# Travel time prediction for trams in Warsaw

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**Abstract.** The paper presents a comparison between different prediction methods for trams time travels in Warsaw. Predictions are constructed based on historical trams GPS positions. Three different prediction approaches were implemented and compared with the official timetables and real time travels. Obtained results show that the official timetables provides only approximated time travel especially in rush hours. Proposed prediction methods outperform the official schedule in the term of time travel precision and may be used as a more accurate source of travel time for passengers.

**Keywords:** transportation, travel time prediction, neural network, decision support system

## 1 Introduction

Time travel prediction is an interesting problem due to its complexity, many real life applications and everyday usability. Planned schedules are no longer enough. Passengers expect more precise information about vehicles arrival time and trip time length. On the other hand, real travel time depends on many factors such as weather conditions, traffic lights, road accidents, number of passengers, traffic flow, driver emotional state or roadworks. All of these parameters are difficult to predict or even measure. However, past researches show that using some additional information, for instance vehicles' GPS locations over a day or data collected by automatic passenger counters, some reasonable predictions could be obtained and their accuracy outperforms planned schedule.

In recent years a growing interest in applying smart algorithms to travel time prediction has been observed, mainly due to its practical applicability in real life domains and at the same time an intrinsic complexity which makes the problem challenging. In effect, numerous new approaches to time travel prediction relying mainly on various statistical models or machine learning techniques were proposed. All methods could be divided into four groups: simple models based on the historical data, statistical models, machine learning approaches and hybrid models.

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First group contains methods based on observation that usually time travels are repeatable between days. Road conditions from previous days can be a reasonable forecast of future condition at the same time of the day and the same day of the week [1]. Some of proposed methods in this group rely on average travel time in previous days [2] and others use average speed as a prediction factor [3].

Methods in statistical model group used several identified factors (i.e. traffic lights, weather) as independent variables and make prediction based on their statistic distributions and correlations. Time series models [4], regression models [5] or Kalman Filters [6], [7] are the most common examples in this group.

Third category of travel time prediction is machine learning models. They perform some learning process on existing data to find an answer for unknown input data. They have good results with huge volume of information, non-linear relationships or noisy information. The most popular techniques are Artificial Neural Networks [8], [9] and Support Vector Machines [10].

Also some hybrid models [11], [12] were used to solve time travel prediction problem. In this group some combination from previously presented methods are combined. Increasing trend to utilize hybrid algorithms to improve the prediction accuracy could be observed in recent years.

We refert to [13] for a more in-depth overview and detailed description of the respective methods.

This paper presents comparison between travel time prediction methods for trams in Warsaw. Predictions are computed based on vehicles' GPS locations and the official timetables. Performed experiments show usability level of used methods for real life trip planning including vehicles changes.

The remainder of this paper is arranged as follows. Section 2 presents overview of tram's infrastructure in Warsaw and shows used data sources, their quality problems and proposed solutions. In Sect. 3 detailed descriptions of implemented methods are provided. Experiment result are presented in Sect. 4. Last section is devoted to conclusions and directions for future research.

## 2 Warsaw trams infrastructure and data sources

Warsaw is the capital city of Poland with population estimated at 1.744 million residents [14]. Nearly 82% people travel every day and 47% of them use public transport as the main travel method [15]. The available means of transport in Warsaw are buses, trams, trains and subway. This paper considers only trams because at the moment of writing this paper travel agency provides complete information (GPS locations for all vehicles) only for trams. Warsaw trams infrastructure contains 26 trams lines with about 240 stops. Tram drivers are obligated to stop on all stops on planned route (no request stops). There are no night or special lines. Services for all lines run every day. The earliest tram departures at 3:30 AM and the latest arrives to the depot at about 1:30 AM. Three schedules versions are used during a week: weekday schedule (from Monday to Friday), Saturday schedule, and Sunday and holiday schedule.

Two main data sources in this research are used. The first one is information about the official schedules planned by Warsaw Public Transport Authority. This source contains stops locations, routes and lines on stop planned times. For each stop time also brigade number is provided. This number, combined with line number, is unique identificator for vehicle. Data from this source are reliable, because it is used every day by travel agency workers to assign vehicles to given routes.

