

# Predicting bus ridership based on the weather conditions using deep learning algorithms

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## ABSTRACT

This study proposes a new approach to predict bus ridership based on the weather conditions while accounting for additional factors such as large events, holidays, and bus cancellations. For this purpose, a deep learning algorithm - multilayer perceptron (MLP) networks - is implemented using smart-card data from the bus network in the Twente Region in the Netherlands. The prediction was carried out under three scenarios: (1) without the weather conditions (base model), (2) with the weather conditions of the same time as the boarding time into buses, and (3) with the weather conditions of an hour ahead of boarding time into buses. The results showed that the application of the MLP is very promising in forecasting bus ridership considering the meteorological parameters. The average errors were improved by 4.9% on weekdays and 2.8% on weekends as a result of including the meteorological parameters in the models. The improvements were even more prominent on weekdays with moderate to extreme weather conditions (for instance, heavy precipitation, strong wind speed, and low temperature). However, the models showed higher errors during the morning peak hours on days with heavy rainfall and strong wind speed.

## Introduction

Travelling is an outdoor activity subject to weather conditions such as rain, snow, wind, and thunderstorms. Severe weather conditions could induce significant variations in transport demand, affecting people's willingness to travel, as well as their decisions in choosing destinations, departure times, and transport modes (Cools et al., 2010; Guo et al., 2007; Heinen et al., 2010). Such variations have considerable impacts on the ridership levels and operations of public transport (PT), especially when a service operates close to its capacity (Correia et al., 2021). Several studies have shown that precipitation, wind speed, and temperature influence the travel behaviours of PT users (Correia et al., 2021; Guo et al., 2007; Zhou et al., 2017).

Depending on the intensity of weather conditions, public transport users (e.g., bus passengers) may adjust their travel behaviours differently, such as changing destinations, and departure times, switching to other modes, or cancelling their travel. For instance, Zhou et al. (2017) found that heavy rainfall may negatively influence people's willingness to make trips in the first place. Furthermore, unpleasant travel experiences during severe weather conditions may also cause modal shifts from public transport to private cars, further increasing the complexity

of the relationship between PT ridership and weather. On the other hand, cyclists may switch to buses during extreme weather conditions since cycling is no longer appealing, especially in the Netherlands, where cycling is one of the main transport modes. Thomas et al. (2013) found that up to 80% of the variations in the cycling demand in Dutch cities are due to weather fluctuations. As a result, PT ridership levels, particularly buses, could increase or decrease depending on the weather conditions.

Over the past few years, public transport operators and meteorological institutes have generated and stored a wealth of data. Such data provide potential opportunities to develop data-driven techniques to forecast public transport ridership concerning the weather conditions. Several studies have used deep learning algorithms to predict travel demand based on the weather conditions (Correia et al., 2021; Fontes et al., 2020; Xue et al., 2020). However, the impact of weather conditions on PT ridership depends on the local context, including local weather conditions, built-in environment factors and the quality of alternatives. For example, modal shifts between cycling and PT in the Netherlands frequently happen, especially during severe weather conditions (Creemers et al., 2015). Furthermore, even though previous studies provided model errors (e.g., mean absolute error and mean

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squared error) to validate their models, only a few have elaborated on when and where their models performed well compared to the actual values. It is worth mentioning that relying solely on the meteorological parameters without considering additional factors, such as large events, school holidays, and public holidays could also downgrade the prediction accuracy.

The main objective of this study is to predict the bus ridership in the Twente region<sup>1</sup>, the Netherlands (shown in Fig. 1), based on the weather conditions. For this purpose, we will apply a deep learning algorithm called multilayer perceptron network using the smart-card data collected between January 1, 2018, and December 31, 2019, and relevant meteorological data of this period. This study focuses on achieving a realistic ridership forecast, which could provide valuable insights into bus travel demand in the region. Such insights are essential to improving service resilience and operational efficiency under different weather conditions. It will also help public transport planners in their decision-making concerning operating schedules and managing disruptions caused by extreme weather conditions.

The remainder of our study is structured as follows. Section 2 provides a literature review and the theoretical background concerning the impact of weather conditions on travelling. Section 3 elaborates on the modelling methods and MLP models. Section 4 provides information about the data sources and related data processing. Section 5 provides the results of our study. The results are discussed in section 6, followed by the conclusion and recommendations for future studies in section 7.

## Literature review

Various studies in the literature have examined the relationships between weather conditions and public transport ridership (Böcker et al., 2013; Cools et al., 2010; Habtemichael et al., 2012; Kwon et al., 2013; Sabir et al., 2010). It is evident that severe weather conditions, such as heavy rain, snow, hurricanes, and winter storm, cause operational problems, traffic congestion and incidents and, thus, hinder the quality and availability of transport services (Singhal et al., 2014; Tao et al., 2016). More specifically, such weather can disrupt the regular operations of public transport services (Dimitrov & Ceder, 2016), resulting in unpleasant travel experiences for passengers and potentially altering the ridership levels in the long term (Hofmann and O'Mahony, 2005).

Furthermore, weather fluctuations can influence travellers' behaviour, including their decisions to avoid travelling or change their destinations, travel modes, departure times, or routes (Cools et al., 2010; Correia et al., 2021). According to Van Acker et al. (2010), two components form the core of the travel decision hierarchy. The first type is called reasoned factors, such as attitudes and preferences. Attitude refers to the positive, negative or mixed response to stimuli that influence an individual's behaviour (Gärling et al., 1998). Preference refers to an individual's activity that identifies his/her intention to behave in a certain way. The second component in the travel decision hierarchy refers to habits and impulsive decisions. Habits refer to situation-specific behaviours that have become automatic and happen without conscious decision-making (Van Acker et al., 2010). In comparison, impulsive behaviour/decision is defined as spontaneous intentions to do something without thoughtful considerations (Park and Roehl, 2016). That being said, weather conditions can intervene in various aspects of individuals' travel behaviour, including attitudes, preferences, and habits. Cools et al. (2010) found that individuals may reschedule, reroute or even cancel their trips due to severe weather conditions. However, the magnitude of weather influence on PT ridership differs between days of the week (weekdays and weekends) and time of day (peak and off-peak

hours). The authors concluded that modes and departure times are the most prevalent travel behaviour changes due to weather conditions. A survey in Brussels showed that people are reluctant to use PT, mainly buses, during rainy hours (Khattak & De Palma, 1997). A similar study by (Hofmann and O'Mahony, 2005) detected a decrease in bus ridership in Dublin during rainy hours. Singhal et al. (2014) further examined the impact of weather conditions by considering temporal variations. The authors found that weather conditions, mainly rainfall, impact morning trip more than midday and afternoon periods. On the other hand, sunny and warm weather might increase PT ridership, as was the case in Chicago (Guo et al., 2007). Overall, severe weather conditions negatively impact the ridership levels and the operations of PT services, predominantly when a service operates close to its capacity (Correia et al., 2021).

