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Wenzel, Peter; Jovanovic, Raka; Schulte, Frederik

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A Neural Network Approach for ETA Prediction in Inland Waterway Transport

Peter Wenzel[1], Raka Jovanovic[2], and Frederik Schulte[1](✉)

[1] Technical University of Delft, Mekelweg 5, 2628 Delft, CD, Netherlands
{p.a.wenzel,f.schulte}@tudelft.nl
[2] Qatar Environment and Qatar Environment and Energy Research Institute, Hamad bin Khalifa University, PO Box 5825, Doha, Qatar
rjovanovic@hbku.edu.qa

Abstract. Ensuring the accuracy of the estimated time of arrival (ETA) information for ships approaching ports and inland terminals is increasingly critical today. Waterway transportation plays a vital role in freight transportation and has a significant ecological impact. Improving the accuracy of ETA predictions can enhance the reliability of inland waterway shipping, increasing the acceptance of this eco-friendly mode of transportation. This study compares the industry-standard approach for predicting the ETA based on average travel times with a neural network (NN) trained using real-world historical data. This study generates and trains two NN models using historical ship position data. These models are then assessed and contrasted with the conventional method of calculating average travel times for two specific areas in the Netherlands and Germany. The results indicate by using specific input features, the quality of ETA predictions can improve by an average of 20.6% for short trips, 4.8% for medium-length trips, and 13.4% for long-haul journeys when compared to the average calculation.

Keywords: Neural Networks · Machine Learning · Inland Waterway Transport · Estimated Time of Arrival Prediction

1 Introduction

In 2021, the total volume of goods transported on European inland waterways was 524 million tonnes, increasing by 3.9 % compared with the previous year. The complete transport reached 136 billion tonne-kilometres, up 3.3 % of the prior year [9]. Inland Waterway Transportation (IWT) is part of the critical infrastructure that provides essential services that are substantial to the safety and the economic and social welfare of society [20]. Therefore inland waterway infrastructure maintenance and management is critical but not ideal. In 2015, for example, around 85% of locks, 73% of weirs, and 87% of pumping stations were in an inadequate state of repair [20]. Navigation hazards and safety measures in inland waterways play an important role. For 2010, 2011, and 2013, the

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most frequent accident was the collision with infrastructure and bridges. This type accounted for 38–40% of all accidents. The second most frequent type of accident was the collision between ships (18–19%). Due to increasing low water periods caused by climate change, low water levels will lead to smaller vessels and, therefore, an increase in transportation costs [13]. In order to make accurate predictions, it is critical to consider and account for exceptions in the inland waterway network.

Intermodal connectivity and transport efficiency in inland waterways are crucial to model cost competitiveness compared with other transportation modes such as road and rail [21]. Waterway transportation has an irreplaceable key position in the entire transportation development process. It is also one of the important modes of transportation to have a significant ecological impact [12].

The maritime operations in a port involve many parties, including pilots, tug boats, boatmen, agents, supervision agencies such as customs and police, stevedores and others. The arrival of a ship triggers activities at all these parties, who then determine the performance of the port as a whole by each contributing their specialist activity [19]. The need for reliable tools to verify and ensure the accuracy of the estimated time of arrival (ETA) information provided by ships as they approach ports has never been more critical than it is today [3, 6]. This paper establishes a groundwork for future research by demonstrating the advantages of using neural networks (NN) with simple input parameters for ETA prediction in inland waterway transportation. The development and testing of various NN architectures make it possible to consider external factors such as weather forecasts, river depth forecasts, and infrastructural factors when predicting ETA.

In Sect. 2, this paper presents the related research. The methodology used is delineated, and the process of data preparation is provided in Sect. 3. Moving on to Sect. 4, the training of our neural network model is detailed, along with the accompanying results. Finally, the conclusion of the paper offers the limitations and potential future research in Sect. 5.

2 Related Research

The utilisation of Automatic Identification System (AIS) data for ETA prediction in seagoing vessels is a widely researched topic. It has been shown in various research work [11,15,23] that data-driven algorithms achieve higher accuracy in terms of the time of ETA error. The main goal of this research work is to improve ETA time calculation to improve efficiencies in port operations. Valero [18] predicts ETA times to improve short sea shipping. El Mekkaoui [8] focuses more on the improvements of predictions for bulk ports, and Pani [16], and Yu [23] focus on container and transhipment terminals. The applied methods in overseas shipping research used vary from machine learning algorithms such as NNs [2,7], random forest [23], reinforcement learning [17], bayesian learning [15] and deep learning [8,11] to pathfinding algorithms [1].

