to the best of the authors' knowledge. To that end, this research aimed to analyze the prediction performance of Fitrnet by using Strategic Road Network (SRN) level data from England over 72 months.

We employed multiple iterations of the Fitrnet model to investigate and simulate travel time reliability data, ultimately identifying the most effective configuration. Our findings revealed that a feedforward neural network comprising five hidden layers demonstrated exceptional proficiency in forecasting Predicted Travel Time (PTI). To assess the model's consistency and robustness, we conducted experiments using three distinct training dataset sizes – 23, 30, and 37 items – to predict the subsequent three PTI elements. A rolling time window encompassing five consecutive data points was implemented in each scenario to showcase the method's stability. The results, presented in Tables 3, 4, and 5, demonstrated the model's accuracy in PTI prediction, with the 37-item dataset proving optimal. Notably, the low Mean Absolute Percentage Error (MAPE) values, aside from two exceptional cases, underscored the promising predictive performance of the proposed model, validating its applicability. Furthermore, the researchers cautioned against increasing the training dataset size beyond 37 items, as it may lead to overfitting, highlighting the delicate balance between model complexity and data sufficiency in achieving accurate predictions. In terms of numerical comparison, this study could achieve the MAPE minimum value of 1.14% in first scenario and in 92% of cases (22 of 24), the values of MAPE were less than 10%, hence considered high precise prediction. The other studies utilizing Fitrnet could not achieve this level of accuracy, such that Cousins et al. stated that the minimum value of RMSE utilizing Fitrnet in their work was almost 5%. The same statement was mentioned by Sennefelder et al., but in their work, the values of MAPE was reported to be 3.6%, larger than minimum value of MAPE in our work. Finally, in the paper of Shahbazi et al., the authors could achieve errors less than 1%.



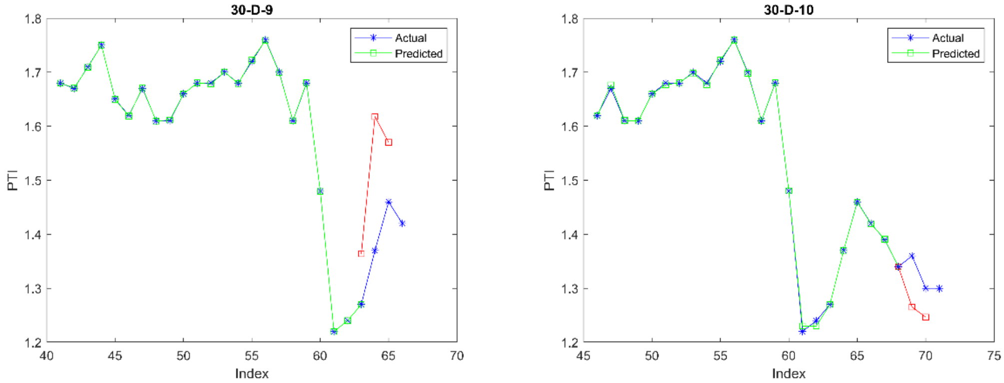
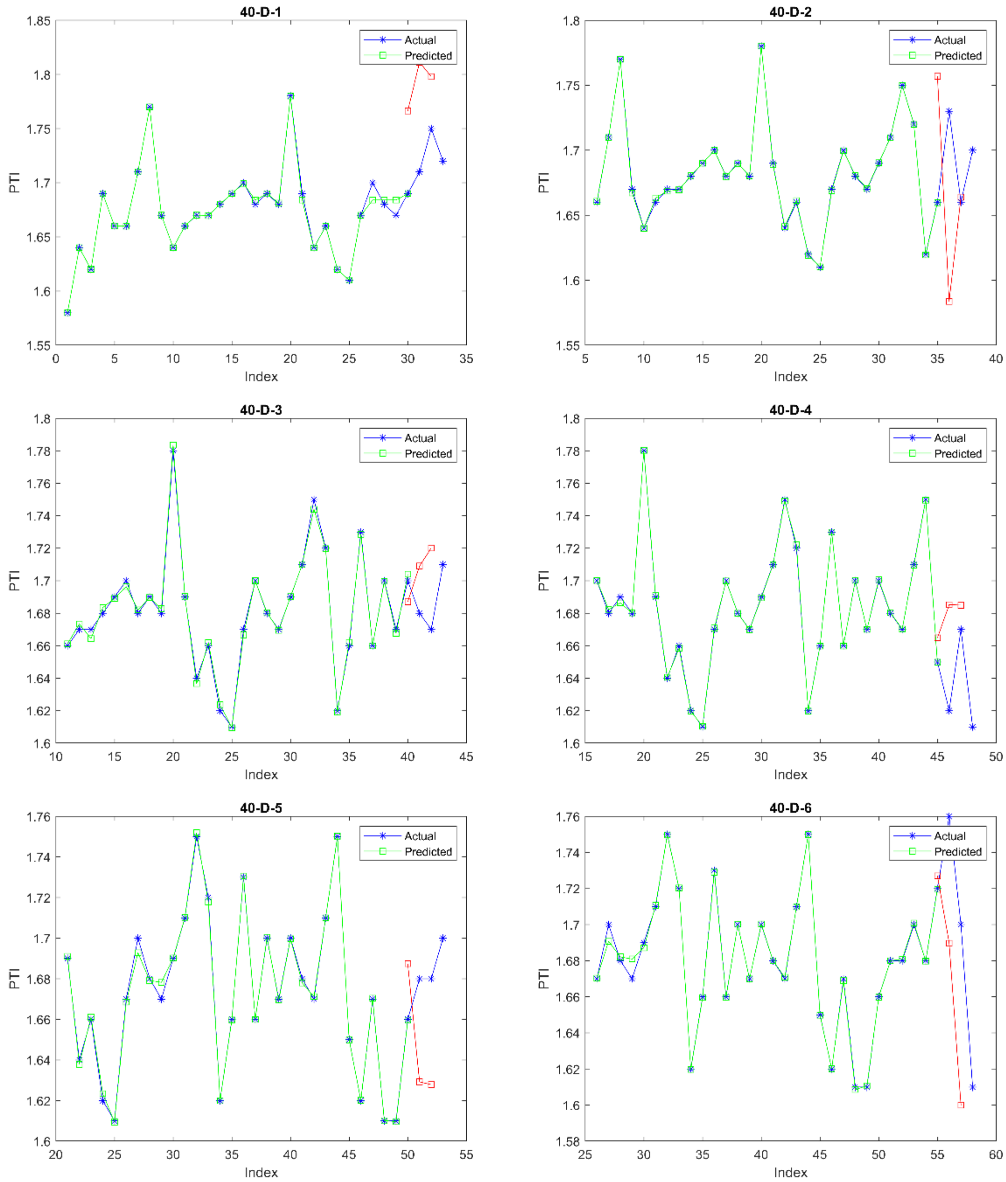