However, the impact of weather on public transport ridership depends on the local context, including local weather conditions, built-in environment factors and the quality of alternatives. In the Netherlands, cycling is one of the main travel modes in the country, and changes in the cycling demand are associated with changes in the PT demand (Creemers et al., 2015). At the same time, cycling is the most susceptible transport mode to weather conditions (Sabir et al., 2010). Many studies have shown frequent modal shifts between cycling, walking, and PT, particularly buses. For instance, Sabir et al. (2007) examined the impact of weather on modal shifts in the Netherlands, in which the authors found that strong wind speed, low temperatures, and precipitation cause modal shifts from bicycles to cars and urban public transport. In a later study (Sabir et al., 2010), the authors found that the number of cyclists in Dutch cities significantly decreases and PT ridership increases during heavy rainfall and extremely cold temperature. When the temperature drops below zero, the demand for buses, trams, and metro (BTM) increases by 17% compared with the demand at 0–10 °C. Similarly, demand for BTM increases by 6% during moderate rains (up to 6 mm/hour). In the Dutch context, strong wind (more than 6 Beaufort) and snow have negative impacts, and visibility (less than 300 m) has positive impacts on the BTM and cycling demand. Notably, the impacts of these meteorological parameters on train ridership is much smaller (Sabir et al., 2010). Weather conditions also vary locally within cities resulting from urban microclimates, such as urban canyons. Helbich et al. (2014) have shown geographic heterogeneity in cycling in Rotterdam in the Netherlands, under various weather conditions, particularly between dense central urban environments and surrounding lower-density areas.

Furthermore, weather conditions may amplify existing variations in public transport ridership, for example, when major events are happening, such as national holidays, school holidays, and football matches. Therefore, analysis of the impact of weather on ridership needs to control for such events and related changes in the PT capacity (Karnberger & Antoniou, 2020; Li et al., 2015). For instance, the temperature rises during the summer period, while, at the same time, the number of public transport users decreases due to school holidays, not necessarily the temperature.

Concluding from the literature, the direction and magnitude of meteorological impacts on local public transport ridership vary significantly across studies in the literature. Depending on where the studies are conducted, some stated that severe weather conditions would increase PT ridership, whereas others found the opposite. However, almost all studies consistently agree that weather conditions influence individuals' decisions to change their travel plans. Such correlation between weather and travel behaviour can be used to predict PT demand, more specifically, buses. Nowadays, many PT operators in the Netherlands and elsewhere can access a considerably large amount of data over the past years via smart cards and tickets that could be used to obtain a realistic prediction of ridership at different levels. This will enable the operators to make better short-term and long-term plans for their services. Furthermore, having a good prediction of demand in the upcoming days and weeks will help operators to manage their resources

<sup>1</sup> Twente is a region in the eastern Netherlands, the most urbanized part of the province of Overijssel, with nearly 620,000 inhabitants. Its largest cities are Almelo, Hengelo, and Enschede, the latter being the main city of the region.

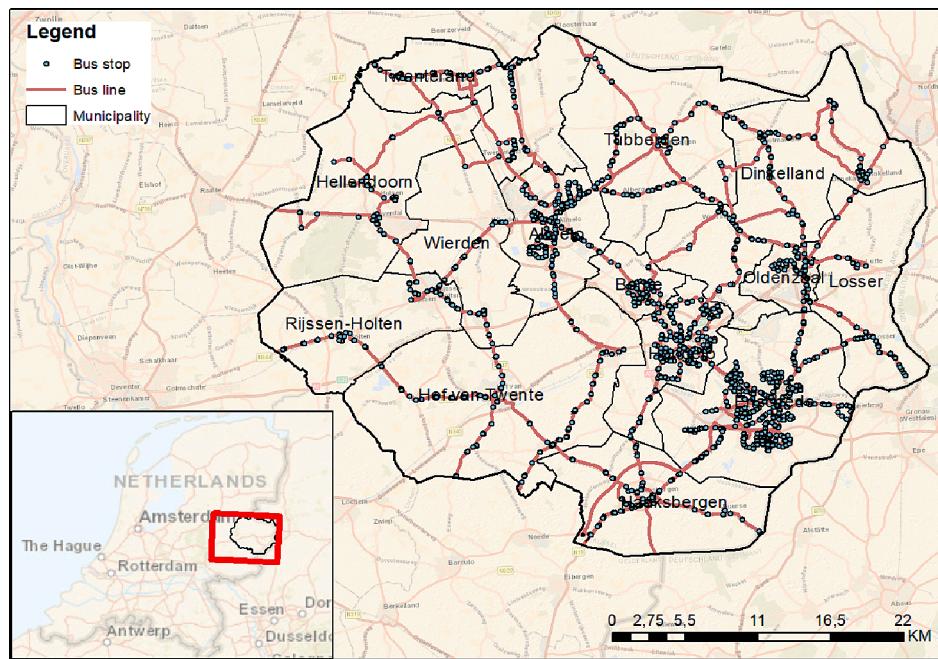


Fig. 1. Twente bus network.

more efficiently (Arana et al., 2014; Gkiotsalitis, 2021; Gkiotsalitis & Alesiani, 2019; Gkiotsalitis & Cats, 2020).