There are significant differences in IWT when estimating the ETA for seagoing vessels. Water levels and weather conditions are crucial factors that can affect the vessel's speed and route. Also, ports are only sometimes fixed, and routes may need to be adjusted accordingly, making ETA prediction more complex. Limited research is carried out to address ETA predictions in the context of IWT specifically. Zhong et al. [25] proposed a deep learning method based on bi-directional long short-term memory recurrent neural networks (BLSTM-RNNs) for restoring AIS trajectory data and applied it to inland ship trajectory restoration. The paper focused on ETA prediction in IWT. Noman et al. [14] developed a data-driven approach for ETA prediction using gradient boosting decision trees (GBDT), multi-layer perceptron neural networks (MLP), and gated recurrent unit NNs (GRU) algorithms trained on past inland waterway AIS data. The approach was tested for both natural and artificial waterways, and the results showed that the GRU model outperformed the other models in accuracy and efficiency. Overall, both papers focused on ETA prediction in the context of IWT and proposed different machine-learning algorithms to address this problem. Zhong et al. [25] focused on restoring AIS trajectory data, while Noman et al. [14] focused on developing a data-driven approach for ETA prediction. Two closely related papers have been identified. The paper of Xie and Liu [22] proposed a deep learning model based on long short-term memory networks (LSTMs) for vessel traffic flow prediction in inland waterways. The model was designed to predict a wide range of traffic flow aspects, including short-term, long-term, and the influence of water level factors. Yu et al. [24] explored deep learning approaches for AIS data association in the context of maritime domain awareness. The paper presented two methods for inferring ship association probability. One predicts the ship's position before computing association probability, while the other compute association probability directly using only longitude, latitude, and time.

The literature review highlights the significance of accurate ETA predictions in facilitating port operations. Specifically, the research emphasises sea-going vessels, mainly in deep sea ports, with relatively less attention paid to inland waterway shipping. However, predicting precise ETA times in inland shipping for smaller terminals, river terminals, and transhipment terminals is crucial. Achieving reliable IWT, comparable to rail and road transportation, is vital to encourage a modal shift towards IWT.

Unlike a road network with numerous crossings and decision points, a river network is relatively straightforward. Derrow-Pinion [5] put forth a technique in their publication that involves dividing a road network into segments and transforming it into a graph. They subsequently employ a Graph Neural Network (GNN) to analyse the network. Our approach uses real-world AIS data to segment the river network data, thus simplifying the network. This simplification allows us to use a NN for travel time prediction.

In line with the works of Fancello [10] and Yu [24], a NN is employed for ETA time prediction. Yu [24] partitions the Baltic and North Seas close to Copenhagen into segments and utilises track projection and ETA prediction on the dataset. This work also creates segments for the inland waterway. Meanwhile, Xie [22] incorporates data from the Wuhan Yangtze River, including water levels that fluctuate during flood periods throughout the year. This model does not consider water levels. The author optimises the model instead of comparing the prediction outputs to average calculations.

3 Methodology

This work's objective is to predict the duration it takes for ships to travel from the initial location A to the final location B, with a route passing through several segments s. An A* algorithm is implemented to determine the segments travelled from A to B, followed by the typical industry practice of computing the average travel time. Afterwards, a NN is designed and trained to compare the model's predictions with the computed average. Our methodology and data preparation process are outlined in Sect. 3, while the training of our NN model and the corresponding results are presented in Sect. 4.

3.1 Data Description and Data Preparation

The maritime domain utilises the AIS to enhance ship traffic safety through real-time broadcasting of vessel information, including identity, speed, location, and course. For this study, prefiltered AIS data was downloaded from a cooperation partner via an API call. The received data contains the position data of the ships, including the following information, MMSI (Maritime Mobile Service Identities, the unique ship number), Status of the ship (underway, moored, etc.), speed over ground, course over ground, true heading, time of last update, ETA, destination (manual input from the skipper), data source, maximum draught of the ship, new streaming update and location (latitude and longitude). The data were filtered based on the "Moored" status and vessels, not in motion, requiring a speed over ground greater than zero.

