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Estimation of train dwell time at short stops based on track occupation event data: a study at a Dutch railway station

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SUMMARY

Train dwell time is one of the most unpredictable components of railway operations, mainly due to the varying volumes of alighting and boarding passengers. However, for reliable estimations of train running times and route conflicts on main lines, it is necessary to obtain accurate estimations of dwell times at the intermediate stops on the main line, the so-called short stops. This is a great challenge for a more reliable, efficient and robust train operation. Previous research has shown that the dwell time is highly dependent on the number of boarding and alighting passengers. However, these numbers are usually not available in real time. This paper discusses the possibility of a dwell time estimation model at short stops without passenger demand information by means of a statistical analysis of track occupation data from the Netherlands. The analysis showed that the dwell times are best estimated for peak and off-peak hours separately. The peak-hour dwell times are estimated using a linear regression model of train length, dwell times at previous stops and dwell times of the preceding trains. The off-peak-hour dwell times are estimated using a non-parametric regression model, in particular, the *k*-nearest neighbor model. There are two major advantages of the proposed estimation models. First, the models do not need passenger flow data, which is usually impossible to obtain in real time in practice. Second, detailed parameters of rolling stock configuration and platform layout are not required, which makes the model more generic and eases implementation. A case study at Dutch railway stations shows that the estimation accuracy is 85.8% - 88.5% during peak hours and 80.1% during off-peak hours, which is relatively high. We conclude that the estimation of

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dwell times at short stop stations without passenger data is possible.
KEYWORDS: Prediction; dwell time; estimation; short stops; track occupation; regression model

1. INTRODUCTION

Model predictive control has recently been widely used in railway traffic control research, especially in the field of rescheduling [1-5]. Prediction of train dwell times at stations is one of the most important phases in solving the problem. It provides the predicted train trajectories and conflicts to the train dispatchers and is thus an important input to adjust the timetable to resolve the conflicts between train paths. The estimation of dwell times, especially at short stops on main lines, may have a great influence on the result of conflict detection. Short stops are stops on the open track where sidings are usually not available and where trains only dwell for alighting and boarding, after which they immediately continue their journey. The short stop stations have three characteristics. First, they have no siding track, so there is no opportunity for fast trains to overtake slower trains at such stations; second, there are no passenger connections, so the dwell time does not contain passenger connection time; and third, the dwell times are not scheduled. The dwell times at short stops are usually less than one minute. Because the precision of the timetable is one minute, these dwell times are an integrated part of the overall running time over the open tracks between stations. A good estimation of these dwell times is thus required to be able to predict headway conflicts on the open tracks and arrival times at the main stations at the end of the open tracks.

Thus far, dwell times at short stops have not been well estimated. Previous studies [6-9] show that the number of boarding and alighting passengers is the main determinant of the dwell times, especially at stations that have no passenger connections from one train to another. However, due to the difficulty in obtaining passenger demand in real time, most of the existing models, which represent dwell time as a function of the number of boarding and alighting passengers, cannot be used for real-time rescheduling. This is a great challenge for more reliable, efficient and robust train operations. Another challenge associated with the dwell time estimation approach is the model generality. In the past, most of the dwell time estimation models were based on the station layout, rolling stock configuration and passenger demand. However, these variables can be different in different cases which may limit the model generality. For example, different passenger alighting and boarding behaviors in different countries can hardly be described in one model. To resolve these challenges, Li et al. [10] analyzed the influence of the available factors on dwell times from a new perspective, namely, based on track occupation data of Dutch railways, finding that the dwell times at short stop stations are different from those at large stations where train overtaking and passenger connection times are scheduled within the dwell times. Moreover, the dwell times at short stops are influenced by the day of the week, peak hour, and train length in addition to the number of alighting and boarding passengers. This motivates this research: to examine the possibility of developing a dwell time prediction model based on predictors without passenger demand, and improving the generality by excluding specific parameters of station and rolling stock from the model.

This paper first assesses the existing train dwell time estimation methods by comparing their strengths and weaknesses. Second, it selects independent variables, based on the principle of generality and the exclusion of passenger demand, that can be used for estimation. Then, it gives a relatively generic and practical dwell time estimation model using the selected variables. The model neither includes passenger demand which cannot be obtained in real time, nor the detailed parameters of rolling stock configuration and station layout, which may influence the generality.

The remainder of the paper is organized as follows. Section 2 contains a literature review. Section 3 analyzes the influencing factors of dwell times and presents a conceptual model. Section 4 presents the dwell time estimation model. Section 5 validates the proposed model and describes a case study using track occupation event data at Dutch railway stations. We end this paper with conclusions and discussions for further research in section 6.

2. LITERATURE REVIEW

To obtain a more general and practical model, an extensive review of the existing literature is necessary. The existing studies typically concentrate on two types of dwell time modelling approach: regression models and microscopic models.

Among regression models, parametric regression models have been widely adopted. In the earlier literature, the dwell time was estimated as the sum of a constant (representing door opening and closing times and departure preparation time) and the alighting and boarding time (passenger service time). Lam et al. [11] developed a linear regression model to estimate the dwell time as a function of the number of alighting and boarding passengers per train. The assumption of the study is a uniform distribution of boarding passengers on the platform, which may be not true for many stations. According to an investigation on Dutch railways, there are clear concentrations of waiting and boarding passengers around platform access facilities [6]. Wirasinghe and Szplett [12] developed a linear regression dwell time estimation model considering a non-uniform distribution of boarding passengers, calculating the passenger service time of each door and estimating the dwell time as the maximum passenger service time over all doors of the train. Lin and Wilson, Parkinson and Fisher, and Puong [13-15] took the number of standing passengers in the vehicle and their interactions with boarding and alighting passengers into account and developed nonlinear estimation models to reflect such interactions. The problem with these models is that many background variables are not included, such as the composition of the passenger population (e.g., with or without luggage, mobility), configuration of the rolling stock, and the type of station, which have an irrefutable impact on the dwell time [6,7, 16].

To estimate the effect of the configuration of the train on the dwell time, Weston [17] introduced door width factors for the train into a nonlinear regression model. Weston's model is the most comprehensive model of these regression models. It considers the number of alighting and boarding passengers, the interactions between alighting passengers, boarding passengers and standees, and the width of the doors. According to Weston's model, the dwell time will be the same given the same door width of the train and the same number of passengers. However, this may not be true because these models neglect essential factors such as the interior layout of the train and horizontal and vertical gaps between the train and platform, which are obviously different from train to train and also depend on the platform where the train stops. Harris [18] tested Weston's model and found that the interior layout of the train should be considered to improve the model accuracy. Jone [19] estimated the alighting and boarding times at a specific station as a function of the numbers of alighting and boarding passengers and different train services that imply the influence of rolling stock. However, the occupancy of the train and the interaction between passengers are not considered. Buchmueller et al. [8] proposed a dwell time calculation model for regional trains of the Swiss Federal Railways (SBB). The dwell time is estimated as an aggregation of different sub-process times. The distribution of the sub-process times depends on the vehicle type and the number of boarding and alighting passengers, which is analyzed based on sensor data in the trains. The dwell time is calculated as the aggregation of these sub-process times. This model is the most generic one, but it has a disadvantage that the occupancy of the train is not considered. It is also not clearly stated how the distribution times of the sub-processes are aggregated. Furthermore, it is very expensive to install detectors at each door of each running train.

These studies have demonstrated that the dwell time of a train could be modelled by passengers, rolling stock, and station and operation factors. However, none of the existing models fully take all of the influencing factors into account. Hence, these models are not generic, as they cannot be used widely for other trains and stations.

Towards a more generic estimation model, researchers tried to use more general variables in their regression process. Hansen et al. [1] and Kecman and Goverde [5] found that there is a strong relationship between the train dwell time and train arrival delay (or earliness). They estimate the dwell time of a train as a function of its arrival delay, which is derived from track occupancy data of the Dutch Railway. This means that the dwell time of a train is determined mainly by whether it is delayed, no matter how many passengers board and alight or what rolling stock type is used. This makes the model applicable for real-time use. However, later research shows that the error of the model for dwell time estimation is even larger than the corresponding scheduled dwell times. This may be because the linear dependency between the dwell time and delay may be true for early arrival trains at large stations, where the train should wait until the scheduled departure time. However, there is no evidence that it is appropriate for short stop stations, where the dwell time is not scheduled explicitly, and the train driver locks the doors and departs as soon as the alighting and boarding process is finished. When the accuracy of the proposed model is carefully checked, it shows that although all of these models fit more than 80% of the data, most of the mean absolute percentage errors are not reported. According to Puong's model [15], the standard error is 4.04 s, and the mean value of the dependent variable is 27.76 s, which implies an error of 14.55%, while the error of Kecman's model [5] for short stop stations is approximately 15%. That means that there is still space to improve the accuracy of the dwell time estimation regression model.