## Modelling

Artificial neural networks (ANNs) are mostly used for complex problems with non-linear relationships (Correia et al., 2021). In the engineering context, ANNs are used for pattern recognition, forecasting, and data compression. In this study, a fully connected and feed-forward multilayer perceptron neural network is used, in which the output from each neuron of the input layer and the hidden layers are connected to all neurons in the next layer (Gupta & others, 2013). These algorithms have been widely used in travel demand forecasts. Even though the MLP falls into the category of intermediate ANN algorithms, it provides relatively better results when a real-valued quantity is predicted. It can learn non-linear relationships to map data to a higher dimensional space. Additionally, MLP is more resistant to over-fitting than other types of neural networks (Bishop & Nasrabadi, 2006). This is because it has more parameters (due to additional hidden layers) and can quickly learn the underlying structure of the data. Furthermore, MLP is very flexible and can be applied to different datasets. This allows us to replicate them with slight changes in the dataset.

It is worth mentioning that there are several (relatively more complicated) ANN algorithms, such as recurrent neural networks (RNNs), long-term, short-term memory (LSTM), and convolutional neural networks (CNNs), that are used for prediction purposes. Many studies have tested these algorithms on time series forecastings, such as (Vateekul et al., 2021) and (Halyal et al., 2022). Through a pre-test of MLP, LSTM, support vector machine (SVM), and multiple linear regression (MLR), we found that MLP performs significantly better with and without accounting for meteorological parameters. The LSTM showed larger mean absolute errors (MAEs) when accounting for the weather conditions. The reason is that LSTM (RNNs in general) keep track of previous nodes in their hidden state vector and project them to the subsequent nodes (for more details, refer to (Medsker & Jain, 1999)). Nevertheless, since weather conditions can increase/decrease travel demand with little dependency on the travel demand of the previous hours, and LSTM cannot identify abrupt changes caused by weather conditions. Similarly, SVR and MLR exhibited relatively larger errors

with and without accounting for the weather conditions compared to the MLP models. Therefore, we selected MLP as the best prediction model for our dataset.

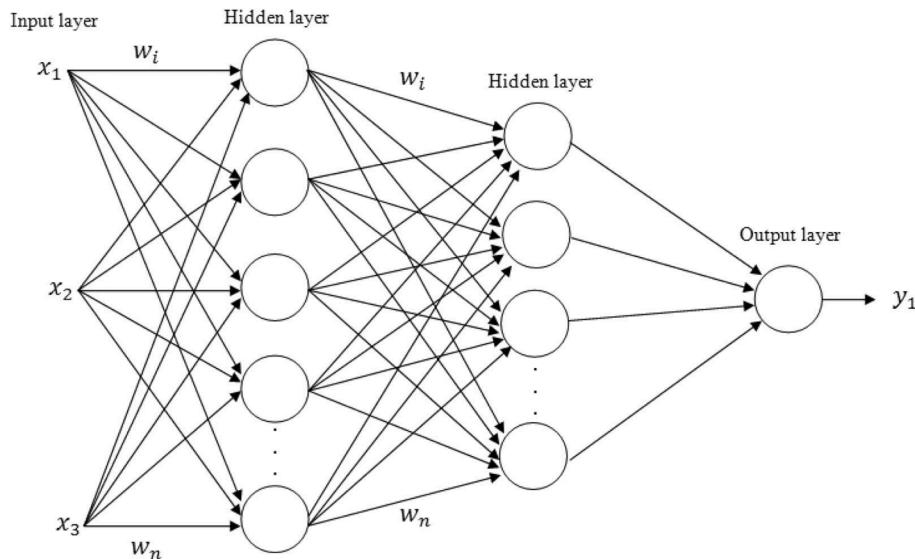
### Multilayer perceptron network

Multilayer Perceptron network is a feed-forward and supervised ANN that provides a non-linear mapping of explanatory parameters (inputs) and corresponding variables (outputs). It consists of an input layer, one or more hidden layer(s), and an output layer. The input layer consists of a set of neurons referring to the selected features, for example, meteorological parameters. The hidden layer transforms values from the input layer with a linear summation of weights and feeds them to the next layer. Whenever there is more than one hidden layer, the output from one hidden layer is fed to the following hidden layer. The last hidden layer transforms values to the output layer, which, in this case, is the number of passengers per hour. Given a training dataset with a set of features  $X = x_1, x_2, \dots, x_n$  and the output variable  $y_t$ , the model learns a non-linear function approximation and updates the weights  $w_i$  after each iteration. Fig. 2 represents a hypothetical architecture of the MLP network with two hidden layers and three input variables.

Since the MLP performance depends on the value of its *hyperparameters*, determining the optimal hyperparameter values is crucial. These hyperparameters are hidden layer size, activation function, solver, learning rate, and alpha (parameter of regularisation term). The hyperparameter tuning consists of identifying the optimal values for the hyperparameters. For this purpose, preliminary experiments were carried out to specify the MLP hyperparameter values. The search was conducted with different ranges of each hyperparameter as follows:

- Hidden layer size: [(256, 128, 64, 32, 16),(128,64,32, 16), (64,32,16), (100)]
- Activation function: [tanh, rectified linear unit (relu), logistic]
- Solver: [stochastic gradient descent (SGD), adam]
- Alpha: [0.1, 0.01, 0.001, 0.0001]
- Learning rate: [constant, adaptive]

In order to find out the optimal configuration of hyperparameter



**Fig. 2.** Architecture of MLP network (Coutinho et al., 2018).

values, Grid-Search is implemented in Python using the Scikit-learn library with 1000 iterations. It tries all combinations of the previously mentioned hyperparameter values, evaluates the model for each combination by applying a cross-validation method, and finally chooses the one with the best performance.

In general, we aim to build an association between the meteorological parameters and bus ridership. The primary notion behind the prediction is to train the model with the historical data and then predict the future ridership while considering the input parameters as covariates. In addition to the meteorological parameters, national holidays, school holidays, football matches, and cancelled trips are also inserted in the model (see Table 1). Though Christmas holidays are also part of the national and school holidays, travel behaviours differ during this period of the year compared to other holidays. Therefore, these days are categorised as a separate variable.

