ARTICLE TYPE

Predicting Ship Arrival Times at (Provincial) Bridges

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Abstract

This paper proposes a method to predict ship arrival times, specifically measured 500 meters before reaching provincial bridges. Our approach leverages a machine learning model trained on three years of Automatic Identification System (AIS) data. This model integrates historical arrival times and various real-time factors, such as the current speed of the ship.
Utilizing a random forest regression model, we achieved a root mean square error (RMSE) of approximately 5 minutes between predicted and actual ship arrival times, as validated by the three-year data set. However, the accuracy varied slightly depending on the specific bridge type in the test set.
Accurate prediction of ship arrival times has significant benefits for traffic management. These predictions could allow for timely traffic diversion to faster routes, which are especially crucial for emergency traffic such as ambulances and fire trucks. And facilitate the coordination of multiple ship crossings during a single bridge opening, if they arrive shortly after each other
Moreover, the model contributes to environmental sustainability. By reducing traffic congestion, it indirectly leads to lower greenhouse gas emissions, emphasizing the model's climate-positive potential.

Keywords: Ship ETA prediction, Traffic management, CO2 reduction, Congestion reduction

1. Introduction

The Province of South Holland manages several bridges, especially in dense packed region of South Holland a bridge opening will certainly cause congestion especially during rush hours CBS 2010.

This issue has elicited calls for action from several political parties, aiming to address the traffic congestion resulting from bridge openings. Although it is not feasible to entirely eliminate congestion caused by bridge operations, it is possible to optimize it using various strategies **sspzh2019**.

One such strategy involves predicting the estimated times of arrival (ETAs) for ships at bridges. With accurate ETAs, road traffic can be rerouted to potentially faster alternatives, or bridge openings can be consolidated for multiple ships if their arrival times are close together.

This paper primarily focuses on predicting a ship's ETA 500 meters before it reaches a bridge. This distance is significant because bridge operators commence the bridge opening process when ships are 500 meters away.

The training data for our model consists of three years of historical Automatic Identification System (AIS) data. In brief, AIS data is gathered from transceivers mounted on ships, which provide unique identification for each vessel, GPS coordinates (longitude and latitude), the ship's course, and speed. This data is acquired from Rijkswaterstaat (RWS).

2. Related work

Bodunov et al. 2018 et al presented a study that not only predicts a ship's ETA but also its anticipated destination. They employed a feed-forward model for these predictions. However, the paper appears somewhat limited in detailing the variables incorporated into the model, focusing primarily on the model itself. Their work primarily aims at predicting events weeks ahead, in contrast to our focus on minute-scale predictions.

Veenstra and Harmelink 2021 et al explored the use of previous ETA predictions as inputs for ETA prediction models. Their findings demonstrate that previous ETA predictions hold predictive value, likely due to the model's ability to adjust and learn from prior erroneous predictions, exhibiting a form of self-learning.

Flapper 2020 et al employed gradient boosting to rank the importance of various features in predicting ETAs. They identified the following order of importance for the features: Distance to ETA target, Latitude of ETA target, Longitude of ETA target, Target ETA ID, Time from previous point, Ship Length, Current Longitude, Previous ID, Distance from previous point, Ship Width, Previous Longitude, Current Latitude, Previous Latitude, Ship Depth, Day, Current ID, Hour, Ship Type, and Month.

In their work at Uber, Hu et al. 2022 replaced an XGBoost algorithm with a deep learning residual model for ETA prediction. This model utilizes the distance and maximum driving speed for a selected route from a routing system as inputs. It then attempts to adjust the predictions by incorporating residual parameters based on real-time data.

3. Materials and Methods

3.1 Study area

We focused solely on provincial waterways, which means that only AIS data corresponding to these waterways were included in our analysis. Additionally, we considered only the provincial bridges in the vicinity of Leiden, as illustrated in the study area displayed Figure 1.

Figure 1. The study area encompasses provincial waterways, highlighted in blue, and ETA prediction points for each bridge in the region if Leiden. The color of each circle represents a bridge, which may have one or multiple sides for making ETA predictions.

3.2 Data preprocessing

Data preprocessing is necessary since the raw AIS data must be transformed to determine whether specific ships pass certain bridges. Additionally, the provincial waterways are segmented into 100-meter sections, which simplifies the calculation of ETAs based on AIS positions.

3.2.1 Bridge Passages

We have three years of AIS data, comprising records from 2019, 2020, and 2021. To determine whether a particular vessel, as identified by its AIS trace data, will pass under a given bridge, we must preprocess the data to calculate potential bridge passages. To achieve this, we draw a line across each bridge and then verify whether the AIS trace data of a specific ship passes this line, on either the right or left side.

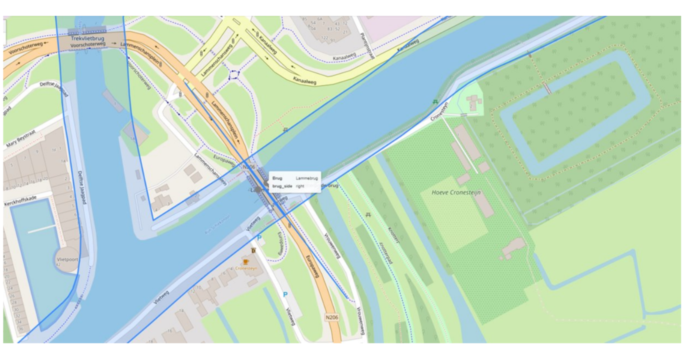

Figure 2. In order to see if a AIS trace passages a certain bridge we draw a line to see if the AIS data passes this line.