Second source used in this paper is real trams' positions form GPS transmitters placed in vehicles. Every tram sends its current position with about 15 seconds frequency. They are available in files with information about line, brigade, log time and coordinates - one file for each day. Table 1 presents some computed properties for this data from 22nd September 2016. There are some quality issues such as trams positions outside Warsaw territory, vehicles disappears in the middle of the route, logs duplicates or abnormal tram's routes. The reason for most of them is probably wrong position sent by GPS transmitter. To make reliable predictions (and also get real tram on stop time) for these data some quality improvement actions were performed. All logs with coordinates outside Warsaw territory and duplicates were removed. Also average speed between all pairs of consecutive logs was computed and if this speed is greater than 100 km/h one of these logs are deleted. Also if distance between two consecutive logs was less than 2 meters, it was recognized as GPS error and second log's coordinates were changed to the previous log's coordinates. Above mentioned modifications affected about 15% of original data.

| **Parameter** | **Value** |
|---:|:---|
| All logs | 993263 |
| Unique logs (unique triples [time, line, brigade]) | 861054 (86.7%) |
| Logs from Warsaw territory | 991639 (99.84%) |
| Average time between logs from the same tram | 18.2 s |
| Average distance traveled between logs | 71.12 m |
| Unique pairs: [line, brigade] | 305 |
| Unique pairs: [line, brigade] in schedule | 375 |

**Table 1.** Basic parameters of received real trams positions.

One of the first challenge was precisely estimating real time of arriving tram on a stop from GPS data. It is essential component for all methods to determine tram delays and compare predicted time with real tram on stop arrival time. Available data are stop's coordinates and tram coordinates with time from GPS transmitter. The most natural way to get tram to stop arrival time is to define a radius $r$ and when distance between the stop and the tram is less than $r$ it means that the tram is on the stop at that moment. However, in Section 2 it was showed that average time between subsequent GPS logs is 18.2 seconds and average distance that tram covers in this time is about 71 meters. It means that $r$

should be at least 36 meters, because otherwise tram may log its position before and after $r$ meters from the stop and algorithm will miss the stop. Moreover, this approach is too imprecise, because it does not provide exact tram's arrival time, but time that the tram is at most $r$ meters from the stop. For instance, traffic lights in near distance before stop may cause few minutes difference between real and computed arrival time.

Thus, it was necessary to find another way. Figure 1 presents proposed method for computing tram on stop time based only on distances between GPS logs coordinates and stop position. At the beginning first ($A$) and last ($B$) tram's logs coordinates in the stop's ($S$) neighborhood (defined as a circle with given radius and center in considered stop's position) are obtained. This allows determining from what direction tram arrived to stop and what direction it moved after that. Based on this directions bisector of angle $ASB$ is created. Let call it *arrival line*. The moment of crossing that line is equivalent to the moment of visiting the stop by the tram. Time of first log after arrival line crossing may be quite imprecise because tram could move quite far from the stop at that moment. Better option is to assume that trams speed is constant and get time difference between last log before and first log after crossing the line and compute the moment of tram stop arrival proportionally to these logs distances from the stop. In experiments neighborhood radius was set to 300 meters.

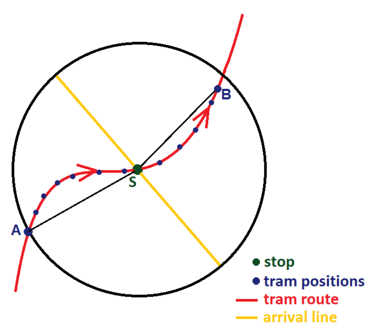


**Fig. 1.** Graphical illustration of method for determining tram to stop arrival time.

Figure 2 provides average time between all stops pairs during the day obtained from the official timetable and computed form real trams positions. All values are greater in real data which means that the official schedule is imprecise and may be improved. Furthermore, morning (from 7 to 9) and afternoon (from 15 to 18) rush hours could be easily noticed. The official timetable provides longer travel times for those hours, however in reality differences between those hours and the others are greater.