Note that MLP performs better and faster when the parameters are standardised, for example, to a range of 0 to 1 (LeCun et al., 2012). Inserting the actual values of the parameters as presented in Table 1, which are mixed with both continuous and categorical variables with

different units, will make the MLP models unstable (Zheng et al., 2016). This is because MLP is sensitive to input variables, and large weights will be given to variables with large values during the training process. Therefore, standardising the input and output variables enables the model to learn easier, especially with a large spread of values (Kothari and Oh, 1993). In this study, we standardised the set of input parameters using 'Robust Scaler' from the Scikit-learn library.

The MLP network is implemented under three scenarios on weekdays and weekends separately. The first scenario refers to the base model where the MLP accounts only for temporal and additional parameters (see Table 2), such as school and public holidays, football matches, and bus trip cancellations. These parameters can influence travel demand regardless of the weather conditions. We included the meteorological parameters in the following scenarios. First, we added the weather conditions of the same hour as boarding time into buses, which refers to Scenario 2 of the study. Second, the weather conditions from one hour ahead of boarding time are inserted into the prediction model (Scenario 3). The assumption is that individuals change their travel decisions based on the weather conditions observed during their departure times (hereafter same-hour weather conditions) or the weather conditions of the following hour (hereafter next-hour weather conditions). Comparing the performance of all three models, we can determine the impact of weather conditions on the models' accuracy and the travel behaviour of bus users.

Table 2 shows the complete list of parameters that are taken into consideration in each scenario.

### Data sources and processing

The data used for this study consists of public transport smart-card data (known as OVChipkaart) provided by Keolis Nederland, the bus service provider of the Twente region, and meteorological data retrieved from the Royal Dutch Meteorological Institute (KNMI)<sup>2</sup>. The datasets are integrated considering the boarding time (check-in transactions) and hourly averaged meteorological parameters for the Twente region.

Each OVChipkaart record represents a single transaction generated as a cardholder uses his/her card to tap in/out during boarding and alighting. The information recorded for each transaction includes trip details, such as the date and time of check-in and check-out, bus stops,

<sup>2</sup> Koninklijk Nederlands Meteorologisch Instituut - the Dutch national weather service.

**Table 2**

Set of input parameters included in the base model and scenarios.

	Meteorological parameters									Temporal parameters		Additional parameters				
	T	WX	WY	RH	SD	PA	PD	R	S	DW	H	SH	PH	CH	F	CT
base model										x	x	x	x	x	x	x
C2	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
C3	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x

bus lines, user types, and card ID. The smart-card data contains transaction records from the Twente bus network between January 1, 2018, and December 31, 2019. After screening the data for outliers and invalid values, such as missing check-in/check-out, around 15 million data points were recorded within these two years. For the purpose of this study, the smart-card data has been aggregated on an hourly basis, from 6:00 am to 11:00 pm.

The meteorological data were measured at station 290 - a weather station located in the north of Enschede next to the Twente airport. The data includes the hourly measurements for several meteorological parameters, including temperature, wind speed, wind direction, humidity, precipitation amount, precipitation duration, sunshine duration, air pressure, radiation, and cloud cover. However, not every weather parameters are influential on bus ridership or travel behaviour in general. Because travel choice behaviour is primarily affected by weather forecast<sup>3</sup> rather than actual measurements, we considered only parameters that are usually available on the weather forecast websites or mobile apps (e.g., KNMI, buienradar, buienalarm). These parameters are temperature, humidity, wind speed and direction, precipitation amount and duration, and sunshine duration. It must be noted that the wind speed and wind direction are transformed into new parameters: wind speed in X (east) and Y (north) directions. The negative values indicate the wind speed from opposite directions, west and south.

Table 3 shows the descriptive statistics of the smart card and the weather data. The number of passengers (patronage) ranges from 1 to 4911 per hour. Regarding the meteorological parameters, the temperature can go below zero (-10 °C), mainly in January and February, and up to 39.8 °C in July. The sunshine duration and the precipitation duration are measured based on the one-hour scale. Since the weather data is on an hourly basis, 1 means that it was sunny for the entire hour and 0 means no sunshine. The precipitation amount refers to the

magnitude of rainfall and snow and is measured in millimetres per hour (mm/hour). The difference between rainfall and snow is made by two other parameters: rain [0,1] and snow [0,1]. For example, if the rain parameter is 1, the precipitation refers to rainfall, and if the snow is 1, it indicates there was snow. As mentioned in the previous section, the wind speed and direction are transformed into two new parameters, wind speed in X and Y directions. For these parameters, the minimum values (-13.16 and -19.00) refer to the wind speed from the west and south. So, the wind speed from the south is the strongest; also, the wind speed from the west is higher than the wind speed from the east. We used 80% of the dataset to train the models and 20% to test them.

## Results

Table 4 provides an overview of the architecture and performance of the MLP models under three scenarios after tuning for the optimal hyperparameter values. We used MAEs and the explained variance score (EVS) to compare the performance of the models. MAE refers to the average differences between predicted and actual values concerning the test dataset. EVS is used to assess the goodness of fit of a model. The score implies how much of the variance in the dataset is explained by the model. A higher EVS means that the model is a better fit for the data, where 1.0 is the best possible score.

Regarding the hyperparameter tuning, including and excluding the meteorological parameters from the model resulted in different MLP network architectures concerning the hidden layer size, activation function, alpha, and learning rate. Regardless of the architecture, the model error is notably reduced due to including the meteorological parameters. The MLP base models have the highest MAEs, in which the weather conditions were not included. On weekdays, the MAE in the base model is 292.0, whereas it is 211.57 in C2 and 223.01 in C3. Comparing with the average ridership on weekdays, 1628 passengers/hour, the errors are 17.9%, 13.0%, and 13.7% in the base model, C2, and C3, respectively. This implies that compared to the base model, the same-hour and next-hour weather conditions have improved the models' performance by 4.9% and 4.2%. The model with the same-hour weather conditions slightly outperformed the model with the next-hour conditions. This is also reflected in the EVS values, where the C2 and C3 models better fit the dataset. On the weekends, the prediction error also reduces by including the next-hour weather conditions in the model. Considering the average bus ridership on the weekends, 429 passengers/hour, the MAE has been reduced from 13.3% in the base model to 10.5% in C3, which is also the best fit for the dataset considering its EVS value, 0.953. Similarly, the model with the same-hour weather conditions performs better than the base model but slightly worse than the C3 model.