3.2.2 Provincial Waterway 100 meter Sections

To streamline the process, we divide the provincial waterways into sections of 100 meters each. This strategy simplifies ETA predictions as it shifts the focus from calculating an ETA for a specific AIS GPS position to generating predictions for each 100-meter section of the provincial waterways for each bridge. This approach also yields more data for making predictions. Gathering a sufficient amount of data for a specific AIS GPS position is considerably more challenging than for a 100-meter waterway section.

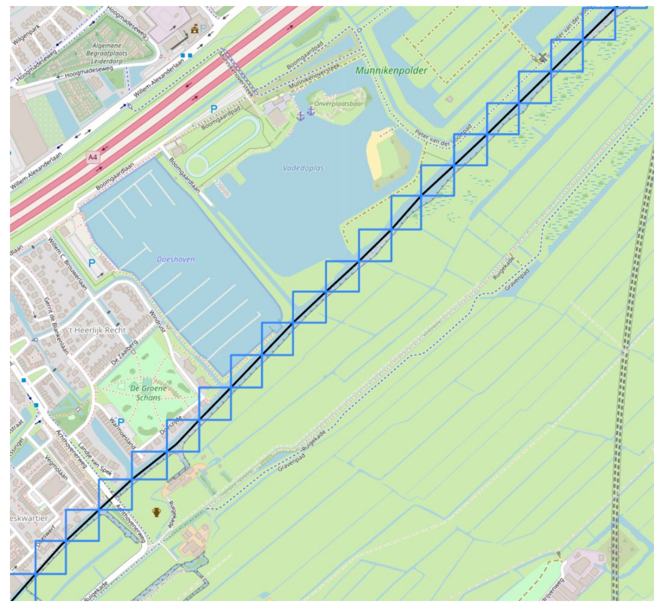

Figure 3. The provincial waterways are divided into 100 meter sections, for each of these sections the average historical arrival times are calculated to various bridges.

For each of these 100-meter sections of provincial waterways, we calculate the average historical travel time taken by ships to pass a given bridge, based on the computed AIS trace bridge passage data. We make the assumption that a ship takes the shortest route to a specific bridge. To ascertain this shortest route, we represent the sections as a graph and apply a shortest path algorithm.

We then store each section and its associated average historical travel time to each bridge in a database. With this setup, a simple database lookup can be performed for a specific AIS GPS position. This lookup will determine which section of the provincial waterway it is in and reveal the historical travel times to reach a certain bridge. This forms one component of our prediction model but can already be utilized to predict ETAs.

4. Input Data and Model

Inspired by Hu et al. 2022 we combine the average travel time in a Provincial Waterway segments, which can be seen a basic routing system, to a bridge with real time information variables. The input variables for the model are as follows: Historical travel time, current Speed Over Ground, Category of the ship, randomised ship id, length of the ship and the current month.

4.1 Historical Average Travel Time to Bridge

We calculate the historical average travel time to a bridge as follows. We start with the assumption that a ship located in the current provincial waterway segment will take the shortest path to a bridge. To determine this route and its associated distance, we represent the segments as a graph and apply a shortest path algorithm. We then divide this distance by 1.94444. This factor is equivalent to a speed of 7 km per hour, the typical speed at which ships sail, but converted into seconds. As a result, we obtain the estimated number of seconds it would take for the ship to reach the specific bridge. This value thus represents the historical average travel time to a bridge.

4.2 RandomForest Regressor model

We employ the Random Forest Regressor model provided by the Python scikit-learn package Pedregosa et al. 2011. To find the optimal parameters, we performed a grid search, which identified the optimal parameters as a 'random_state' of 42 and the 'criterion' set to MSE. The data was divided into training and testing datasets, with a 70/30 percent split favoring training data over testing data, respectively.

4.3 Results

The table below presents the results in terms of Mean Error and Root Mean Squared Error, quantifying the difference between the actual arrival time and the predicted ETA 500 meters before a bridge. Given the potential discrepancy between the 500-meter mark before a bridge and the nearest AIS signal to that location, these results should be interpreted as indicative rather than definitive.

Table 1. Results on model predictions difference between the ETA and the actual arrival time before a bridge on the test set.

Bridge	Mean Error	Rooted Mean Squared Error
Wilhelminabrug Leiden	0:02:50	0:04:53
Julius Caesarbrug	0:02:55	0:04:44
Leiderdorpsebrug	0:02:41	0:05:06
Waddingerbrug	0:03:22	0:05:52
Rhijnvreugdbrug	0:03:01	0:05:42
Kanaalbrug	0:02:56	0:05:11
Lammebrug	0:03:40	0:05:58
Hooghkamerbrug	0:03:07	0:05:09
Spanjaardsbrug	0:03:43	0:06:44
Stevensbrug	0:03:28	0:05:58
Hoflandbrug	0:03:05	0:05:31

5. Discussion

RME for all the bridges was around 5 minutes on the test set, if this error margin is acceptable is being debated. Sometimes are is discrepancy between 500 meters before the bridge and the most closed AIS GPS position of a ship. A filter can be made with the AIS GPS data to be within a interval region close to the 500 meters point. But that would also leave us with less training data.

Further more, more experimentation can be done with deep learning models, which was alas out of the scope of this paper

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