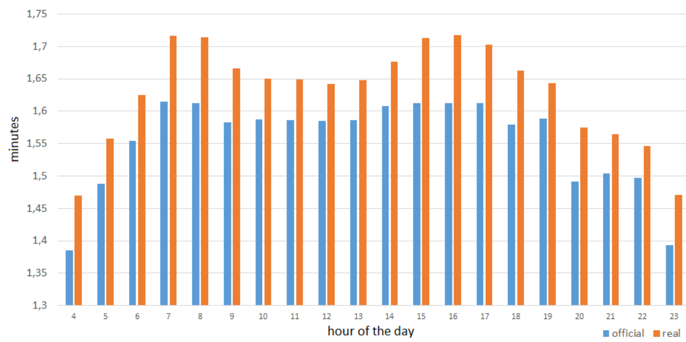


**Fig. 2.** Comparison between average time between all stops pairs by hour of the days for the official schedule and real travels.

# 3 Prediction methods

This section provides detailed description of implemented trams travel time prediction methods. Three approaches are chosen for comparison: *current delay propagation*, *historical average time travel* and *artificial neural network model*. To simulate real time prediction arbitrary day $d$ and time $t$ are selected and available data in prediction process are: the official timetables for day $d$ and all days before that day, trams' GPS positions before day $d$ and for day $d$ until time $t$. Based on this data prediction for next 2 hours for all trams is made.

## 3.1 Current delay propagation

One of the most natural way to make real time prediction for tram on stop arrival time may be finding current vehicle delay and propagate it to next stops on planned route. This simple idea is base for first proposed method - *current delay propagation*. In this approach for all trams independently last visited stop $s$ before time $t$ is determined based on vehicles' GPS positions. Current delay $d$ is difference between computed arrival time for the stop $s$ and time from the official timetable (i.e. time that this vehicle was planned to arrive to the stop $s$). Then, for all non-visited stops on considered vehicle's route, predicted arrival time is planned time from the official schedule summed with computed in previous step delay $d$.

This method is very simple and does not use any historical data. It may give good result if the delay reason for the vehicle is a single accident (for example too late depot leave or congestion on traffic lights) and do not repeat until the end of route. However, this method is not able to predict future problems or delay changes, which is important disadvantage. It is expected to obtain better results for vehicles near the end of its route than for vehicles which recently leave the depot and probably their current delay is low. Furthermore, for vehicles that do not start service before prediction time $t$, this approach is not able to make any prediction and it just returns time from the official timetable.

### 3.2 Historical average time travel

The second approach is modification of previous method. Basically, it is intended to reduce first method disadvantages, i.e. take into consideration historical time travels or usual road fraction traffic conditions. The main idea is to use average time travel from previous couple of days as an estimator for current day times. One of the main factors which has big impact on time travels is time of the day. Thus, to make predictions more accurate computed average times should depend on start travel time. It also may be better to consider the same kinds of days (week days, weekends) together, because road traffic differs from each other. *Historical average time travel* method same as previous method searches for last visited stop $s$ based on GPS positions. Then, iteratively for all stops from $s$ to the end of route, historical average time between consecutive stop pairs is added, i.e. in first step historical average time between the stop $s$ and the next stop is added to the arrival time to the stop $s$ computed based on GPS logs, in next step historical average time is added to arrival time predicted in previous step etc. Historical average time mentioned above is computed based on real times for the same days of week in last 30 days from all travels between considered stops pair at given hour. Only historical travel times for the same time of the day (the same hour) as prediction time of the day are included to computation.

### 3.3 Neural network model

Third approach for trams time travel prediction is machine learning technique and it uses artificial neural networks approach. In recent years neural networks gains popularity very fast in lots of domains, due to its ability to solve complex non-linear problems. Many different kinds of neural network were described in literature. In this paper one of the first and the most simple neural network architecture is used - multilayer perceptron (MLP) with backpropagation learning method. The main idea behind MLP is to learn some relationships between given examples in form of input and expected output data. Learning process is realized by changing weights between neurons according to some principle. Then MLP is able to correctly give information (make prediction) about unseen example. Neural networks can generalize information, ignore noises and identify underlying relationships even if they are hard to explain. For more details about neural networks, MLP architecture or backpropagation learning process we refer to [16].