The MAE and EVS terms discussed previously provide limited insights into the actual accuracy of the models. One cannot conclude if the predictions have acceptable accuracy compared to the actual values. Therefore, we tested the MLP models on a few randomly selected days<sup>4</sup> from the test dataset to assess when and why the models performed better or worse. Fig. 3 represents the prediction results on a weekday and a weekend. As shown in Fig. 3-a, the MLP models have better

**Table 3**

Descriptive statistics of the smart card and weather data.

Parameter	Mean	Standard dev.	Min	50%	Max
Demand (patronage/hour)	1105.58	1099.96	1.00	634.00	4911.00
Temperature (°C)	11.07	7.34	-10.10	10.60	39.80
Sunshine duration (hour)	0.22	0.36	0.00	0.00	1.00
Precipitation duration (hour)	0.07	0.22	0.00	0.00	1.00
Precipitation amount (mm/hour)	0.08	0.48	0.00	0.00	29.80
Relative humidity (%)	77.67	17.90	17.00	82.00	100.00
Rain [0,1]	0.20	0.40	0.00	0.00	1.00
Snow [0,1]	0.01	0.11	0.00	0.00	1.00
Wind speed in X direction (m/sec)	-1.05	2.77	-13.16	-0.94	9.85
Wind speed in Y direction (m/sec)	-0.81	2.81	-19.00	-0.69	8.86

<sup>3</sup> Note that weather forecasts are replaced mainly by the actual measurements as soon as they are available. Thus, we could not find any sources that provide historical data on weather forecasts.

<sup>4</sup> The actual dates are removed from these figures due to the privacy policy of the smart-card data provider.

**Table 4**  
Models' architectures and performances.

Scenario		Hidden layer size	Activation function	Solver	Alpha	Learning rate	MAE	EVS
Weekdays	base model	(64, 32, 16, 8)	tanh	adam	0.1	adaptive	292.00	0.90
	C2	(128, 64, 32, 16)	tanh	adam	0.01	constant	211.57	0.94
	C3	(64, 32, 16, 8)	tanh	adam	0.1	adaptive	223.01	0.94
Weekends	base model	(128, 64, 32, 16)	relu	adam	0.001	constant	57.26	0.92
	C2	(256, 128, 64, 32)	tanh	adam	0.1	adaptive	51.00	0.94
	C3	(128, 64, 32, 16)	tanh	adam	0.1	adaptive	45.23	0.95

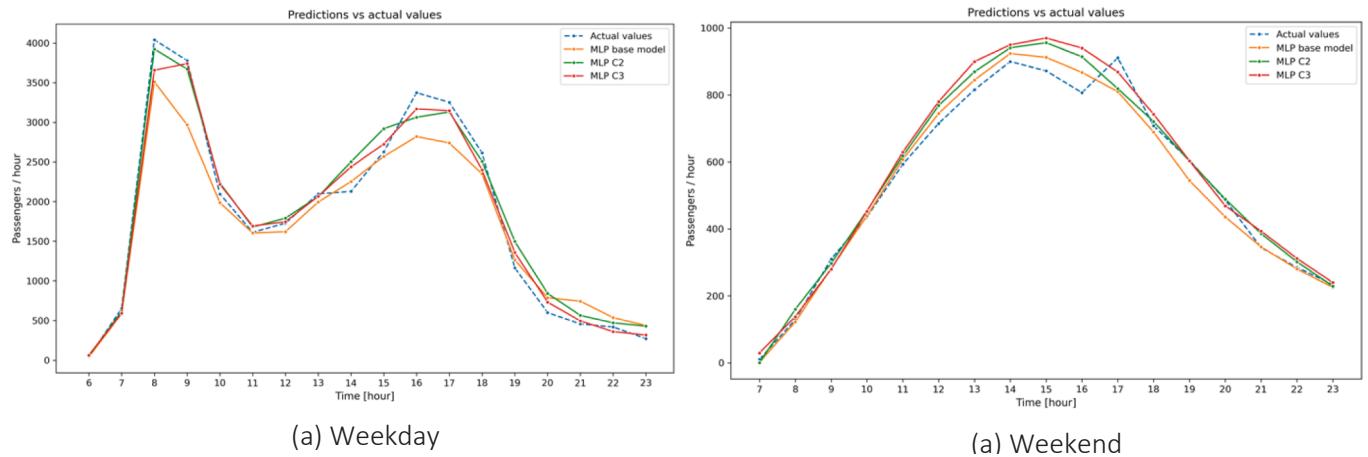


Fig. 3. Predicted vs actual ridership on randomly selected days.