Segments with a radius of 2.5 km are generated to cover the entire area. The position data, consisting of start latitude, longitude, and end latitude and longitude, is mapped to start node ID and end node ID. The position data is then looped through to eliminate multiple position data for each segment, keeping only the data closest to the midpoint of the segment. The resulting table is referred to as segment crossings. The crossing duration is computed from the start and end times of each segment crossing. For each segment, the number of ships crossing it is calculated. Segments with less than 50 appearances and trip durations below 50 s are excluded. From the resulting ship-crossing data, the stop time and destination were dropped from the dataset. The dataset was further enriched by adding this additional data, such as compass bearing. Any rows with missing values were removed to ensure data integrity and accuracy in the analysis. A NN model is created to predict the duration to travel from one segment to another.

To improve the reliability of predictions for IWT, it is advisable to make predictions for individual segments and obtain accurate predictions for complete ship trips that traverse multiple sections. Therefore, developing and incorporating trip-level prediction models in addition to segment-level models is recommended. Consequently, an algorithm was created to identify the travels of a ship and add a trip ID to the dataset. The code iterates over all segment's crossings and adds a new value, "trip id". For each row, it assigns a trip ID based on the MMSI (an identifier for a vessel), the start time, and the start and end nodes. If the MMSI changes or the time difference between consecutive rows is more than 1000 s seconds, or the start node of the current row is not the same as the end node of the previous row, then it increments the trip ID counter. The following Fig. 1 shows a sample trip in the dataset.

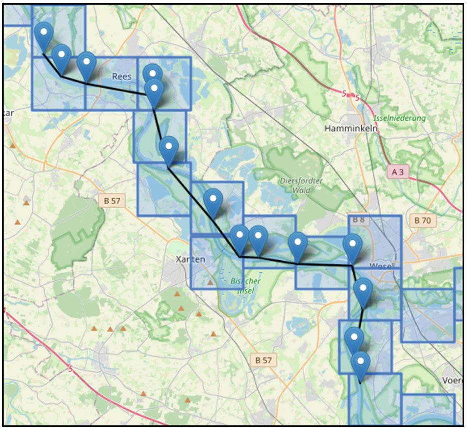


Fig. 1. River network with segment ids

3.2 Average Travel Time Calculation

Similar to Derrow-Pinion [5], the Average Travel Times (ATT) between each pair of cells are calculated based on the actual times d_s for a ship-crossing s. The ATT is calculated by the sum of the duration of the ship-crossing $\mathrm{d_s}$ of the number of start and end node pairs N and then divided by N.

$$ATT = \frac{\sum_{i=1}^{N} t_i}{N} \tag{1}$$

3.3 Neural Network

Transposing and describing train features in Python is an essential step in preparing the data for machine learning, as it ensures that the data is organised in a format suitable for training models and provides valuable information about the characteristics of the features. To ensure that the features are organised in the correct format for training the model, train features are transposed and described. Using z-score normalisation in the previous approach could have been more effective in producing accurate results. This paper utilised min-max normalisation to scale the data between 0 and 1, preserving the original range. The equation for min-max normalisation is as follows:

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{2}$$

x is the original value of the data, $min(x)$ is the minimum value of the data, $max(x)$ is the maximum value of the data, and x' is the normalized value of x between 0 and 1. The numerator, $(x - min(x))$, subtracts the minimum value from the original value to measure the distance between the original value and the minimum value of the data. The denominator, $(max(x)-min(x))$, calculates the range of the data by subtracting the minimum value from the maximum value. By dividing the distance between the original value and the minimum value by the range of the data, the resulting value is normalised between 0 and 1.

A validation set that is not used for training but to evaluate the model's performance on unseen data is created. 80 % of the data are used for training, 20 % are used for validating the model. The actual travel duration was excluded from both the train and validation datasets.

The used input parameters are the following: the id of the start segment, the id of the end segment, the Status of the ship (underway, moored, reserved), Course over ground, True heading, Time of last update, ETA, Destination (manual input from the skipper), Data Source, Maximum draught of the ship, new streaming update, location (latitude and longitude), compass bearing and the actual travel time from origin segment to destination segment.

Several correlations can be observed among the provided input parameters. The course over ground and true heading is typically closely related, representing the direction of ship movement. The time of last update and the new streaming update are correlated, with the new streaming update expected to have a more recent timestamp. The maximum draught of the ship and moored status might be correlated, as the draught becomes less critical when the ship is stationary. Furthermore, a correlation exists between the specified destination and the estimated ETA, as the ETA reflects the projected time of reaching the destination.