Microscopic simulation is another approach in research on dwell time estimation. Microscopic simulation models are used to explain some uncertainties of passenger behaviors. These models focus on passenger alighting and boarding behavior and estimate the dwell time of the train by repeated simulations of the passenger alighting and boarding process, recording the dwell time as the average passenger alighting and boarding time of each run. Zhang [21] proposed a microscopic simulation model to estimate the dwell time as a function of the alighting and boarding passengers and the width of the door. Yamamura [9] developed a multi-agent simulation model that also considers the effect of the layout of the rolling stock. These models can describe the train layout and the behavior of passengers in a very flexible and detailed way. However, these models need to be improved because factors such as the horizontal and vertical gaps between the train and the platform are not considered. The applicability of these models in real time use is also doubtful due to their time-consuming calculations and lack of detailed input.

A comparison of existing models is shown in table 1. In table1, only the models that are publicly available are refereed. These models are listed according to whether and how the influencing factors of train dwell time are included. For a more detailed description of these influencing factors, we refer to section 3.2. In summary, all of these models cannot easily be used for real-time estimation and prediction because of the lack of passenger data, low accuracy or time-consuming nature. Therefore, in the next few sections, we will develop a model that can overcome these problems.

3. CONCEPTUAL MODEL

3.1 Dwell time formation

The dwell time is defined as the difference between the train departure and arrival times,

$$DT = t_d - t_a \tag{1}$$

where DT, t_a and t_d indicate the dwell time, arrival time and departure time of the train, respectively. The arrival time is defined as the time when the train changes its state from moving to standing still, and vice versa for the departure time.

Between the arrival time and the departure time, there are at least five processes [8], which are shown in figure 1: door unlocking, door opening, alighting and boarding, door closing, and train dispatching process (signal aspect changing, switch changing and route preparing, and driver operating time). Apart from the train dispatching process, the other processes depend on different doors of a train. Because there is usually more than one door per train, the dwell time is determined by the control door with the maximum time consumption. This is also the main idea of most existing models.

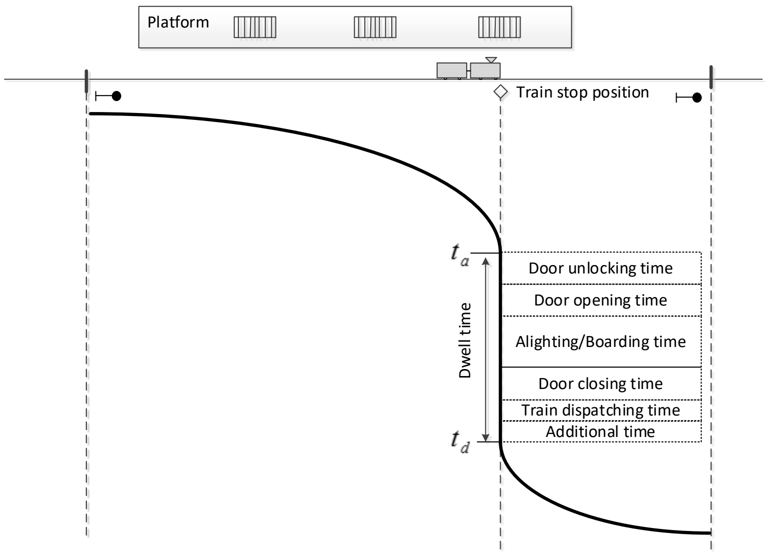


Figure 1: Composition of train dwell time

For some large stations, the actual dwell time is more complicated. It cannot be neglected that other trains also affect the dwell time of a train, for example, train overtaking and meeting, coupling and decoupling, changing running direction, waiting for passenger connections, and the operation margin time for delay recovery, all of which may cause additional time consumption.

3.2 Dwell time conceptual model

The dwell time could be represented as a function of different influencing factors. These influencing factors can be classified into five categories: passenger, rolling stock, station, operation and external factors. Passenger factors include both the number of passengers (number of boarding passengers, number of alighting passengers and number of passengers in vehicle) and the passenger characteristics (gender, luggage, handicap, etc.). These factors influence the alighting and boarding time. The influences from the rolling stock are threefold. First, different types of rolling stock have different door control systems, which influences the door unlocking time, door opening time and door closing time. Second, the number and width of doors, as well as the horizontal and vertical gap between the train and platform, determine the capacity of the doors and influence the passenger boarding and alighting time. Third, the interior layout of the train (seat arrangement, aisle width, and space near the door) may limit the speed of alighting and boarding, thus influencing the alighting and boarding time. Station factors include the position of access facilities on the platform and the layout of the yard. The former has an impact on the alighting and boarding time of a door by influencing the distribution of passengers on the platform, while the latter influences headways between consecutive trains, and thereby the train dwell time. The railway operation factors, such as train delays, train overtaking and meeting, train coupling and decoupling, passenger connections, and operation margins can also introduce extra time to a train's dwell process. External factors include the weather and traffic conditions at level crossings near the platform, which would also have an influence on the train dwell times. Based on this analysis, a conceptual model of the train dwell time is shown in figure2.

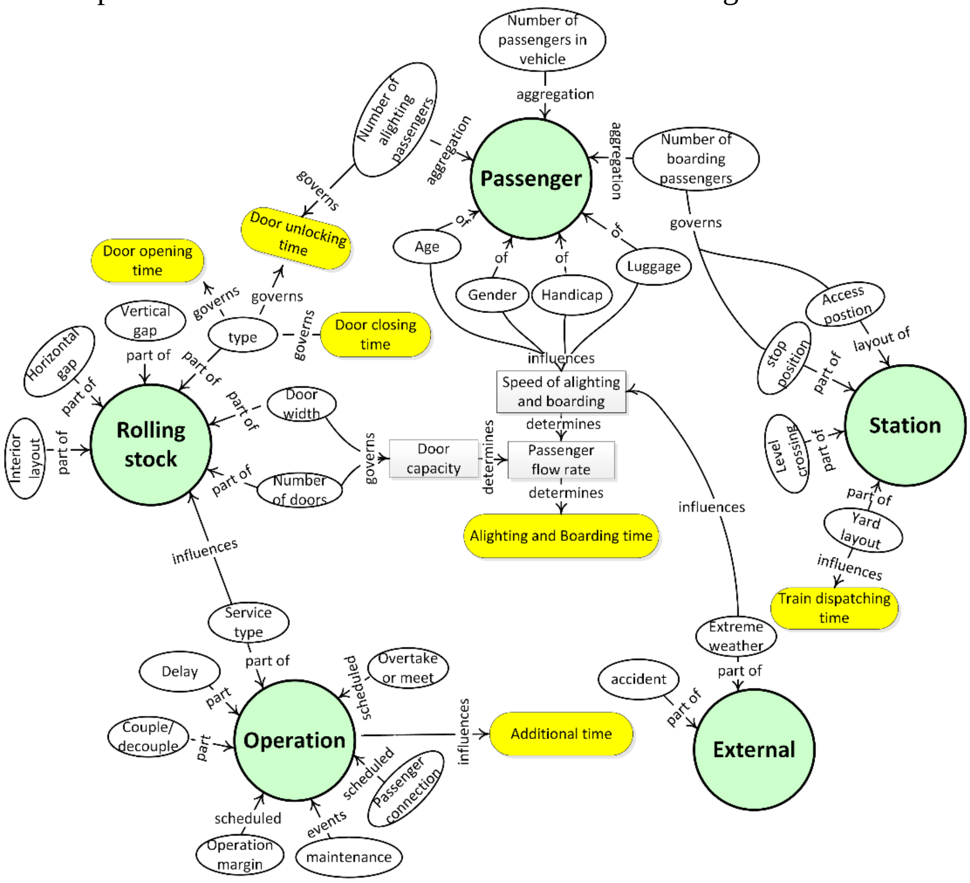


Figure 2: Influencing factors of train dwell time

For short stops, train overtaking and meeting and passenger connections do not play a role. The external factors such as weather conditions are unpredictable, so the operation factors and external factors can also be neglected. The main factors for estimating the dwell times at short stops would be the passengers, rolling stock and station. Because the passenger demand is not available, the best predictors could be from the rolling stock and station factors. This is the basis of the predictor selection.