In this paper separate neural network for each route is created. The output value is predicted tram's time travel from the stop $s_i$ to the stop $s_j$. As input four values were chosen:

- order number of stop $s_i$ in route,

– order number of stop $s_j$ in route,
– travel time from route's start (first stop in route) to stop $s_i$,
– prediction time of the day.

Third information (travel time from route's start to stop $s_i$) is computed based on GPS trams' positions. It provides information how trip is realized so far. It depends on actual traffic conditions, so it contains important information for time travel prediction. Time of the day (the last input information) also has influence on time travel, because traffic changes during the day. Based on performed experiments a one-hidden layer perceptron with 40 neurons in hidden layer was chosen. The learning rate was set to 0.03, the momentum to 0.9 and the number of training epochs was equal to 250. Figure 3 shows used neural network architecture. Learning data set contains information for the same days of week in last 30 days from all travels on given route.

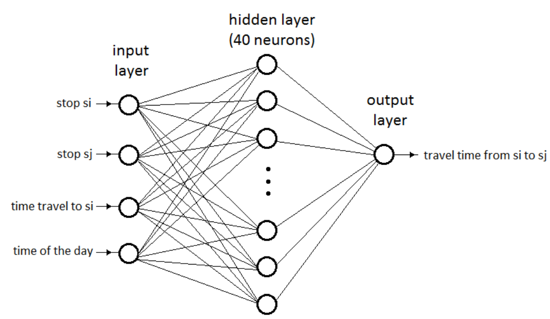


**Fig. 3.** Proposed neural network architecture.

To make prediction for particular tram at given time of the day $t$ last visited stop $s$ before $t$ is determined based on vehicles' GPS position and travel time $x$ from route beginning to stop $s$ is computed. To predict arrival time for all non-visited stops in route learnt neural network is used, i.e. for stop $s_j$ arrival time is computed by adding to $t$ output value of neural network with input values: stop's $s$ order number in route, stop's $s_j$ order number in route, $x$ and $t$.

## 4 Experimental results

All methods presented in previous section were previously used in other researches to predict bus time travels. However, to the best of our knowledge, this paper presents the first experimental results for trams travels prediction. Also, unlike most of papers in this domain, performed experiments do not focus on single trips and verify prediction independently for different vehicles. Presented results take into consideration trams changes. It simulates passenger view, for whom the most important parameter is to know accurately how long trip form particular stop to another chosen stop takes (including all necessary changes). It is assumed that total trip time includes also time spend waiting on the start stop for the first tram.

For the purposes of tests a sample of 1000 random tram stop pairs has been selected. Loop stops and pairs of stops closer to each other than 5000 meters (in the straight line) has been excluded from the drawing. The pairs has been then used to compute actual trip itineraries on 22 September 2016 at four different hours (8:00, 12:00, 16:00 and 20:00) with five different timetables. Three of the timetables were generated based on three different prediction models, one was the official Warsaw Public Transport Authority timetable and one was computed based on the historical GPS records (real schedule). This setup yielded total of 20,000 tram trips itineraries that were later used for the analysis.

The actual timetables were created in the General Transit Feed Specification (GTFS) format. That included both conversion of the official timetables to the GTFS format as well as creating the GTFS files from scratch for the prediction models. Trips itineraries were computed with the Open Trip Planner server instance. Default graph search timeouts were turned off and so all obtained results were fully deterministic.

