1	PREDICTION OF VESSELS' ESTIMATED TIME OF ARRIVAL (ETA) USING MACHINE
2	LEARNING - A PORT OF ROTTERDAM CASE STUDY
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ABSTRACT

The hinterland transportation of incoming containers at container terminals is a complex problem, due to the various actors involved and their often conflicting interests. A promising solution towards the problem for hinterland network operators is that of synchromodality, a concept that refers to real-time network planning for hinterland transportation. However, one of the main hindrances to the implementation of this concept is the current absence of an accurate way to predict the estimated time of arrivals (ETA) for containerships calling at port container terminals. This results in huge uncertainty over the types and amounts of cargo that reach the terminals, which in turn hinders the fast and cost efficient distribution of cargo to inland destinations.

The current paper will propose and compare machine learning techniques for predicting the ETA of containerships calling to the Port of Rotterdam, by combining position GPS data with weather predictions. The added value of providing such an information tool to the stakeholders involved in the inland container transportation is investigated.

Key words: Estimated Time of Arrival (ETA), container vessels, Neural Networks, Support Vector Machines, container terminals, weather conditions, hinterland transportation.

1. INTRODUCTION

Maritime container shipping has a central role in today's global economy, since it accounts for a significant part of the world trade. The Port of Rotterdam serves as a port of call for numerous containerships each year, a fact that places it among the most important terminals in continental Europe. The majority of container terminals within the port, are operated by the European Container Terminals (ECT). ECT is also operating a number of inland terminals, and through its subsidiary company, European Gateway Services (EGS) provides inland transportation services connecting the Port of Rotterdam (PoR) with the ECT maritime terminals. As part of its value-adding strategy, EGS has developed new transportation products based on the concept of synchromodality aiming to offer differentiated high level services to the region's intermodal market [1]. The concept of synchromodality refers to an intermodal transportation network with an online planning system, able to make real-time adjustments to meet all the delivery requirements [2].

However, one of the main problems that ECT along with other container terminal operators is facing lies in the lack of accurate predictions of the Estimated Time of Arrival (ETA) of the containerships calling at the ports. This results in huge uncertainty over the types and amounts of cargo that reach the terminals every day, which in turn hinders the fast and cost efficient transshipment and distribution of products to inland destinations. Therefore, the accurate estimation of the exact arrival time of containerships at the Port of Rotterdam is expected to have a positive impact on the overall efficiency of supply chains.

Despite contractual obligations to notify the ETA 24 hours before arrival to the port, ship operators often have to revise it due to unexpected events like weather conditions, delays in a previous port and so on [4]. However this revised ETA is not always communicated to the terminal operators on time. A vessel's delay entails delayed containers unloaded in the terminal leading to delayed containers transported to the hinterland side. For planners, decisions such as berth and equipment allocation or Human Resources (HR) planning can be supported by the development of tools providing information on the exact vessel arrival times.

The aim of our research was to apply machine learning techniques to measure the potential accuracy improvements in predictions of ETA's of containerships, on a medium-range time horizon. We use data on ship movements together with weather data and compare two different techniques, Support Vector Machines (SVM) and Neural Networks (NN). In addition, we briefly assess the added value of a more accurate prediction of ETA to stakeholders involved in hinterland container transport.

The remainder of the paper is structured as follows: Section 2 presents an overview of the existing literature on the computation of ETA's in the maritime ports context. Section 3 describes the data that was available for our research. In Section 4 model development is explained in detail. Section 5 describes and compares the results of different approaches. Section 6 analyses the value of the provision of this information to the stakeholders involved in the container transport. Finally, the paper concludes by presenting the main findings and proposing areas for further research.

2. LITERATURE REVIEW

Our literature review revealed that despite the recent important technological innovations, the uncertainty and variation in daily demand forecasting still remains a challenge for port operators [6].

The arrival of the vessel is of vital importance, since it initiates the whole process of container transportation to hinterland destinations. Therefore, providing a solution to the problem of the uncertain ETA is essential for optimizing the allocation of handling

equipment and increase the efficiency of the terminal. An accurate containership ETA is perceived of high importance by port operators, as well as hinterland transportation parties [7] that need this information in order to plan adequately for barge or rail capacity and schedules.