The created model design is adapted from Chondrodima [4] using similar parameters for performance evaluation and hyper-parameter selection. This is a sequential NN model, an artificial deep-learning architecture. The sequential model is a linear stack of layers, where the output of one layer serves as the input for the next layer sequentially. The model has three layers, the first dense layer with 30 output units and 510 trainable parameters. The activation function is a ReLu function-the second dense layer (hidden layer) with 30 output units. The activation function is a ReLu function. The third and final dense layer, with one output unit, represents the model's output prediction. It has 31 trainable parameters. The activation function is a ReLu function. The model has 1,471 parameters, all of which are trainable. The parameters of the model are adaptively adjusted during training based on the patterns and information contained in the training data. This adaptive learning process allows the model to learn the appropriate representations and relationships in the data, enabling it to make better predictions on new, unseen dataThese parameters are adjusted during training to optimise the model's performance on the given task. The model has no non-trainable parameters, meaning all parameters are updated during training. Figure 2 shows the design of the NN.

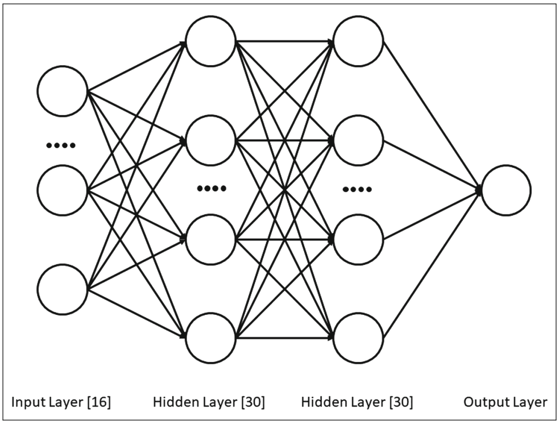


Fig. 2. NN with three layers, an input layer, two hidden layers and one output layer

Similar to the work of Xiu [22], the root two widely used criteria are adopted to measure the error of the predicted data, they are the Root Mean Squared Error (RMSE) and the Mean Relative Error (MRE). These criteria are commonly used to evaluate the accuracy of predictive models.

4 Results

A case study was conducted to demonstrate the higher accuracy of neural network-based ETA prediction for IWT. The code was implemented in Python within a Google Colab environment, utilising an Intel Xeon CPU @2.20 GHz, 25 GB RAM, a Tesla K80 accelerator, and 12 GB GDDR5 VRAM.

The following section provides an overview of the case study data and an evaluation of the model training results. Subsequently, the predictions are compared with the average results of the entire network and two specific areas.

4.1 Case Study Data

This study's position data covers January to April 2022 and encompasses a 50km radius around Rees. Figure 3 shows the segments.

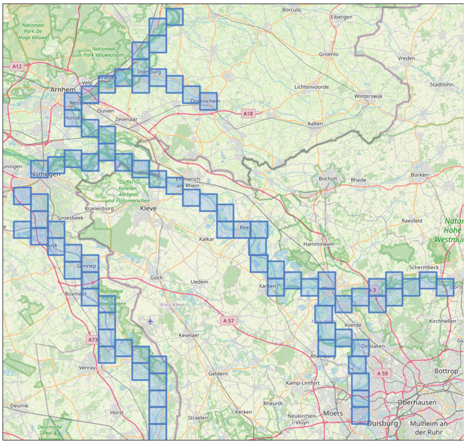


Fig. 3. Filtered river network segments with applied filters

The resulting area contains the busy area in Duisburg, a crossing close to Doornenburg, the border crossing in Bimmen, and a straight line without any stops between Emmerich and Wesel. After data preparation, 82 segments and 152,650 rows of ship-crossing data were obtained. Figure 3 illustrates the remaining segments post-data filtering.

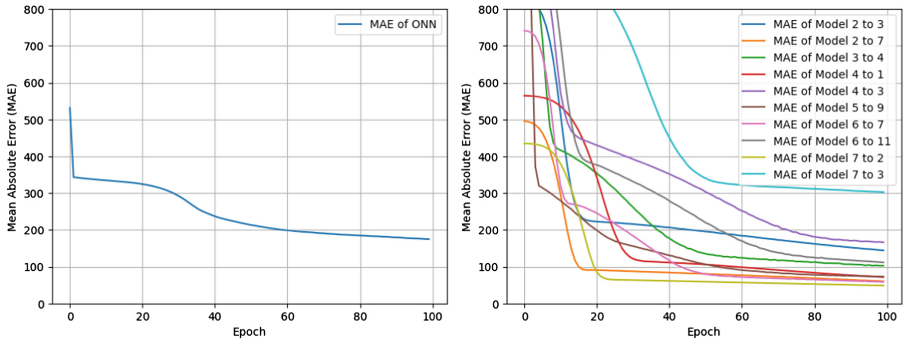
4.2 Model Evaluation

For comparison, two different approaches were employed. The first approach, the Overall NN (ONN), involved using the entire network to train the model. The second approach Individual NN (INN), utilised individually trained models for each start and end node pair. The training and validation are made for the same in the dataset, allowing for a comprehensive assessment of the performance of each method.