Fig. 3. The actual (blue stars), simulated (green circle), and predicted (red square) PTI values in different periods where the first 23 elements are used for training the model



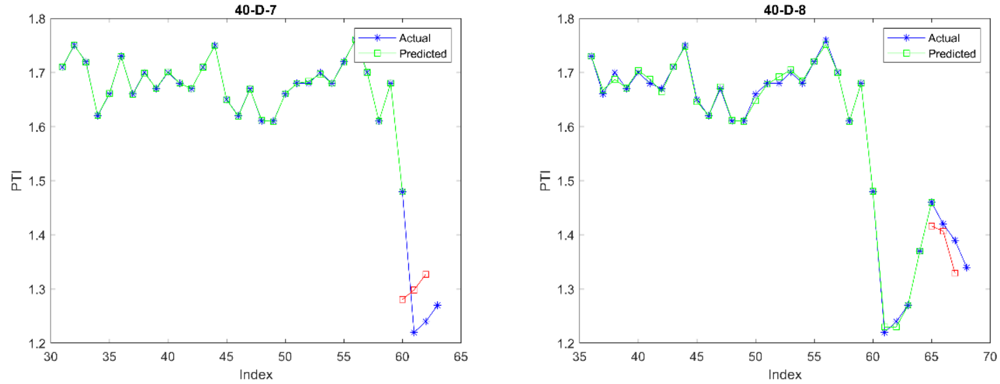


Fig. 4. The actual (blue stars), simulated (green circle), and predicted (red square) PTI values in different periods where the first 23 elements are used for training the model

Fig. 5. The actual (blue stars), simulated (green circle), and predicted (red square) PTI values in different periods where the first 37 elements are used for training the model

As future research, this study proposes two broad ideas that can be considered. The first one is the application of methods like Genetic Algorithm (GA) that can be used for hyperparameter tuning. As analyzed by researchers, the values of hyperparameters are set before the learning process begins. In this study, many of these hyperparameters were set to the default values, which might change the occurring results. Furthermore, enriching the dataset can effectively address concerns regarding its size.

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