In their research Gambardella *et al.* [6] proposed a forecasting tool that calculates the daily container flows in and out of a terminal by combining two different modules. The first one uses past data to predict the number of containers loaded on a vessel expected to call at the port. The second module estimates the total number of containers expected to be transported by truck, as a function of the ship's ETA. The only model capable of predicting ETA is presented in [4] and employs NNs to reduce the uncertainty of port arrival time to approximately 6 hours. However, it only accounts for a 24-hour time horizon, without including weather information but addressing vessel delays due to port operations. This simulation model was able to decrease work shifts from four to two and reduce terminal operating costs. A simulation model was developed to assess the Panama canal capacity under different operating conditions. One of the model modules predicted the vessel ETAs and ready times (a time that a vessel is ready for transit through the canal) based on historical data [18].

In the literature, attempts to model the weather effect on vessel speed using physics based deterministic models were made [10]. Specifically, the variables used for short term speed predictions were: the nominal speed of the vessel (based on the power of the ship's engine in rounds per minute), the impact of the wind on the sailing speed, as well as the impact from currents and waves. By taking into account the direction of the vessel, equations are built for determining the actual speed of the vessel at that particular point. In addition websites such as Marine Traffic, Shipment and Hermess [8,9,10] are available that can estimate real-time vessel ETA for free. It should be highlighted here that these ETAs refer to short term predictions.

Moreover, a major implication of late vessel arrivals at the port is that the process of assigning manpower and equipment becomes significantly more complicated. In case of delayed vessel arrival workload peaks are created resulting to lower terminal service levels [12]. A new berthing place must be assigned to the delayed vessel, more cranes are simultaneously put into use and usually extra movements for transporting the containers in the yard are required.

From the literature review it can be concluded that there is a lot of room for improvement in the prediction of ETA at container terminals. Accurate medium and long-term ETAs are expected to assist the planning activities of port operators and of the stakeholders involved in the process of inland container transportation. Specifically, the existing models account for a 24-hour time horizon without taking into account weather predictions. The contribution of this research is to expand the time horizon to medium range predictions (i.e. up to 5 days prior to vessel arrival), by using big data and accounting for weather conditions.

3. DATA COLLECTION

The data used for model development were collected from two sources: the AIS (Automatic Identification System) and weather prediction data. AIS is a mandatory system for ships above 300 tons gross tonnage that is sent between ships and between a ship and a shore-based station. Messages can contain three different types of information: static, voyage related and dynamic. Static information includes the ship's name and size; voyage related information includes the ETA predicted by the captain and the destination; and dynamic information includes speed, course and position. The three different types of information

differ in reliability. The dynamic information is provided by the technical equipment of the ship (e.g. GPS) and is quite reliable. Voyage related information is inserted manually for every voyage and therefore it contains many errors. Static information has to be entered once per AIS transponder and in general is more reliable than voyage related information [11].

Numerical weather predictions and currents were acquired from the ECMWF (European Centre for Medium-Range Weather Forecasts) and NOAA (National Oceanic and Atmospheric Administration) models respectively. From the ECMWF model the weather magnitude and direction was used, whereas the currents and waves, both in magnitude and direction, were obtained from NOAA. The weather and currents data were mapped, based on time and location, to the voyages under examination.

Data for the voyages on the Asia – Rotterdam route (direct route without taking under consideration other western European ports of call), from January 2015 until February 2016 were collected. Totally, 600 voyages were used. From each voyage observations were collected every few minutes. Although a large amount of observations per voyage was available, the total number of voyages remained relatively low for applying machine learning techniques, since they require abundant data. In order to cope with this problem, the size of the Neural Networks and Support Vector Machines had to be kept to a minimum, by inserting a low number of variables in the model.

Specifically, the following input variables were used as input:

• AIS Data

- o Latitude (degrees)
- Longitude (degrees)
- O Distance to be covered (km/h)
- o Current speed of the vessel (km/h)
- o Change in speed over the last 3 hours (km/h)
- Average speed based on last 12 hours (km/h)
- o Time used for calculating the average speed (hours)
- o Length of the ship (meters)
- o Breadth of the ship (meters)
- o ETA of the ship's agent (number of days)

• Weather Data

- Current U-Component (m/s)
- Current V-Component (m/s)
- Wind U-Component (m/s)
- Wind V-Component (m/s)
- Peak wave period (s)
- o Peak wave direction (degrees)
- o Significant wave height (m)

After collecting the positional and weather data of the voyages for the past year, a preprocessing step took place to select the relevant information and to build the input vector with a set of variables relevant for predicting the ETA.

4. MODEL DEVELOPMENT

This chapter describes the methodology followed for developing the ETA prediction model by applying Support Vector Machines and Neural Networks. Firstly some information is given on the NNs followed by a description of the method application used to develop the models. Then SVMs and their applications are described.