The most important measure to compare proposed prediction methods is difference between the real travel time and predicted travel time which can be called prediction error. This measure shows method's accuracy. Table 2 shows comparison between prediction methods and the official timetables by this measure for tested times of the day. In all cases *historical average time travel* approach yielded the best results. Average absolute prediction error is about 2 minutes. Average planned time travel was 45 minutes, so prediction error is equal 4%. Worst results were obtained by the official timetables - more than 3 minutes. Noticealso that in rush hours (8:00 and 16:00) all prediction errors gave worse results than for the others tested hours (12:00 and 20:00). Thus, travel time prediction in rush hours seems to be more difficult problem. *Neural network model* obtained nearly as good results as the best method for rush hours. *Neural network model* also is the best method for rush hours in the terms of number of travels for which method obtained the lowest absolute prediction error (42% and 44% travels).

| | 08:00 | | 12:00 | | 16:00 | | 20:00 | | All | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Diff | Best | Diff | Best | Diff | Best | Diff | Best | Diff | Best |
| Official timetables | 180.53 | 36% | 172.30 | 29% | 203.61 | 25% | 166.75 | 29% | 180.79 | 30% |
| Current delay prop | 178.41 | 30% | 118.94 | 34% | 172.99 | 27% | 98.33 | 33% | 142.17 | 31% |
| Historical avg travel | **159.70** | 37% | **104.80** | **41%** | **137.83** | 40% | **89.25** | **49%** | **122.89** | **42%** |
| Neural network | 161.70 | **42%** | 138.40 | 38% | 149.92 | **44%** | 143.01 | 40% | 148.25 | 41% |

**Table 2.** Comparison between prediction methods in terms of average absolute differences (in seconds) with real travel times (Diff) and percentage of number of times given method obtained the best result (Best). Best results for each time of the day are bolded.

For all methods predicted time travel is more often shorter than real time travel. This difference was the greatest for *current delay propagation* method (nearly 2 times often predicted time was shorter) and the lowest for *neural network model* (only 2% less longer predicted time travels).

In performed experiments only time travel from one stop to another was considered (no matter what lines and how many of them), so trams lines in predicted travels may be different than those in real travels. Table 3 provides details about that differences in predicted and real travels. Nearly 75% overall predicted travels were realized by the same trams lines as in reality and 70% also by the same brigades. The better prediction method is (based on results from table 2) the more travels are realized by the same vehicles as predicted. There is also less trams lines matching in rush hours which confirms greater difficulty for making prediction for these cases.

| | 08:00 | | 12:00 | | 16:00 | | 20:00 | | All | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Lines | Brig | Lines | Brig | Lines | Brig | Lines | Brig | Lines | Brig |
| Official timetables | 64% | 49% | 70% | 61% | 61% | 43% | 69% | 63% | 66% | 54% |
| Current delay prop | 68% | 60% | **81%** | **76%** | 68% | 57% | 82% | 79% | 75% | 68% |
| Historical avg travel | 71% | 62% | **81%** | **76%** | 72% | 62% | **84%** | **81%** | **77%** | **70%** |
| Neural network | **74%** | **66%** | 77% | 73% | **74%** | **66%** | 77% | 74% | 76% | **70%** |

**Table 3.** Percentage of travels realized with the same lines (Lines) and the same lines and brigades (Brig) as in predicted travel. Best results for each time of the day are bolded.

## 5 Conclusions and future work

Three methods for travel times prediction for trams in Warsaw were proposed and tested: *current delay propagation*, *historical average time travel* and *neural network model*. They basic idea is to predict travel time based on current vehicles position (current delay) and historical travels. This data are obtained from trams GPS positions in every 15 seconds. All proposed methods outperform prediction based on the official timetables. The best method - *historical average time travel* reduced prediction error from 3 minutes (for the official schedule) to 2 minutes. Furthermore, results showed clear difference between rush hours (8:00 and 16:00) and the others tested hours (12:00 and 20:00). Time travels are longer in rush hours and more difficult to predict. In this case *neural network model* yielded the best results. This paper presented that even simple methods may improve travel time prediction and may be used to provide more accurate information for passenger.

In further steps making comparison between delays and prediction methods during holiday week and normal week is planned. Traffic is observable smaller during school holidays in Warsaw so it would be interesting to check if this difference also could be noticed in time travel predictions. Also making similar researches for buses in Warsaw and comparison them with trams is planned.

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