The model was trained using data from January to March, and the training process involved 100 epochs. The history epoch loss graph shows the model's MAE change over successive epochs and is illustrated in the following Fig. 4.

Similarly, the validation loss graph shows the change in loss on a separate validation set during training. The validation graph provides insights into how well the model generalises to new data. Since the validation loss remains consistently low with the training loss, the model performs well on both the training and validation data. After the 20th epoch, the ONN model's learning rate is not improving significantly. For the different INN models, the learning drops at the 80th epoch.

Xie [22] conducted predictions on a more granular level. The evaluation metrics for the models are crucial, and the Root Mean Square Error (RMSE) for the ONN model is 5.8%, and the Mean Relative Error (MRE) is 12.32 %. For



(a) Loss function for ONN (b) 10 sample loss functions for INNs

Fig. 4. Loss and Validation Loss Function shows the differences between ONN and INN

the INN model, the RMSE is 25%, and the MRE is 35.8%. However, the model trained in this study produced similar results for a one-day prediction.

4.3 Comparison of Averages to NN

NNs are commonly evaluated by randomly partitioning data into training, validation, and testing sets. However, this section uses historical data to predict future data. Although the predicted data is also historical, it represents the future concerning the training data used. A future dataset containing 59,000 entries of start and end segment information for April was obtained and preprocessed for analysis.

$$t = (s_1, s_2, \ldots, s_n) \tag{3}$$

A trip t contains multiple segment-crossings s_i, for $i = 1 \ldots n$. Using the structure of the trip t, the total duration is calculated using the following equation.

$$d_t = \sum_{s=1}^{N_s} d_s \tag{4}$$

In (4), N_s is defined as the number of segments per trip. Each segment-crossing has a duration of d_s. Therefore the sum of all segments crossing is the duration of the trip d_t.

$$ATT_t = \sum_{s=1}^{N_s} ATT_s \tag{5}$$

The averages ATT_t are calculated for all the segment-crossings s in trip t.

$$ATT = \frac{\sum_{t=1}^{N_t} ATT_s}{N_t} \tag{6}$$

For all trips N_t in the test dataset, the average ATT is calculated. The following Eq. 7 shows the prediction error PE for the Average Calculation (AC):

$$PE_{AC} = ATT - \sum_{t=1}^{N_t} d_t \tag{7}$$

PE_{AC} is calculated by substracting the sum of all trip durations d_t from the average travel times.

To create trip duration predictions from the NN, the algorithm iterates over each segment in the route and predicts the duration of the segment-crossings. The predicted duration is added to the current timestamp, which serves as an input to the NN, and this updated timestamp is used to make the next prediction for the next segment crossings. Predictions are made for ONN, and INN uses the same methodology. Both the ONN and INN models are employed to generate the predictions.

$$PNN_t = \sum_{i=1}^{N_s} PNN_i \tag{8}$$

The prediction duration of the trip for the NN (PNN) is the sum of all segment crossing predictions.

$$PNN = \frac{\sum_{i=1}^{N_t} PNN_i}{N_t} \tag{9}$$

For all trips N_t in the test dataset, the average of PNN is calculated.

$$PE_{NN} = PNN - \sum_{i=1}^{N_t} d_i \tag{10}$$

The prediction error for the NN is calculated by subtracting the sum of all trip durations from the PNN.

The dataset was analysed and segmented into short trips (3 segment crossings), medium trips (9 segment crossings), and long trips (18 segment crossings). To compare different trip lengths, long trips with more than 18 segment crossings were truncated to 18 segment crossings, ensuring that at least 100 trips were available for each trip length category.

The results of ETA prediction error using the three different models - AC, ONN, and INN - on different data sets with varying numbers of segments and durations. The first column in table 1 indicates the number of crossed segments N_s per trip t, while the second column represents the duration d_t in seconds. The following three columns show the average predictions made by each model for the respective data sets. Finally, the last three columns indicate the relative standard deviation in percentage for each model's predictions.