4. METHODOLOGY

The train dwell time estimation for rescheduling can be described as estimating the dwell time of a train (target train) at a station (target station) given real-time information related to that train and historical data. In most cases, the number of alighting and boarding passengers, which is the most important independent variable, is unknown in real time. Therefore, existing dwell time estimation models, which heavily rely on the actual passenger demand, cannot be effectively used. The main idea of this paper is to find substitute variables that can reflect the passenger demand and to predict the dwell times by using these substitute variables. Most importantly, these variables should be available in real time.

The modelling approaches to similar estimation problems include parametric regression models and non-parametric regression models. The former could provide a clear way to show the effect of each predictor on the dependent variable. However, it is difficult to use parametric regression when there are complicated non-linear relationships between different variables. To some extent, non-parametric regression models can solve this problem. This paper first selects predictors based on the influencing factor analysis and data availability and then it tries to find the relationship between the dwell time and the predictors by applying a parametric model. In case the parametric model cannot fit the data effectively, a non-parametric model is proposed. The estimation accuracy of the model is assessed by performance indicators.

4.1 Predictor selection

As analyzed in section 3, the best predictors of dwell time are the passenger, station and rolling stock factors. Based on this assumption, possible predictors are selected. Given the dependent variable $\hat{D}T_k^s$, which indicates the dwell time of target train *k* at target station *s*, this paper initially selects 11 independent variables as possible predictors that can reflect the three influencing factors to some extent, and more importantly, these predictors can be directly available in real time. The main variables and their meanings are shown in table 2.

In table 2, variables 1 and 2 reflect the time variation of the dwell time. Both predictors can reflect passenger demand without the exact number of alighting and boarding passengers. The peak period is determined based on the passenger demand of the railway in the Dutch railway network as $AT_k \in [6:30, 9:00) \bigcup [16:00, 18:30)$ on weekdays [22]. Statistics [10] show that dwell times in the peak hours are significantly different from during the off-peak hours (p-value = 0). P_k can be considered as a vector that contains one dummy variable, which indicate the peak and off-peak, respectively. Variables 3-10 are possible predictors that could be derived from track occupation data and timetable data. Variable 3 is set because different train lengths require different stop positions, which have a great impact on the dwell time. Variable 4 is selected due to the assumption that train delays may increase the number of passengers on the platform. For frequent service where the passenger arrival time is uniform over time, the higher the delay, the more passengers on the platform, and the dwell time would be influenced correspondingly. Variables 5 and 6 are based on the assumption that there are some relationships between dwell times of consecutive stations. In other words, if the dwell time at one short stop is longer than normal, this may also hold for other trains at other short stops. These variables can also reflect influences from the rolling stock because for a target train, the rolling stock has not been changed from the previous station to the target station. Variables 7 and 8 are based on the assumption that there are some relationships between the dwell times of consecutive trains. These two variables can reflect influences factors from the station because the station remains the same for consecutive trains. Because the length of the previous train may be different from that of the target train, variable 9 is also chosen. Variable 10 is a historical variable. Due to the limited number of cases, we use the dwell times on the same day of the last week as a historical variable, instead of the historical average. We also tested other variables such as headways, including the headway between the target train and the preceding train, the headway between the target train and the following train, and more complicated time series variables including the historical average dwell times of the target train, historical average dwell times of the target train at the previous station and the second previous station, and historical average dwell times of the preceding trains at the target station. However, these variables appear to have very weak relationships with the dwell times of the target train at the target station.

4.2 Estimation models

Based on the selected variables, both a parametric regression model and a non-parametric model are applied.

4.2.1 Parametric regression model

A parametric regression method is introduced to find the quantitative relationships between the selected independent variables and the dependent variable (Table3). The independent variables are fitted by using a step-wise estimation approach. First, we started fitting the regression model from a simple linear model with the minimum number of variables (Model 1). By looking at the influence of each variable separately, more variables are gradually chosen (Model 2 - Model 6) to see whether a better result can be obtained. The decision about the order in which a variable is entered into the model depends on the significance of the relationship between the new variable and the dependent variable as well as the improvement of the estimation accuracy upon adding the new variable. Some non-linear items are also added to examine whether they can improve the accuracy of the model. The non-linear items include both quadratic items and interactive items (Model 7, Model 8 and Model 9). Due to the earlier finding that the dwell times fit the log-normal distribution [10], there is an additional model (Model 10), which is evolved from Model 9. The dependent variable in model 10 is based on the natural logarithm of the dwell time of the target train at the target station instead of the dwell time. The resulting estimation is transformed back to the raw scale by exponentiation. By applying a logarithmic transformation, a normally distributed set of data can be obtained. Another previous study has also shown that such a transformation is statistically warranted [14].

Because the significance of an independent variable is different from the synthesis effect of multiple variables, the significance of each parameter is estimated by using the t-test after a model is selected. Any variable with a large p-value, which indicates that the parameter is not significantly different from zero, is removed from the model. Other combinations are also tested. However, the performances of the other combinations are not better than those of these ten models.

4.2.2 Non-parametric regression model

A non-parametric regression model is also used to estimate the dwell times, especially on the part of the dataset where the parametric model has low accuracy. The reasons are twofold: First, the relationship between the dwell time and the independent variables might not be linear. Taking the delay factor as an example, if the delay is small, the effect of the delay on the dwell time is not significant. However, large delays have a great impact on dwell times due to the accumulation of the boarding passengers. Second, the dwell times at short stops do not fit a normal distribution, which is a compulsory condition of linear regression models. In this case, a linear regression would be likely to fail. An alternative is to use a non-parametric regression. The basic approach of non-parametric regression is influenced by its roots in pattern recognition [23].

The non-parametric regression has been widely used in urban traffic estimation and prediction [24,25], where particularly the method of *k*-nearest neighbors (*k*-NN) was applied. This approach will be used in this paper for its fast calculation and relatively good accuracy. In the *k*-NN method, it is assumed that the dwell time DT_i depends on a series of variables $x_i, i = 1, 2, 3, \cdots, n$. Given the measurement of x_i at the moment of prediction, one can find similar cases (called nearest neighbors) from historical data based on the distance between the historical data points $x_{hist,i}$ and the current observation x_i. The smaller the distance, the more likely DT_i equals $DT_{hist,i}$. More generally, the forecast of DT_i can be computed as the mean of the dwell times of the *k*-th nearest neighbors.

$$DT_i = \frac{1}{k} \sum_{hist-i=1}^{k} DT(x_{hist-i}) \tag{2}$$

The core problem is to define the distance function and the choice of *k*. The simplest way to define this distance is to use the absolute sum of the differences of independent variables $d = \sum |x_i - x_{hist}|$. Other functions include the non-weighed Euclidean distance $d = \sum \sqrt{(x_i - x_{hist})^2}$ and the weighted Euclidean distance $d = \sum w_i \sqrt{(x_i - x_{hist})^2}$ to show the importance of each variable. Different values of *k* will be tested to obtain the minimum estimation error.

4.3 Performance measure

The estimation accuracy is evaluated in terms of the performances of two indicators, the mean absolute percentage error (MAPE) and the root mean square error (RMSE). The MAPE is used to measure the estimation accuracy. The RMSE is also selected to show the actual error when the result is used as an input of the real-time rescheduling model, where the total error is calculated based on the combination of the running time and dwell time.

$$\text{MAPE} = \frac{1}{N} \sum \left| \frac{\hat{D}T_k^s \text{-} DT_k^s}{DT_k^s} \right| \times 100\% \tag{3}$$

$$\text{RMSE} = \sqrt{\frac{1}{N-p} \sum (\hat{D}T_k^s - DT_k^s)^2} \tag{4}$$

where $\hat{D}T_k^s$ and DT_k^s indicate the predicted and observed dwell times of train k at stop s, respectively. N is the total number of trains observed, and p indicates the number of degrees of freedom.

5. CASE STUDY

The purpose of the case study is to calibrate and validate the proposed parametric and non-parametric models based on field data. First, a dataset is created based on Dutch railway stations; second, the proposed models are calibrated and validated using the dataset; third, the accuracies of the proposed models are compared with those of other existing studies.