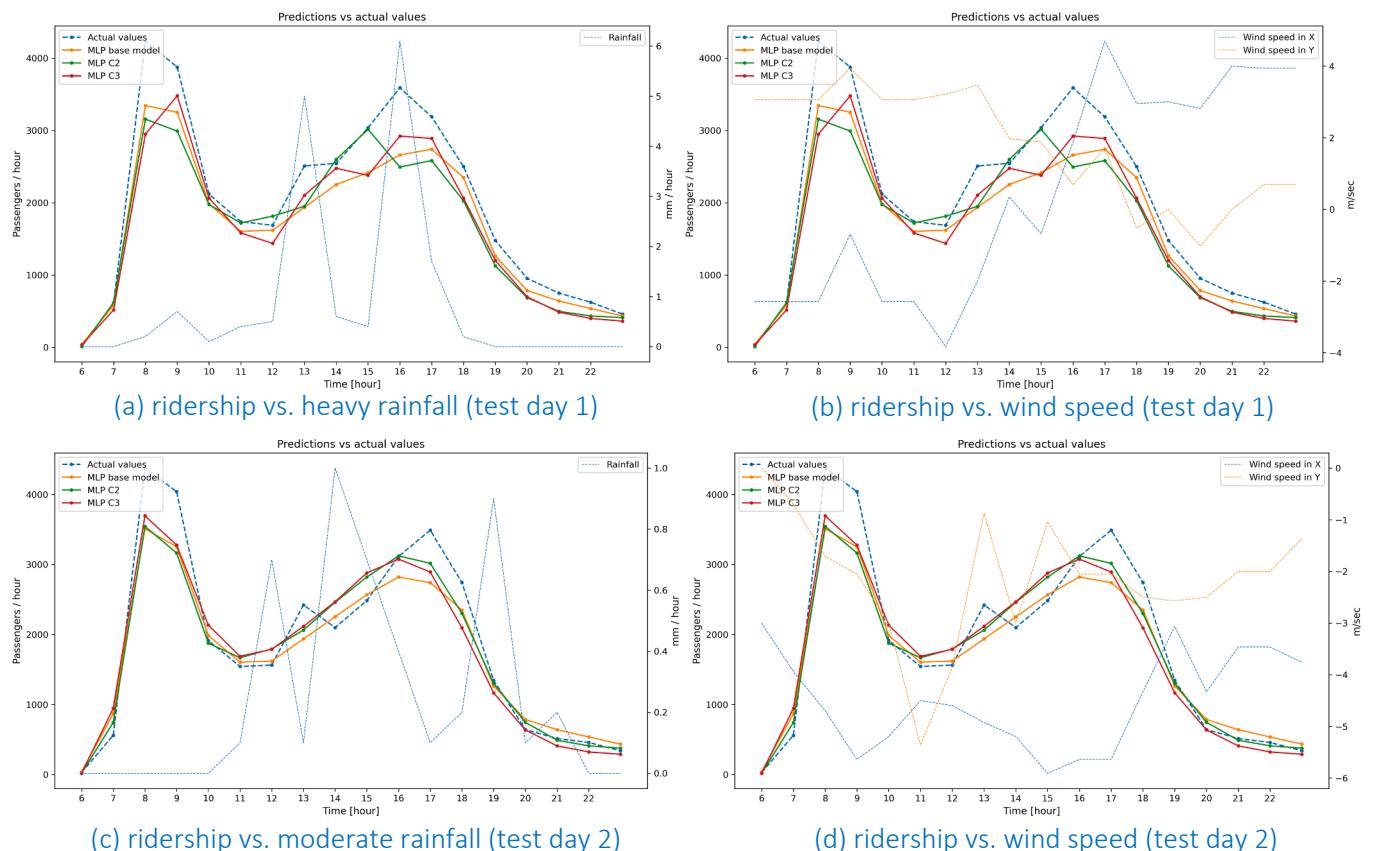


Fig. 4. Predicted vs actual ridership on two randomly selected weekdays.

prediction accuracy on the weekday in C2 and C3 than the base model. The predicted ridership is very close to the actual values, especially during the morning and afternoon peak hours, where the base model has larger errors than C2 and C3. The slightly larger errors between 1:00 pm and 6:00 pm are due to ridership fluctuations on the tested days. However, the bus demand slightly increased after the lunch break (1:00 pm) on several weekdays and was more noticeable on rainy days. On the other hand, there is very little difference between the base model and C2 and C3 on the weekend (as shown in Fig. 3-b). Note that the weather conditions were relatively good, and no major events happened on these days. It is also worth mentioning that the peak demand on the weekends starts slightly after mid-day (12:00 pm), which is not unusual in the Netherlands (also many other countries). The explanation is that people do not commute to work on the weekends and, therefore, the typical weekday morning and afternoon peaks do not happen on the weekends.

Nonetheless, the prediction accuracy drops on days with extreme weather conditions (e.g., heavy precipitation and strong wind). For instance, when the precipitation reaches 5–6 mm/hour, as presented in Fig. 4-a, all MLP models underestimate the ridership during the morning peak hours. Despite obtaining slightly better predictions when including the next-hour weather conditions (C3), all models have relatively higher errors during rainy hours. Associating this with strong wind speed in the Y direction (north and south) (as shown in Fig. 4-b), more people travel by buses on this day, while the models predicted fewer passengers. Unlike heavy precipitation, the ridership does not increase or decrease much during moderate precipitation up to 1.0 mm/hour (see Fig. 4-c). However, rainfall alongside strong wind speed increases the number of passengers per hour during the morning and afternoon peak hours (Fig. 4-d). Overall, extreme weather conditions degrade the prediction accuracy on weekdays under both scenarios (C2 and C3), especially during the morning peak.

On the weekends, the influence of weather conditions on prediction accuracy differs between Saturday and Sunday. For instance, during the heavy precipitation and strong wind from the south on a Sunday afternoon presented in Fig. 5-a and Fig. 5-b, both predicted and actual

ridership levels are indifferent to the meteorological parameters. As shown in the figures, the heavy rainfall and strong wind speed had almost no impact on the actual or predicted ridership. However, on Saturdays (Fig. 5-c and Fig. 5-d), there is a slight increase in bus ridership during moderate precipitation in the morning, followed by relatively moderate wind in the next hour. Even though all models have acceptable accuracy on the weekends, considering the next-hour weather conditions improves the models' performance.

Other meteorological parameters, such as temperature, sunshine duration, and relative humidity, do not cause any instant increase/decrease in the bus ridership. However, including them in the models improves the prediction accuracy considerably. For example, Fig. 6 presents the actual and predicted ridership on a randomly selected weekday when the temperature is below zero in the morning and the relative humidity is high until around 6:00 pm. Compared to the base model, the models with meteorological parameters provide relatively better predictions throughout the day.

During public and school holidays, the travel patterns of bus users become less predictable; thus, the models exhibit higher errors in predicting bus ridership on such days. As shown in Fig. 7-a, there is a noticeable decrease in bus ridership on a school holiday, which make sense because students make up a significant proportion of bus travellers in the region. The striking point is that, unlike other weekdays, the bus demand is higher during the afternoon compared to the morning. We did achieve better results when accounting for the weather conditions, but the predictions are still far from the actual values during the afternoon peak. Unlike school holidays, football matches in the local stadium of FC Twente have a low impact on both actual and predicted bus ridership (Fig. 7-b). Perhaps this is because only bus line 1 passes by the stadium, which is replaced by off-the-record buses during football matches. Since check-in and check-out are not required for these buses, no data is available either.