4.1 Neural Networks

Neural networks are limited imitations of how human brains work [12]. In an artificial neural network, a neuron is a logistic unit that receives inputs through its input wires, uses the logistic unit computation function (such as $Z_{\theta}(x) = \frac{1}{1+e^{-\sum_{i=0}^{n}\theta_{i}x_{i}}}$), and depending on the outcome of the computation, sends an output (signal) to the output wires. A neural network consists of multiple neurons, organized in layers and interconnected with each other via input wires, characterized by their respective weights. Those weights are represented by the 'theta' (θ) parameters in the neural network model. Virtually, a simplistic

representation looks like $[x_0, x_1, ..., x_n]^T \rightarrow [] \rightarrow Z_{\theta}(x)$.

The neural network consists of three distinct layers, namely the input layer, the hidden layer and the output layer made by one node. After being processed at the hidden layer nodes, their outputs are forwarded to the output layer which then makes a prediction, according to its activation function. This feedforward process is characteristic of NNs and given an input vector, it is used to make predictions. The training phase of a neural network comprises of selecting the optimal weights for each of the connections between the neurons. Specifically, given the input vector at the input layer, and the known output that actually occurred, the problem is defined as the estimation of weights for the connections between neurons in order to minimize the error between the prediction and the actual observation. An algorithm used for training the network until the optimal weights are selected, is the backpropagation algorithm [13].

The intermediate or "hidden" layer nodes of the networks are labeled as $a_{20} \dots a_{2n}$ and are called "activation units." The following notation will be applied:

- $a_i^{(j)}$: "activation" of unit *i* in layer *j*
- $\Theta^{(j)}$: matrix of weights controlling function mapping from layer j to layer j+1
- The formula that computes $a_i^{(j)}$ is the following:

$$a_i^{(j)} = g\left(z_i^{(j)}\right) = \frac{1}{1 + e^{-z_i^{(j)}}},$$

27 where
$$z_i^{(j)} = \theta_{i,0}^{(j-1)} x_0 + \theta_{i,1}^{(j-1)} x_1 + \dots + \theta_{i,n}^{(j-1)} x_n$$
, for j=2,...,n (1)

The set of equations (1) describes is the inputs in the first layer of the network that are forwarded to the second layer, after being multiplied with the weights "theta" and then each neuron calculates its activation function.

The prediction error of the neural network can be minimized with the backpropagation training algorithm, as it was mentioned above. For the training set $\{(x^{(1)}, y^{(1)}), ..., (x^{(m)}, y^{(m)})\}$, forward propagation can be implemented to compute $\alpha^{(l)}$, for l=2,3,...,L, with L representing the total number of network layers.

35 Then, using the actual output for period t, the prediction error can be computed as:

36
$$\delta^{(L)} = \delta^{(L)} - y^{(t)}$$
, for t=1,...,m (2)

- 37 So the "error values" for the last layer are the differences of the actual results in the last
- layer and the correct outputs in y.
- To get the error values of the layers before the last layer, we can use an equation that steps
- 40 us back from right to left:

41
$$\delta^{(l)} = ((\Theta^{(l)})^T \delta^{(l+1)}) * g'(z^{(l)}) = ((\Theta^{(l)})^T \delta^{(l+1)}) * (a^{(L)}) * (1 - a^{(L)})$$
 (3)

The aim then is to minimize the error function $\delta^{(l)}$, by choosing the optimal parameters Θ . It is worth noting that due to their ability to compute complex functions, by organizing the neurons in multiple layers, neural networks have proven to be powerful predicting tools. However, one of their drawbacks is that they have a relatively slow training algorithm.

3.1.1 Neural Networks Application

- In this section the network architecture selected for model development, as well as the input variables and network parameters, will be presented.
- 9 For the development of each neural network four parameters must be selected:
 - 1. Variable inputs to the neural network.
 - 2. Number of hidden layers.
 - 3. Number hidden layer(s) neurons.
 - 4. Number of outputs.

The output of the neural network is determined by the forecasting problem, which in ours case is the predicted vessel ETA. The goal is the output to be as close as possible to the Actual Time of Arrival (ATA). The inputs to the neural network are the AIS data for each voyage, and the weather conditions.

Regarding the number of hidden layers, for the majority of the problems, one hidden layer is sufficient for achieving good results [14]. In our case study, the most important variables for model development are the set of speeds selected for the vessel, its distance to the destination and the ETA provided by the agent. Therefore, one hidden layer is expected to be sufficient for finding the relationship between the input and output variables. This, in combination with limited number of voyages used to train the NN (total of 600 voyages), led to the choice of one hidden layer.