5.1 Case study setup

5.1.1 Data collection and processing

The Dutch railway line in the Utrecht – Eindhoven area is selected for this case study (see Figure 3). Utrecht and Eindhoven are the fourth and fifth largest cities in the Netherlands. The railway connecting the two cities has a length of 45 kilometers and contains 13 stations. Utrecht, Eindhoven and Tilburg are the main stations: most trains depart and terminate in these stations. Geldermalsen and Boxtel are basic stations that allow trains to merge, diverge and cross. The remaining stations are shortstop stations. There are two types of train lines in this area: intercity trains and sprinters. Intercity trains only stop at main stations and basic stations, while sprinters stop at all stations. A cyclic timetable is widely used, which means that the same number of trains stop each hour. Taking Utrecht – Geldermalsen as an example, there are 6 trains per hour, including two intercity trains between Utrecht and Eindhoven, two sprinters between Utrecht and Tilburg, and two sprinters between Utrecht and Tiel. In the Dutch railway ticket system, the smart card is used. Passengers need to check in and check out via a machine that is placed on the platform. However, there is no passenger flow control gate. Passengers wait for the train on the platform after they check in. For all trains, the train doors will open only if it is activated manually. That means that when boarding or alighting, passengers need to press the button near the door of the train to open the door either inside or outside; otherwise, the door would remain close even if the train has stopped at the station.

Stations in the corridor are distinguished based on four principles:

- Only short stop stations are selected;

- Consecutive short stop stations are selected, so that the relationship of the dwell times between two successive short stops can be examined;
- Stations at which at least 4 trains stop per hour are selected to ensure as many data as possible for a station;
- If a station has recently been reconstructed (e.g., Utrecht Lunetten), which can cause incorrect occupation data, the station is not selected.

Based on these principles, the stations of Houten, Houten Castellum and Culemborg are selected. The train moving direction from Houten to Culemborg is selected. To obtain the influence from dwell times at the previous station and second previous station, Culemborg station is selected as the target estimation station. Houten and Houten Castellum station are selected as the feeders of predictors. The platform configurations of these three stations are shown in figure 4.

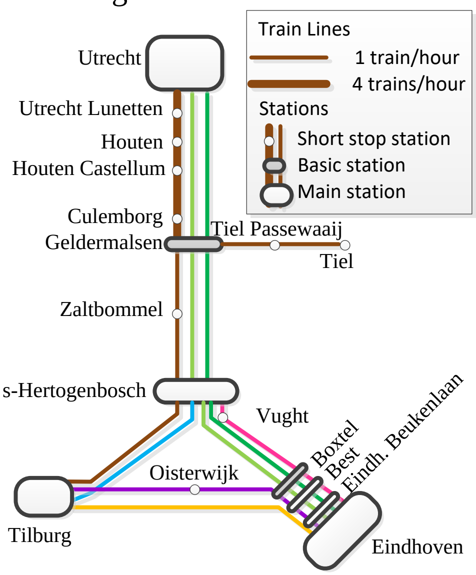


Figure 3: Selected Dutch railway corridor for dwell time estimation

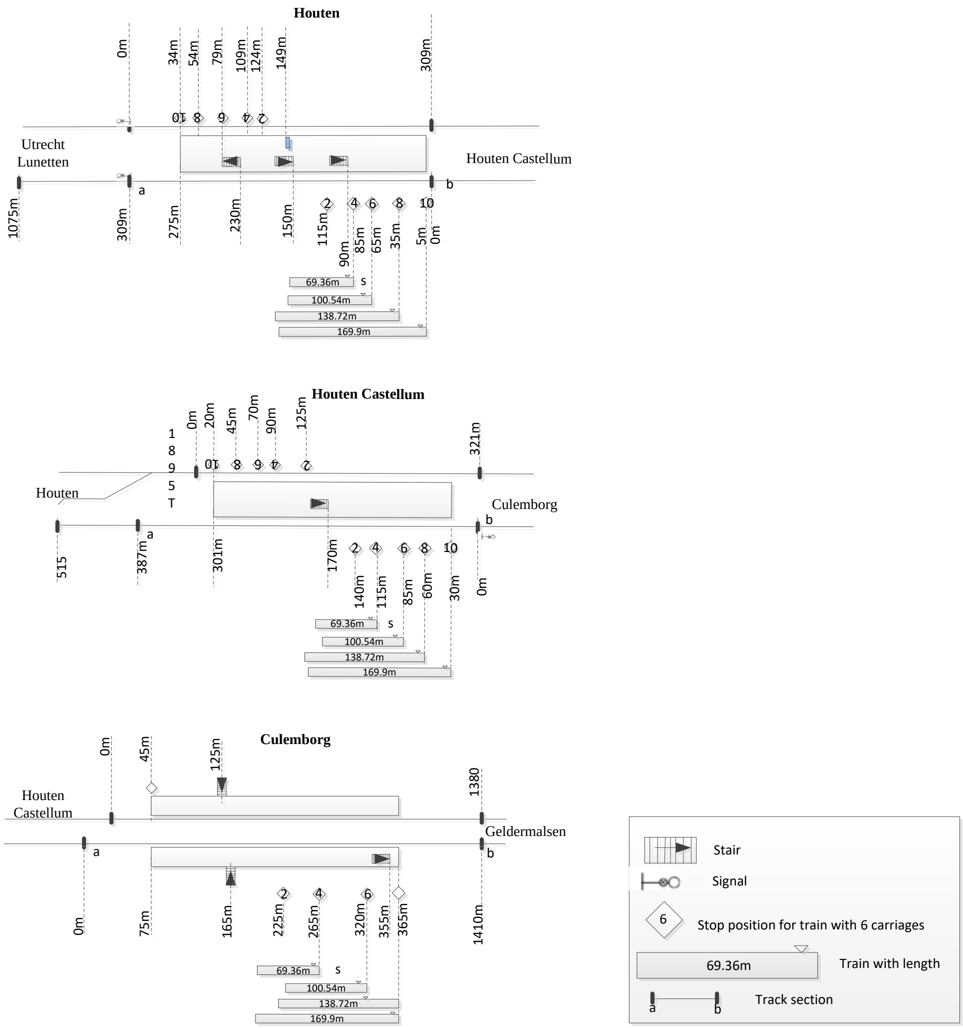


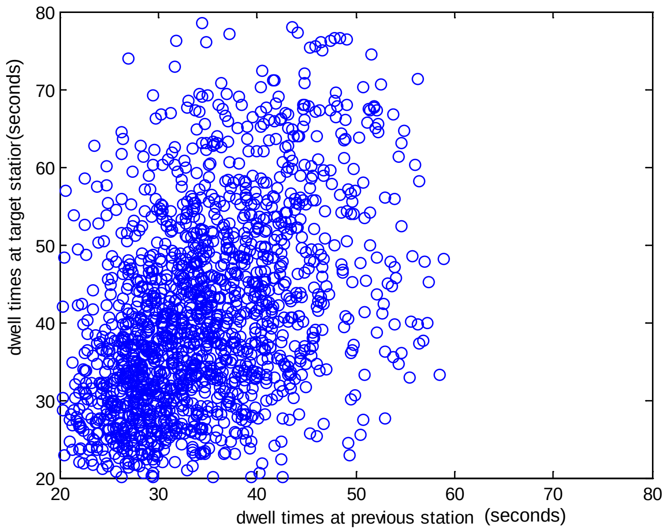
Figure 4: Platform configurations of the selected short stop stations

Two train lines, S6000 and S16000, stop at these selected stations. Both train lines have a train interval of 30 minutes. Thus, there is a train that stops at these stations every 15 minutes.

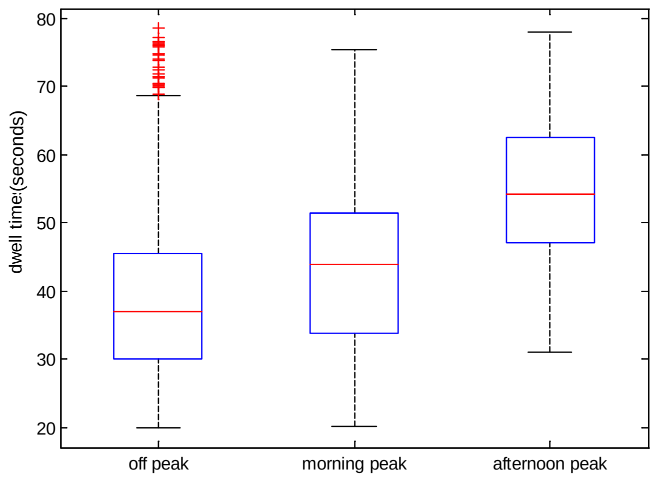
The dwell times at the selected stops and trains are estimated based on the track occupation data. In the Netherlands, track occupation data are collected using a train describer system (TROTS), which provides the exact time of occupation and clearance of track sections [20]. By using a dwell time estimation algorithm [10], a total of 17306 trains running from 1st September 2012 to 30 November 2012 are processed and analyzed.