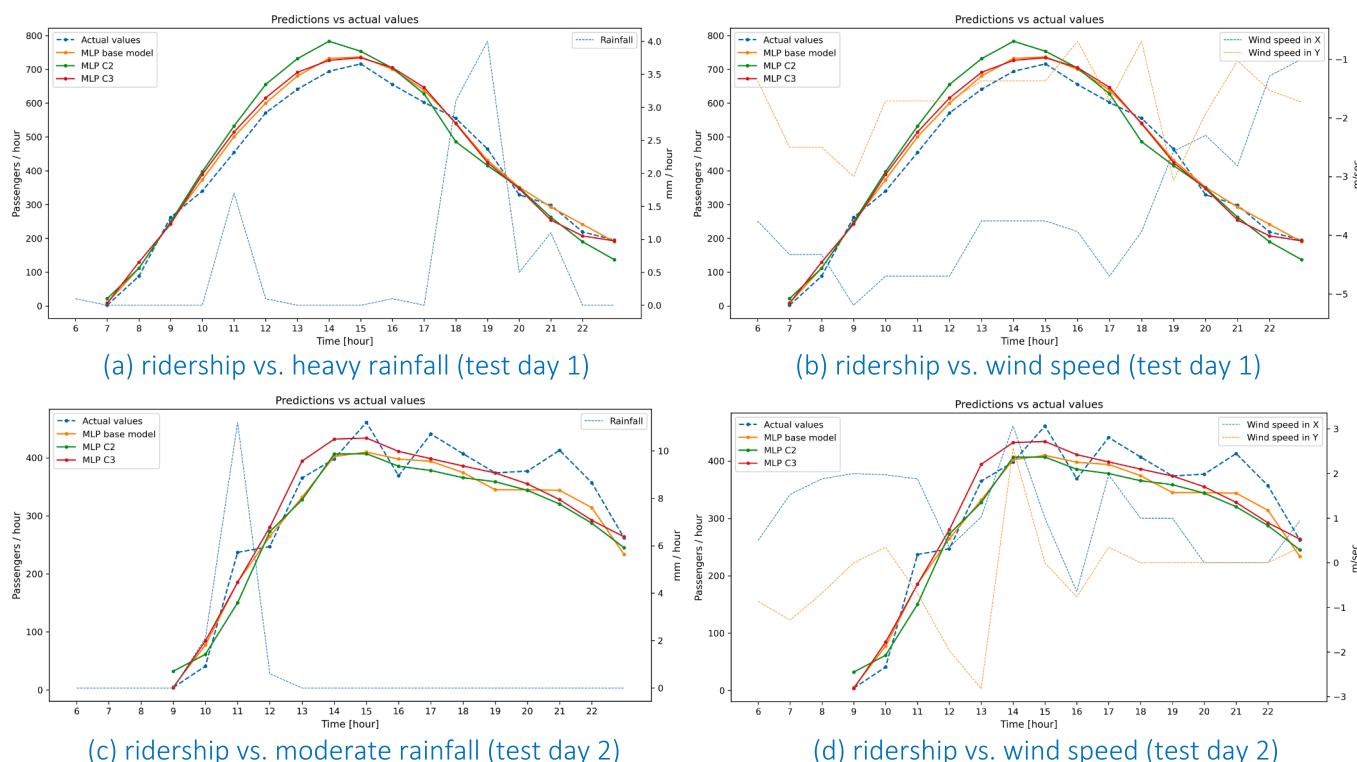


Fig. 5. Predicted vs. actual ridership on two randomly selected weekends.

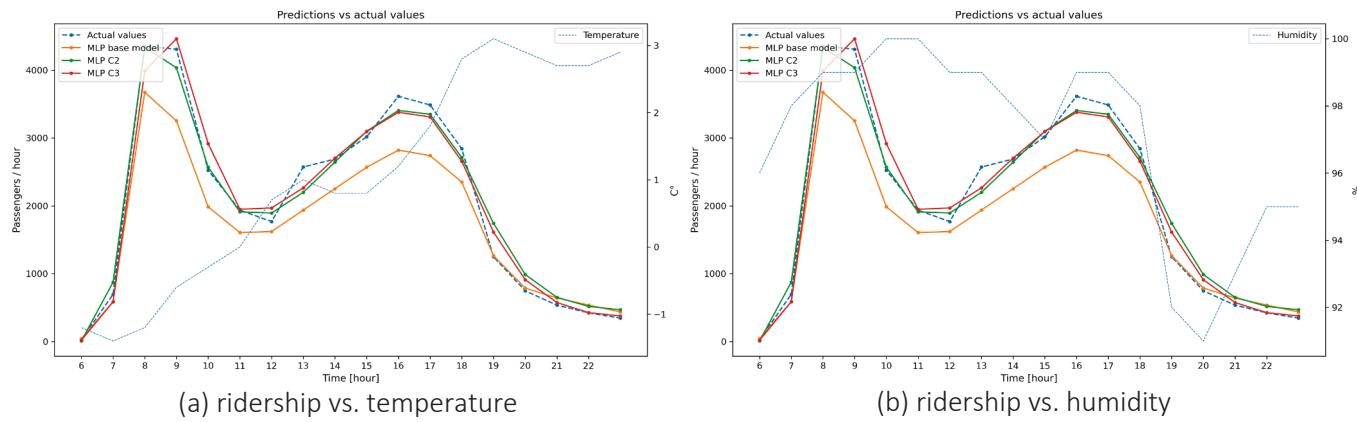


Fig. 6. Predicted vs. actual ridership on weekdays.