Table 1. Results of the comparison of prediction methods

N_s	d[s]	Prediction error			Relative. Std.[%]		
		AC	NN	INN	AC	NN	INN
18	6898	1743	820	1220	25.3	11.9	17.7
9	5944	358	343	539	12.8	5.8	9.1
3	3687	143	34	268	2.4	0.9	2.1

The results indicate that the NN methods have smaller prediction errors than the AC method for all three trip length sets. The relative standard deviation is the smallest for the ONN method for the 3-segment and 9-segment crossings, while the INN method has the lowest relative standard deviation for the 18-segment crossing. Overall, the results suggest that the ONN and INN method are slightly more accurate in predicting segment-crossing duration than the AC method.

Computational experiments have been performed on two selected regions to provide an additional comparison, as shown in Fig. 5.

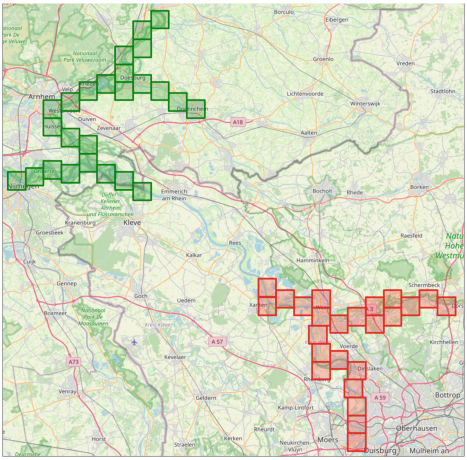


Fig. 5. Area of Kleve (green) and Duisburg (red) for comparison. (Color figure online)

The region surrounding Duisburg is assigned the abbreviation “DUI,” while the red region near Kleve is designated as “KLE.” Given the smaller geographical scope and absence of long-distance port journeys, emphasis is placed on trips with three and 9-segment crossings. After segmenting the data, 100 random samples were selected for each 3-segment and 9-segment crossing trip.

Similar to Table 1, the prediction errors are shown in Table 2 for the three methods: AC, NN and INN.

Table 2. Results of the comparison of prediction methods for DUI and KLE

N_s	d[s]	Prediction error			Relative. Std.[%]		
		AC	NN	INN	AC	NN	INN
9 (DUI)	5500	745	652	742	13.5	11.9	13.5
3 (DUI)	3105	102	38	130	3.2	1.2	4.1
9 (KLE)	6085	774	10	193	12.7	0.1	3.1
3 (KLE)	3578	704	37	111	19.7	1.0	3.1

Trip durations are, in general, a bit shorter in the DUI area. The largest inland port in Europe is located in Duisburg, so the dataset includes shorter trips that involve docking at specific locations within the port. In the case of the Klave region, noisy data may be attributed to crossing the border between Germany and the Netherlands.

5 Conclusion

Previous studies have emphasised the significance of enhancing ETA prediction accuracy for efficient terminal and inland port operations [3,6]. Xie [22] has showcased the effectiveness of using LSTM models for ETA prediction. However, related studies mainly focused on fine-tuning predictions for a single segment crossing rather than predicting entire trips.

The paper discusses the advantages of precise ETA prediction in IWT and uses real-world data to train a dedicated NN. The results demonstrate a considerable enhancement in ETA prediction compared to conventional travel time averages. Additionally, this work showcases how predictions can be utilised for complete ship trips crossing multiple segments using an A* path algorithm.

There are certain limitations that should be considered. Historical data's availability and representativeness could impact the predictions' generalizability. Additionally, the generalizability of the results may be limited if the experimentation is conducted only with specific segment sizes. Including additional input parameters such as weather data and river, depths could improve prediction accuracy. While effective in improving neural network model performance, hyperparameter selection techniques have certain limitations. These include computational complexity, sensitivity to initial conditions, and the need for careful consideration of the search space.

Future work should aim at enhancing the accuracy of results by downloading more historical data. In addition, further experimentation with smaller and larger segments will be conducted. More input parameters, including weather data and river depths, will be added to improve the accuracy of predictions. Future work will further incorporate infrastructural information, such as closed bridges and locks at certain timestamps, to provide more precise predictions. Finally, the results of this study will be compared across different river areas to validate the model's effectiveness. It is anticipated that Graph Neural Networks (GNNs) will be utilised for ETA prediction in IWT. The advantage of GNNs lies in their ability to learn from graph-structured data and model the dependencies among nodes in a graph. In the case of IWT, the river network can be represented as a graph where the nodes represent the various segments and the edges represent the waterways connecting them. By incorporating this graph structure into the GNN, the accuracy of ETA predictions is expected to be significantly improved.

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