5.1.2 Correlation Analysis

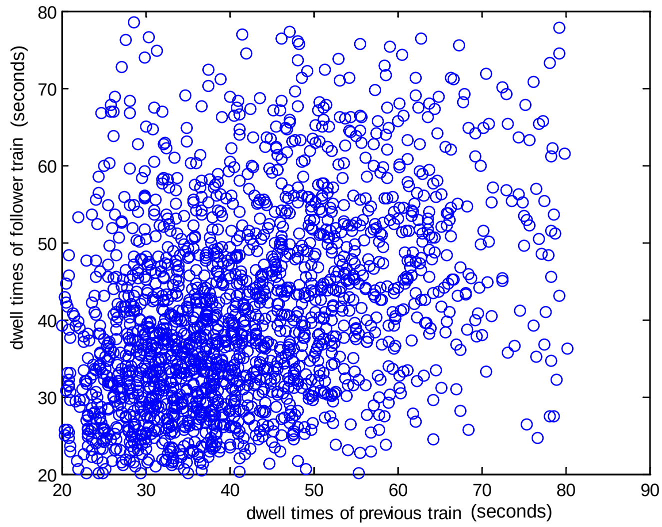
A simple correlation analysis was undertaken to understand the dependent variables and all possible predictors in section 4.1Table 4 shows that all predictors are significantly different from zero ($\alpha = 0.001$). The peak hour, length of the train, dwell times at the previous and second previous stations, and dwell time of the preceding train have weak linear relationships with the dwell time of the target train. The best predictor of the dwell time may be the dwell time of the previous station, with a correlation coefficient of 0.456. Other relatively high correlation coefficients include the dwell time of the second previous station (0.381), peak time (0.376), dwell time of the preceding train (0.376) and train length (0.308). The relationships between these four variables and the dependent variable are shown in figure 5. For relationship plots between the dwell time and other variables, we refer to [10].



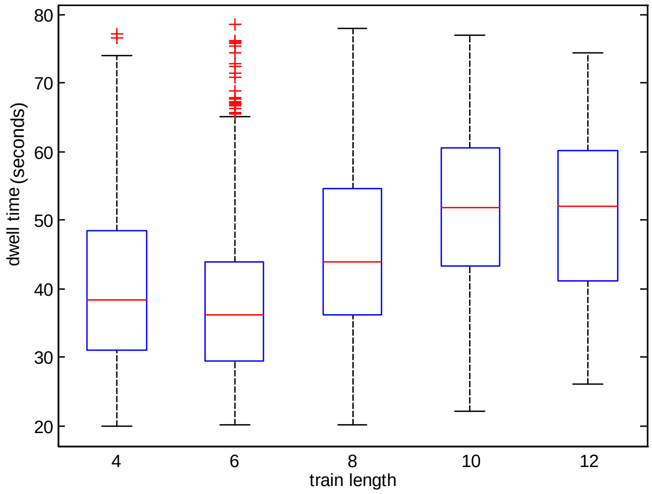
(a) Dwell times between consecutive stations



(b) Dwell times at different periods of a day



(c) Dwell times between consecutive trains



(d) Dwell times for different train lengths

Figure 5: Relationship between dwell time and the most significant variables

From figure 5, it can be seen that the dwell times are rather scattered, although the dwell time between two consecutive trains ranks the highest. The dwell times of off-peak hours are significantly shorter than during the morning peak and afternoon peak. There is a weak linear relationship between the dwell times of the preceding train and the following train. The dwell times of different train lengths are significant. Longer trains lead to longer dwell times. This is because for longer trains, conductors need more time to confirm that there are no passengers boarding before departure. It is also found that the dwell times of train lengths of four and six have a larger standard deviation than those of longer trains. This can be explained because shorter trains have a higher probability of deviating from their stop position and may deviate more from their stop positions than longer trains.

By analyzing the relationships (Table 5) between the ten selected independent variables, the relationships between the dwell times at the previous station and the second previous station, peak hour, train length, last week dwell time, and dwell time of the preceding train seem to be stronger than the others. To avoid overfitting, these variables are tested separately to obtain the best fitting result.

5.2 Parametric Regression results

This subsection presents the parametric regression result by applying the method in 4.2 to the dataset. First, regression models 1 to 10 are applied to the peak hour data and off-peak hour data independently; then, the final model is developed by a certain routine based on the previous step; finally, the final model is calibrated and validated.

5.2.1 Initial regression

The models in section 4.2.1 have been estimated using linear regression for different weekdays, peak or off-peak hours, and different lengths of trains, as well as mixed lengths of trains. The results are compared by using the indicators of adjusted R^2 and RMSE, which are shown in Table 6-9. The following summary can be made:

(1) The estimation results for peak hours are better than for off-peak hours. It is also found that the adjusted R^2 during peak hours is larger than for the same model during off-peak hours. This is because during off-peak hours, the dwell time variation is larger than during peak hours.

(2) During off-peak hours, the R^2 of longer trains' dwell times are much higher than those of shorter trains, which means that the correlation between the dwell time of longer trains and those of the preceding trains and previous stations are higher than for shorter trains. This can be explained by the fact that longer trains have more "rigid" stop positions, so that the spatial distribution of alighting and boarding passengers would not change from train to train; more importantly, travelers may know the positions of the doors for longer trains.

(3) The delay during peak hours may increase the number of passengers on the platform and cause an increase in the dwell time. This effect can be much stronger for shorter trains than for longer trains. This is consistent with the result in table 4. For shorter trains with 4 cars, the adjusted R^2 increased significantly, from 0.245 to 0.722, when a delay is introduced.

(4) Non-linear items do not improve the result significantly, except for the dwell times of eight-car and ten-car trains during the afternoon peak hours and ten-car trains during the weekend.

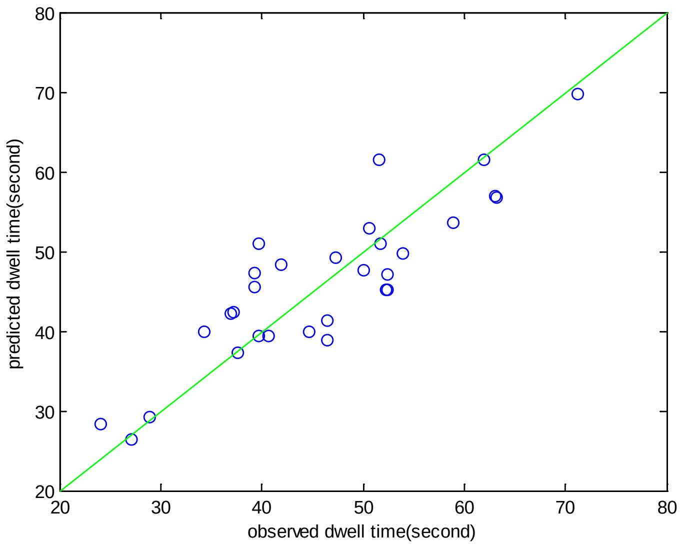
5.2.2 Final model

Next, the peak hour data are analyzed independently by using parametric regression to obtain the final model. Of the above models, the most powerful model is model 5, which is consistent with the previous analysis in table 4. In model 5, the main variables are the dwell times of the previous station, preceding train, second previous station, and second preceding train, as well as the dwell time last week. The final model is obtained by taking the following steps: First, based on this model, low significance variables such as the dwell time of the last week and the dwell time of the second preceding train are removed by using the t-test. Second, if the dwell time of the preceding train remains as an input of the model, the length of the preceding train should be added because the length of the preceding train may be different from that of the target train, which would influence the dwell time significantly. Third, the dwell times at the previous station and second previous station are combined by using their product. This nonlinear item is rooted to keep the same unit for all of the independent variables and the dependent variable. The final model for the dwell time estimation during peak hours is shown in equation 5:

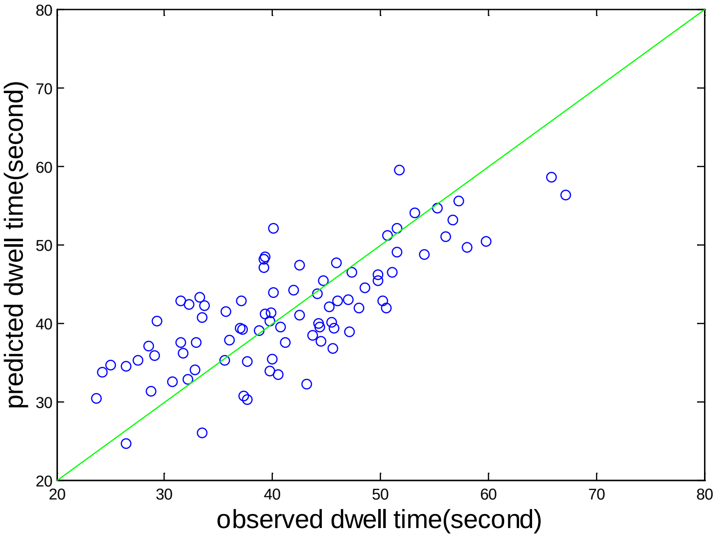
$$DT_k^s = c + \beta_1 L_k^s + \beta_2 L_{k-1}^s + \beta_3 DT_{k-1}^s + \beta_4 \sqrt{DT_k^{s-1} * DT_k^{s-2}} \qquad (5)$$

5.2.3 Model calibration and validation

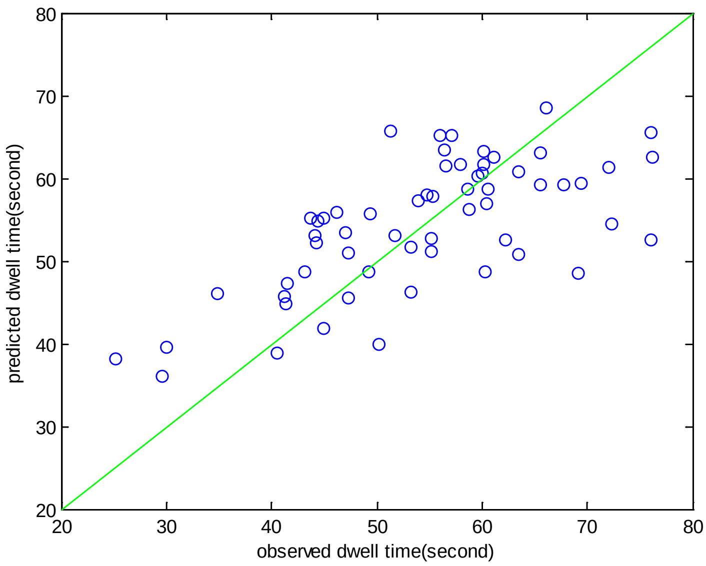
To validate the model, the dwell time data are split into two parts based on the train running date with equal sample sizes. The first part is used for model parameter estimation, and the remaining part is used to validate the model. For all trains during peak hours, the regression model is implemented. The estimated parameters and performance under each train length are shown in table 10. The comparison between the estimation results and the observations is shown in figure 6. In the case of perfect estimations, the observations would be on the line $y = x$ (shown in green). Data points far away from this line represent situations with poor estimation quality.



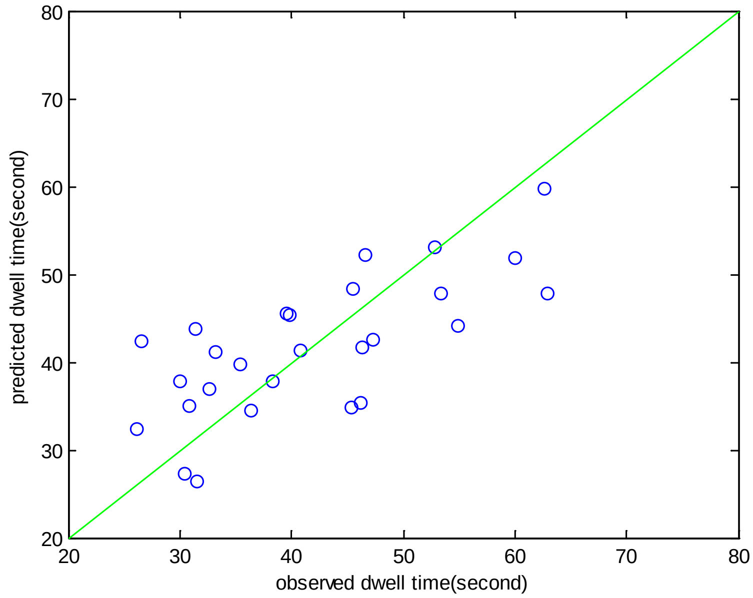
(a) L_k=4



(b) L_k=6



(c) L_k=10



(d) L_k=12

Figure 6: Estimation results of dwell time during peak hours

From table 10, it can be seen that the dwell time of the target train can be estimated by the length of the target train, the dwell time of the preceding train (as well as the length of the preceding train) and the dwell time of the previous stations. The p-values for all parameters are smaller than 0.05, which means that the values of the parameters are significantly different from zero. Despite the overfitting for the train length of eight due to the sample size, the MAPE is from 11.55%-13.55%. The adjusted R^2 is 0.574, showing that the model could explain most of the samples in the dataset. The contributions of the input variables are different. First, the contribution of the target train length to the dwell time is positive **(β_1=0.6)**. In other words, train dwell times tend to be larger for longer trains. This is because for longer trains, conductors need more time to confirm that the passengers have finished the alighting and boarding process. Second, the dwell time of the target train is longer when the dwell time of the preceding train is longer (β_3 **=0.18**), so that if there are more passengers on the preceding train, the possibility a high passenger occupation on this train is large. However, for train lengths equal to 4, 8 and 10, the value of β_3 is zero, so this effect is not significant. This is because the lengths of the preceding train and the target train may be different, which may have a positive or negative effect on the dwell time. Third, the dwell time of the target train at the target station is longer if the dwell time of the target train at the previous station is longer. β_4 =1.09 hints that the dwell times of consecutive stations tend to be the same. If the dwell times of the previous station and the second previous station are large, it is likely that the dwell time of the target train at the target station is also large, and vice versa.

5.3 Non-parametric regression results

The above parametric regression achieves high-accuracy results during peak hours, but during off-peak hours, the accuracy is relatively low (Table 8 - 9). A non-parametric regression model is introduced to predict dwell times during off-peak hours. Two types of variables are selected. Weekday, peak hour and train length are three variables to obtain the selection of the historical data. When predicting DT_i, the historical dataset is chosen based on the same weekday, peak hour properties and train length. D_k^{s-1}, DT_k^{s-1}, DT_k^{s-2}, DT_{k-1}^{s} are selected to calculate the distance between the historical data and the observations.

A total of 1560 records are identified without outliers. The dataset is then split into two parts. The first part, containing 900 records, is used as the learning sample, and the second part, containing 660 records, is used for prediction. The distance function is the sum of the differences and the non-weighed Euclidean distance. Because of the limited size of the learning samples, the value of *k* could only be selected from one to nine. The predicted result is shown in figure 7.

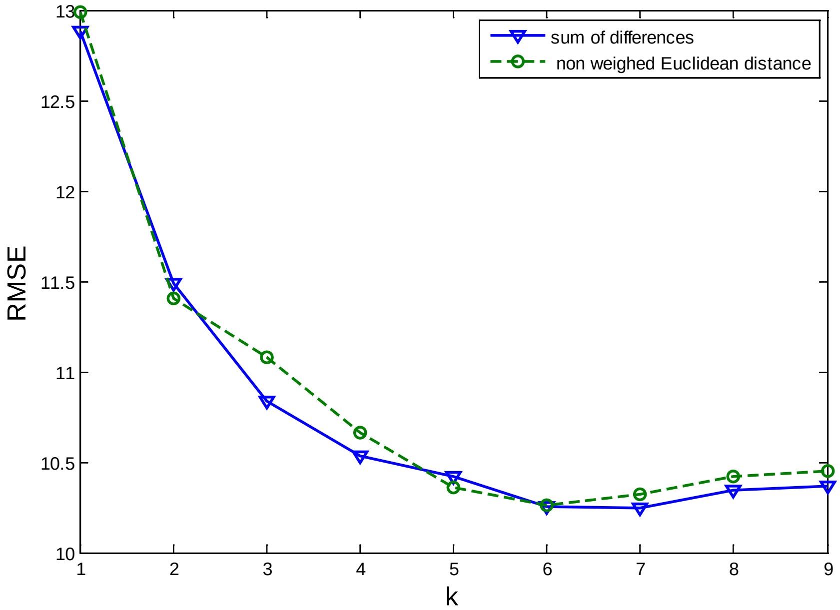


Figure 7: Relationship between *k* and RMSE in *k*-nearest neighbors method

From figure 7, it can be seen that although different distance functions are used, the trend of the estimation errors for different values of *k* is similar. For the sum of differences function, RMSE reaches its minimum value of 10.24 when *k* equals seven. For the non-weighed Euclidean distance, the RMSE has its minimum value of 10.26 when *k* equals six. Both are higher than for the parametric regression model. The MAPE is 19.95% (the estimation accuracy is 80.05%), which is within the acceptable estimation error and better than that using a simple 20% percentile value (RMSE=16.6084), as was used in a previous work [1].