Finally, the number of neurons in the hidden layer is crucial. Using too few neurons may result in model underfitting, meaning that the number of neurons is insufficient to recognize the patterns hidden in the dataset. On the other hand, using too many neurons may result in overfitting, a case when the neural network has more information capacity than that contained in the training set. Different network configurations were tested in order to select the optimal number of neurons. The selected NN presented the lowest error in the validation set and contained 7 neurons in the hidden layer.

Figure 1 shows the NN architecture used for tackling the problem of ETA predictions for sea vessels:

Neural Network for ETA prediction

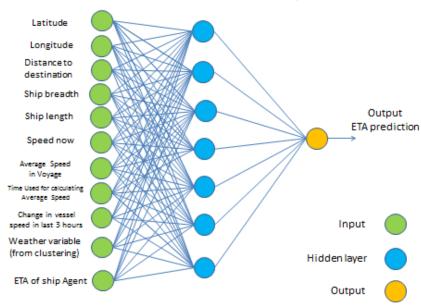


FIGURE 1 Neural Network architecture for ETA prediction.

The dataset consists of 600 voyages, with approximately 4000 observations (AIS data) sent along every route. Predictions regarding the ETA of sea-vessels were performed on a rolling time horizon along the route from west of Sicily until the Port of Rotterdam. Thirteen positions within time intervals of 6-8 hours were chosen for each voyage. From each position, the ETA of the containership was predicted. In the beginning of the route relatively few ships were available in the dataset but when moving closer to the Port of Rotterdam more vessels were added. The total number of examples used for network training and validation was 5380 observations. The datasets was divided in three sets as follows:

- The training set (65% of total data)
- The validation set (15% of total data)
- The testing set (20% of total data)

The selection of how the voyages were distributed among the different sets was random, to avoid a bias due to seasonality effects. For instance, during the winter, ships may attain in general lower speeds due to weather conditions

3.2 Support Vector Machines

<u>1</u>

Support Vector Machines (SVM) are based on the concept of large margin intuition to divide the input vectors into classes, based on their similarity. They are characterized by usage of kernels, absence of local minima, sparseness of the solution and capacity control obtained by acting on the margin. They rely on defining the loss function that ignores errors, which are situated within the certain distance of the true value. This type of function is often called – epsilon intensive – loss function [15]. In linear ε-insensitive Support Vector Regression (SVR) training solves the following constrained optimization problem:

26
$$\min_{w,\xi} \frac{1}{2} ||w||^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*)$$
 (4)

27 The optimization is subject to the constraints below:

$$28 y_i - w * x_i - b \le \varepsilon + \xi_i,$$

$$29 \quad w * x_i + b - y_i \le \varepsilon + \xi_i^*,$$

$$1 \quad \text{and } \xi_i \,, {\xi_i}^* \ge 0 \tag{5}$$

- where w is a weight vector, b is a bias value, (x_i, y_i) is a training sample and its target
- value, ξ_i and ξ_i^* are so-called "slack variables" enabling the model to allow deviations
- between the model output and the target value of training examples larger than ϵ , C is a
- 5 parameter controlling the extent to which such deviations are allowed and n is the total
- 6 number of training samples. Equation (4) is called the primal objective, and its variables
- 7 primal variables. The introduction of Lagrange multipliers α and α^* allow us to reformulate
- 8 the primal objective and its constraints in the following way:

9
$$\max_{\alpha^*} \left[-\varepsilon \sum_{i=1}^n (\alpha_i^* + \alpha_i) + \sum_{i=1}^n (\alpha_i^* - \alpha_i) y_i - \frac{1}{2} \sum_{i,j=1}^n (\alpha_i^* - \alpha_i) (\alpha_j^* - \alpha_i) \right]$$

- 10 $\alpha_i(x_i \cdot x_i)$
- 11 (6)

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subject to constraints:

13
$$0 \leq \alpha_i^{(*)} \leq C$$

14
$$\sum_{i=1}^{n} (\alpha_i^* - \alpha_i) = 0$$
 (7)

- Here, $\alpha_i^{(*)}$ is used to denote both α_i and α_i^* , and α^* to denote the vectors containing all
- 16 α_i^* values. Equation (3) is called the dual objective. The second constraint in (7) is called the
- bias constraint. Once the α and α * that maximize the dual objective are found, a linear
- regression SVM determines the output by calculating equation (8):

19
$$f(x) = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i)(x_i \cdot x) + b$$
 (8)

- The presented SVM model assumes that the relation between x_i and y_i is linear. For this
- 21 application, the radial basis was calculated based on the Kernel function that enhances the
- 22 ability to map similar feature vectors, as determined by their Euclidean distance. Other
- 23 Kernels such as the linear produced large errors, while the polynomial Kernels were
- 24 computationally more expensive.