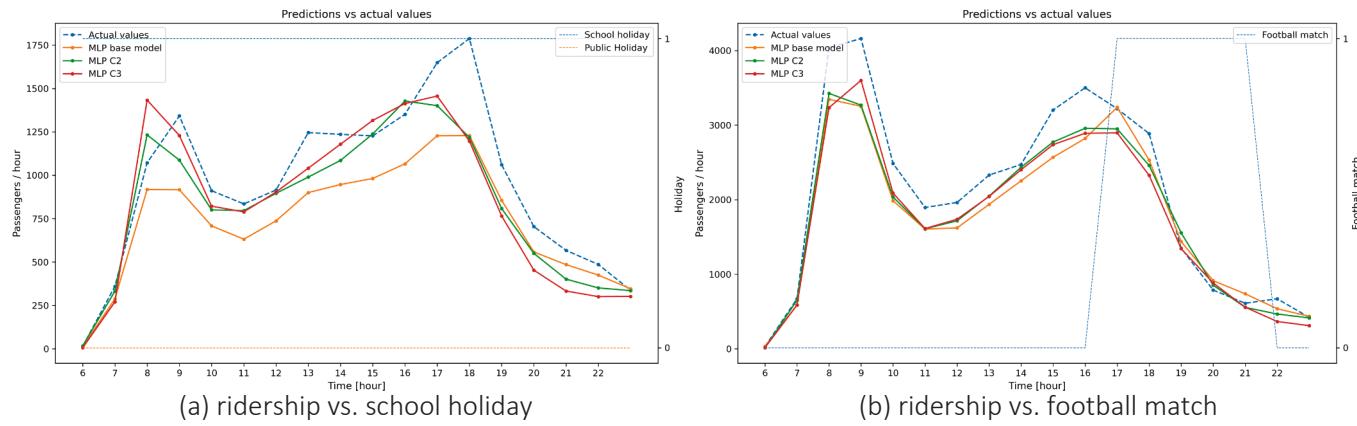


Fig. 7. Predicted vs. actual ridership on weekdays.

## Discussion and limitations

The results show that the deep learning algorithm - MLP network - is a promising approach to predict bus ridership while accounting for the impact of the weather conditions and other relevant parameters. Our predictions are notably accurate on regular weekdays without extreme weather or major events when accounting for the meteorological parameters. However, as the weather conditions worsen, the MLP models show higher errors. Although the prediction errors on weekdays were improved by 4.9% and 4.2% in C2 and C3 compared to the base model, the models showed relatively larger errors during extreme weather conditions. For instance, on weekdays with heavy precipitation and strong wind speed, the MLP models under-estimated the bus ridership at 8:00 am and 9:00 am. Also, the differences between the actual and the predicted ridership were relatively high during the rainy hours. One explanation is that the travel behaviour of public transport users is less predictable during extreme weather conditions. Various modal shifts could happen simultaneously (i.e., from cycling to public transport, from public transport to private cars, or even avoid travelling), making it difficult for predictive models to learn such travel patterns. On the contrary, the MLP models performed better on weekdays with moderately severe weather conditions. On such days, including the meteorological parameters (in C2 and C3) could significantly reduce the models' errors.

The impacts of other meteorological parameters, such as temperature and relative humidity on the bus ridership were not immediate. In other words, these parameters did not cause any abrupt increase or decrease in the number of passengers per hour. However, including them in the models could noticeably improve the models' performances.

The reason could be that these parameters have less influence on their own, but in association with other meteorological parameters results in better prediction of bus ridership. However, the improvements were relatively less on the weekends. Including the meteorological parameters could reduce the MAE by 1.4% in C2 and 2.8% in C3 concerning the weekends' dataset. Despite differences between Saturdays and Sundays, the predictions showed an acceptable margin of accuracy on weekends.

It must be noted that the weather data used in this study was based on the actual measurements obtained from the weather station. Nonetheless, travel behaviour is more subject to weather forecasts rather than the actual measurements. Assuming that people decide whether or not to use public transport based on the weather conditions, only a couple of predicted weather parameters are available to the public. Moreover, the weather forecasts are subject to uncertainties, especially in the Netherlands, where weather can be very unpredictable. Therefore, the accuracy of bus ridership predictions depends on how accurate the weather forecasts are.

Furthermore, the weather forecasts are usually available for the next couple of days, for example, the next seven days. Later than that, the weather forecasts are subject to (very) high uncertainties. Due to this, the prediction models discussed in this study could only be used to predict bus ridership levels in the short future.

Another limitation of this study is that the smart-card data was aggregated on an hourly basis because the weather data was provided on an hourly basis. However, since the bus headway is usually 10–30 min, at least on weekdays, bus ridership might vary on a finer scale than the hourly basis.

## Conclusion

Existing studies have shown that weather conditions can significantly influence public transport ridership. In this study, we forecast the bus ridership in the Twente Region in the Netherlands, concerning the weather conditions, using multilayer perceptron networks and utilising smart-card and the weather data collected in 2018 and 2019. The following conclusions are drawn from the present study: (1) the application of the MLP algorithms is very promising for predicting bus ridership on weekdays and weekends, (2) models with the same-hour and next-hour weather conditions have low errors, where the latter performs better during severe weather conditions, (3) the predictions are relatively less accurate on days with extreme weather conditions than on days with good weather conditions, even though including the next-hour weather conditions improves the models' performance on such days, (4) the MLP network cannot detect small changes in the bus ridership caused by weather conditions or football matches, (5) other meteorological parameters, such as temperature and relative humidity, do not cause instant changes in the bus ridership. However, including them in the models resulted in better predictions.

For future research directions, the MLP models developed in this study could be adapted to a finer level, for example, by predicting bus ridership per bus stop or bus line. In addition, future studies can also account for the impact of spatial-related parameters such as city lines and rural lines. Finally, it might be useful to factor trip purposes (e.g., work, shopping, school) into the modelling and reflect on the impact of the weather conditions on different types of public transport users.

## CRediT authorship contribution statement

**Zakir H. Farahmand:** Methodology, Visualization, Writing – original draft. **Konstantinos Gkiotsalitis:** Writing – review & editing. **Karst T. Geurs:** Writing – review & editing.

## Declaration of Competing Interest

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.

## Data availability

The authors do not have permission to share data.

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