5.4 Discussion

5.4.1 Accuracy comparison with existing models

The accuracy of the proposed parametric model (PM) and the non-parametric model (NPM) are compared with those of existing models reported in the literature (see table 11). Because the dataset of the literature is different from that in this paper, the comparison could have some bias. Still, this comparison could reflect the effectiveness and potential of the proposed model.

From table 6, it can be seen that the model in [15] performs best under the RMSE indicator. When considering the percent error, the parametric model in this paper performs best. Considering that the proposed model does not contain any passenger data and that, the trains are currently scheduled in minutes, this result is promising. The non-parametric model does not perform well. This means that the accuracy of the NPM for off-peak hours still needs to be improved. However, compared to similar cases in [1], the absolute error of the NPM is reduced significantly.

5.4.2 Generality of the model

As is analyzed in section 3, the dwell time of a train is determined mainly by the station, rolling stock and passenger demand. In the past, most of the existing dwell time estimation models were based on these variables. However, the station layout, rolling stock configuration and passenger behavior are difficult to model, which limits the model generality.

The proposed model can also show the effect of the station, rolling stock and passenger demand indirectly. The predictors of the proposed model are mainly the dwell time of the preceding train DT_{k-1}^{s} and the dwell time at the previous station DT_{k}^{s-1} . The common characteristic of the preceding train and the target train is that they stopped at the same station, so parameter β_2 can reflect the effect of the station. The common characteristic of the dwell time at the previous station and the dwell time at the target station is that they are for the same train, so β_3 can reflect the effect of the rolling stock. The passenger demand appears by simply separating the peak and off-peak hour models.

As opposed to existing models, the proposed model does not need to consider the station layout, rolling stock configuration and passenger behavior problems. This is because these factors are included in independent variables in the proposed model, where they could act on the dependent variable directly. Thus, it is more general. However, such generality theoretically holds only if the model is tested in more cases with different datasets.

6. CONCLUSIONS

The main contribution of this paper is its development of a more generalized and more practical estimation model based on train detection data. Although many dwell time estimation models exist based on the number of passengers, they cannot easily be used in real-time rescheduling practice because of the lack of real-time passenger demand. This paper proposed both a parametric regression model and a non-parametric regression model to estimate the dwell times at short stops for real-time scheduling. The main advantage of the proposed model is that it does not rely on passenger data, so it is more practical in real-time rescheduling when the number of passengers cannot easily be obtained. The proposed model also shows the potential for the development of a more general estimation model, despite the different types of rolling stock and station. We conclude that this would be very important for broad applications.

We conclude that the estimation of dwell times at short stop stations is possible without passenger data, but only during peak hours can a relatively high accuracy be obtained. The estimation error of the dwell time during peak hours is 6.2 -8.8 seconds, and the corresponding accuracy is from 85.8% - 88.5%. Because trains are scheduled in minutes, and this model could be used in real-time cases without passenger demand, this accuracy is promising. For short trains during off-peak hours, the accuracy of the proposed estimation model still needs to be improved.

Future work could be performed from three directions. First, to validate to what extent the model is generic. This work will be performed by applying more datasets from different stations of the Dutch railway network and even more datasets from different countries. Second, to improve the model accuracy by trying more variables, such as dwell times at other stations that are related to the target station, not limited only to consecutive stations. Other factors should also be considered, for example, the height between the floor levels of the LRT and station platforms are one important factor to be considered with a parameter when the data sets in other LRT stations in the world are considered. Third, to improve the accuracy by adding passenger demand input. Very recently, passenger check-in and check-out data has become available in the Dutch network, as the smart card has become compulsory for boarding a train. By processing these data, the number of alighting and boarding passengers could be obtained. We believe that including these values in the model could enable a complete input of the influence factors from station, rolling stock, and passenger demand, which can improve the accuracy of the estimation significantly. This work will be performed in further research.

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Table 1: Main features of existing dwell time estimation models

Source	**Model Type**	**Input variables**												
		Passenger				Rolling stock			Station		Operation			External
		Number of A&B	Interaction of A&B	Number of S	Passengers on the platform	Number of doors	Door width	Interior layout	Horizontal & vertical gap	Heterogeneous stations	Peak& off peak time	Service type	Delay	
Lam,1988	Linear Regression	√	×	×	×	×	×	×	×	×	NA	NA	NA	×
Weston, 1989	Non-linear Regression	√	√	√	×	√	√	×	×	×	NA	NA	NA	×
Lin, 1992	Non-linear Regression	√	√	√	×	NA	×	×	×	×	NA	NA	NA	×
Parkinson,1996	Non-linear Regression	√	×	√	×	√	×	×	×	×	NA	NA	NA	×
Puong, 2000	Non-linear Regression	√	√	√	×	NA	×	×	×	×	NA	NA	NA	×
Buchmueller, 2008	Distribution	√	×	×	×	√	√	√	×	×	NA	NA	NA	×
Hansen, 2010	Linear Regression	×	×	×	×	×	×	×	×	×	×	√	√	×
Kecman & Goverde 2013	Linear Regression	×	×	×	×	×	×	×	×	×	√	√	√	×
Jone 2011	Linear Regression	√	×	×	×	NA	NA	NA	√	×	NA	√	NA	×
Zhang, 2008	Microscopic simulation	√	√	×	×	×	√	×	×	×	NA	NA	NA	×
Yamamura,2013	Microscopic simulation	√	√	√	×	√	√	√	×	×	NA	NA	NA	×

Note: A- Alighting passenger; B-Boarding passenger; S- Standee in the train/vehicle; “ √ ” - included; “×” – excluded; “NA”-not applicable

Table 2: Possible predictors

NO	Variables	Meaning	NO	Variables	Meaning
1	W_k	Weekday or weekend	6	DT_k^{s-2}	Dwell time at second previous station
2	P_k	Peak or off-peak	7	DT_{k-1}^{s}	Dwell time of preceding train
3	L_k^s	Train length	8	DT_{k-2}^{s}	Dwell time of previous train on same train line
4	D_k^{s-1}	Departure delay at previous station	9	L_{k-1}^{s}	Length of preceding train
5	DT_k^{s-1}	Dwell time at previous station	10	$DT_{k\text{-hist}}^{s}$	Dwell time of the same train during the last week

Table 3 Parametric regression models

Predictors / Models	Linear items										Nonlinear items		
	Week day or week end	Peak or off-peak	Train length	Departure delay at previous station	Dwell time at previous station	Dwell time at second previous station	Dwell time of preceding train	Dwell time of previous train on same train line	Length of preceding train	Dwell time of the same train during the last week	quadratic items	interactive items 1	Interactive items 2
	W_k	P_k	L_k^s	D_k^{s-1}	DT_k^{s-1}	DT_k^{s-2}	DT_{k-1}^s	DT_{k-2}^s	L_{k-1}^s	$DT_{k\text{-hist}}^s$	$\left(DT_k^{s-1}\right)^2,\left(DT_k^{s-2}\right)^2$	$DT_k^{s-1}*DT_k^{s-2}$	$DT_{k-1}^s*DT_{k-2}^s$
1	×	×			×								
2	×	×			×	×							
3	×	×			×	×	×						
4	×	×	×		×	×	×		×	×			
5	×	×	×		×	×	×	×	×	×			
6	×	×	×	×	×	×	×	×	×	×			
7	×	×	×	×	×	×	×	×	×	×	×		
8	×	×	×	×	×	×	×	×	×	×	×	×	
9	×	×	×	×	×	×	×	×	×	×	×	×	×
10	×	×	×	×	×	×	×	×	×	×	×	×	×

Note: the variables related to the target dwell time in model 10 are transferred to logarithm form.

Table 4: Correlation coefficients of possible predictors and dependent variables

NO	Variables	Correlation	NO	Variables	Correlation
1	W_k	0.178	6	DT_k^{s-2}	0.381
2	P_k	0.376	7	DT_{k-1}^{s}	0.376
3	L_k^s	0.308	8	DT_{k-2}^{s}	0.305
4	D_k^{s-1}	0.224	9	L_{k-1}^{s}	0.101
5	DT_k^{s-1}	0.456	10	$DT_{k\text{-hist}}^{s}$	0.317

*p-value=0.000

Table 5: Covariance of independent variables

	W_k	P_k	L_k	D_k^{s-1}	D_{k-1}^{s}	DT_k^{s-1}	DT_k^{s-2}	DT_{k-1}^{s}	L_{k-1}^{s}	DT_{k-2}^{s}	DT_{k-hist}^{s}
W_k	1	0.225	0.175	0.042	0.012	0.065	0.160	0.239	0.268	0.113	0.157
P_k	0.225	1	0.390	0.236	-0.001	0.259	0.264	0.409	0.244	0.211	0.309
L_k	0.175	0.390	1	0.190	-0.016	0.277	0.195	0.228	-0.015	0.176	0.209
D_k^{s-1}	0.042	0.236	0.190	1	0.006	0.239	0.058	0.178	.0528	0.121	0.123
D_{k-1}^{s}	0.012	-0.001	-0.016	0.006	1	0.001	0.000	-0.04	-0.066	0.035	0.035
DT_k^{s-1}	0.065	0.259	0.277	0.239	0.001	1	0.355	0.242	0.055	0.126	0.160
DT_k^{s-2}	0.160	0.264	0.195	0.058	0.000	0.355	1	0.228	0.0364	0.111	0.207
DT_{k-1}^{s}	0.239	0.409	0.228	0.178	-0.04	0.241	0.228	1	0.217	0.251	0.269
L_{k-1}^{s}	0.244	-0.015	0.053	-0.066	-0.066	0.055	0.0364	0.217	1	0.142	0.090
DT_{k-2}^{s}	0.113	0.211	0.176	0.121	-0.035	0.126	0.111	0.251	0.142	1	0.126
DT_{k-hist}^{s}	0.1570	0.309	0.209	0.123	0.045	0.160	0.207	0.269	0.090	0.126	1

Table 6: Model test during morning peak periods

Model	Train Length									
	4		6		10		12		Mix	
Cases	20		27		16		27		91	
	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE
1	0.193	9.212	0.232	10.953	-	12.083	-	11.122	0.080	11.235
2	0.519	7.112	0.452	9.257	-	12.365	-	11.165	0.164	10.708
3	0.619	6.333	0.439	9.359	-	12.755	0.015	10.824	0.231	10.267
4	0.604	6.454	0.452	9.250	-	13.096	0.010	10.855	0.225	10.310
5	0.643	6.124	0.434	9.407	-	13.275	-	11.067	0.220	10.344
6	0.624	6.288	0.426	9.473	-	13.989	0.162	9.988	0.216	10.369
7	0.557	6.826	0.367	9.947	0.0860	11.460	0.253	9.4292	0.246	10.167
8	0.539	6.964	0.367	9.948	-	12.237	0.259	9.390	0.246	10.176
9	-	0.656	-	0.871	-	6.865	-	0.908	-	0.299
10	0.510	7.176	0.413	9.579	0.3595	9.593	0.258	9.393	0.250	10.140

Table 7: Model test during afternoon peak periods

Model	Train Length											
	4		6		8		10		12		Mix	
Cases	13		52		11		40		37		153	
	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE
1	0.054	8.786	0.207	7.547	0.300	8.598	0.189	8.538	0.071	8.332	0.244	8.782
2	0.223	7.966	0.309	7.041	0.225	9.050	0.201	8.472	0.317	7.146	0.391	7.878
3	0.163	8.264	0.295	7.114	0.255	8.875	0.255	8.182	0.395	6.723	0.389	7.896
4	0.152	8.322	0.339	6.887	0.193	9.235	0.237	8.281	0.377	6.821	0.392	7.875
5	0.245	7.849	0.325	6.960	0.067	9.928	0.285	8.014	0.358	6.926	0.388	7.900
6	0.722	4.762	0.380	6.669	-	10.823	0.329	7.764	0.345	6.998	0.386	7.913
7	0.611	5.638	0.356	6.802	0.831	4.228	0.292	7.977	0.344	7.001	0.386	7.914
8	0.487	6.470	0.398	6.572	0.663	5.965	0.405	7.310	0.372	6.850	0.392	7.874
9	-	20.978	-	0.225	-	19.574	-	0.964	-	0.359	0.345	0.153
10	0.897	2.899	0.407	6.524	-	100.000	0.400	7.346	0.334	7.056	0.385	7.921

Table 8: Model test during off-peak periods on workdays

Model	Train Length											
	4		6		8		10		12		Mix	
Cases	182		499		110		68		9		868	
	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE
1	0.113	10.323	0.073	9.425	0.181	10.262	0.118	10.682	0.208	6.994	0.149	10.371
2	0.119	10.289	0.081	9.382	0.186	10.235	0.259	9.793	0.452	5.813	0.172	10.231
3	0.126	10.246	0.090	9.335	0.254	9.793	0.320	9.377	0.529	5.390	0.211	9.985
4	0.121	10.274	0.090	9.340	0.293	9.537	0.359	9.103	0.448	5.835	0.221	9.921
5	0.120	10.284	0.092	9.326	0.300	9.492	0.405	8.775	0.566	5.174	0.234	9.841
6	0.123	10.261	0.096	9.305	0.294	9.532	0.400	8.812	0.907	2.395	0.246	9.762
7	0.120	10.282	0.116	9.203	0.293	9.537	0.417	8.687	-	-	0.256	9.695
8	0.115	10.307	0.115	9.211	0.288	9.570	0.415	8.699	-	-	0.259	9.677
9	-	0.345	0.132	0.240	0.134	0.246	0.006	0.234	-	-	0.259	9.677
10	0.11	10.341	0.114	9.211	0.274	9.664	0.398	8.826	-	-	0.266	9.632

Table 9: Model test on weekends

Model	Train Length							
	4		6		10		Mix	
Cases	81		195		23		299	
	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE	Adj-R^2	RMSE
1	0.162	11.438	0.107	9.679	0.313	12.228	0.160	10.922
2	0.152	11.509	0.133	9.539	0.404	11.387	0.185	10.756
3	0.203	11.158	0.136	9.521	0.384	11.577	0.197	10.679
4	0.194	11.220	0.133	9.536	0.364	11.761	0.195	10.695
5	0.187	11.271	0.134	9.536	0.374	11.666	0.204	10.632
6	0.176	11.346	0.135	9.526	0.337	12.008	0.205	10.627
7	0.241	10.885	0.135	9.528	0.502	10.411	0.222	10.511
8	0.235	10.932	0.145	9.472	0.508	10.347	0.235	10.426
9	-	0.509	-	-	-	0.871	0.235	10.426
10	0.215	11.069	0.167	9.352	0.433	11.107	0.255	10.289

Table 10: Estimation of dwell time models during peak hours

Parameter\ L_k^s	**4**	**6**	**8**	**10**	**12**	**Mix**
Num of cases	33	79	11	56	64	243
Constant	-27.46 (0.16)	-13.07 (0.01)	60.47 (0.01)	-3.8 (0.01)	-15.62 (0.02)	-14.50 (0.00)
β_1	-	-	-	-	-	0.60 (0.00)
β_2	0.47 (0.00)	1.60 (0.00)	-7.9 (0.04)	1.11 (0.09)	1.89 (0.01)	0.77 (0.01)
β_3	0.00	0.03	0.00	0.00	0.34 (0.00)	0.18 (0.00)
β_4	1.19 (0.00)	1.11 (0.00)	0.85 (0.04)	1.12 (0.00)	0.83 (0.00)	1.09 (0.00)
Performance						
Adjust R^2	0.708	0.577	0.742	0.428	0.653	0.574
RMSE(s)	6.96	6.22	6.44	8.69	6.78	7.95
MAPE	12.65%	13.55%	6.53%	12.98%	11.55%	13.9%

Note: p-values are shown in brackets

Table 11: Accuracy comparison with existing models

	Puong, **2000**	**Hansen**,**2010**	**Kecman**, **2014**	**PM**	**NPM**
RMSE	4.04	16.6	-	6.2-8.8	8.49
MAPE	14.55%	-	Approximately 15%	11.5%-14.2%	19.9%