25
$$K(x, x_i) = \exp(-\frac{||x - x_i||^2}{2\sigma^2})$$
 (9)

where $||x - x_i||^2$ is the Euclidean distance between the two feature vectors and σ is a free parameter.

The SVM generalization performance (estimation accuracy) depends on a good setting of meta-parameters parameters C, ϵ and the Kernel parameters. Existing software implementations of SVM regression usually treat SVM meta-parameters as user-defined inputs. Selecting a particular kernel type and kernel function parameters is usually based on application-domain knowledge and should reflect distribution of input (\mathbf{x}) values of the training data.

- 35 *3.1.1 Support Vector Machines Application*
- For model development the radial basis function kernel in equation 7 was used:

38
$$\max_{\alpha^*} \left[-\varepsilon \sum_{i=1}^n (\alpha_i^* + \alpha_i) + \sum_{i=1}^n (\alpha_i^* - \alpha_i) y_i - \frac{1}{2} \sum_{i,j=1}^n (\alpha_i^* - \alpha_i) (\alpha_j^* - \alpha_j) K(x, x_i) \right]$$
 (10)

1 subject to constraints:

$$2 0 \le \alpha_i^{(*)} \le C$$

$$3 \qquad \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) = 0 \tag{11}$$

- 4 Here, $\alpha_i^{(*)}$ is used to denote both α_i and α_i^* , and α^* to denote the vectors containing all
- 5 α_i^* values. Once the α and α^* maximizing the dual objective are calculated, a linear
- 6 regression SVM determines its output using:

7
$$f(x) = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) K(x, x_i)$$
 (12)

8

21

9 Where $K(x_i, x_i)$ is the radial basis function kernel given by the formula:

10
$$K(x, x_i) = \exp(-\frac{||x - x_i||^2}{2\sigma^2})$$
 (13)

In this paper x_i is the input vector for each voyage, containing the same input 11 variable as the ones used for the NN training. The actual time of arrival y_i is the value 12 13 forecasted by the model. The parameter selection process is of significant importance when training SVMs. Parameter C determines the trade-off between the model complexity 14 15 (flatness) and the degree to which deviations larger than ε are tolerated in optimization formulation. Parameter ε controls the width of the ε -insensitive zone, used to fit the training 16 data. The value of ε can affect the number of support vectors used to construct the 17 regression function. The bigger the ε , the fewer support vectors are selected. On the other 18 19 hand, bigger ε -values results in more 'flat' estimates [15].

Here, the same testing, validation and training sets were applied both in SVMs and NNs.

3.3 Error Metrics used for evaluating ETA prediction

- 22 For evaluating model performance two error metrics were used: the Mean Absolute Error
- 23 (MAE) and the Root Mean Squared Error (RMSE). These metrics can give an indication of
- 24 the average error in hours (through MAE) and the variance of the prediction errors (through
- 25 RMSE), therefore enabling a quick evaluation of the prediction results.
- The MAE is an error metric, commonly used in statistics, to measure the average variance of predicted to observed values. In our case MAE is calculated in hours and is given by the following formula:

29 MAE =
$$\frac{1}{n}\sum_{i=1}^{n}|f_i-y_i| = \frac{1}{n}\sum_{i=1}^{n}|ETA_i-ATA_i|$$
 (14)

- 30 where f_i : the Estimated Time of Arrival (ETA)
- 31 y_i: the Actual Time of Arrival (ATA)
- n: the total number of observations.

The RMSE is a very common error metric in statistics usually applied to evaluate numerical predictions. Compared to MAE, RMSE amplifies and severely punishes large errors. It therefore serves as an indicator for the variance of the prediction errors. The formula used for calculating the RMSE is the following:

37
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - y_i)^2} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(ETA_i - ATA_i)^2}$$
 (15)

- 1 where f_i: the Estimated Time of Arrival (ETA)
- 2 y_i: the Actual Time of Arrival (ATA)
 - n: the total number of observations.

The aforementioned error metrics were used as to compare and evaluate the different methods used for predicting vessel arrivals at the Port of Rotterdam.

5. RESULTS

In this section the results from the application of the methodology described above are presented. Figures 2 and 3 show the Mean Absolute Error (MAE) and the Root Mean Squared (RMSE) in hours predicted by the shipping agent, the NN and the SVM. The error is evaluated in frequent time intervals (every 6-8 hours) from Tunisia, which on average is positioned 120 hours away from the Port of Rotterdam until approximately 20 hours distance from the port. Another point of reference is Gibraltar which is positioned on average 80 hours from the Port of Rotterdam.

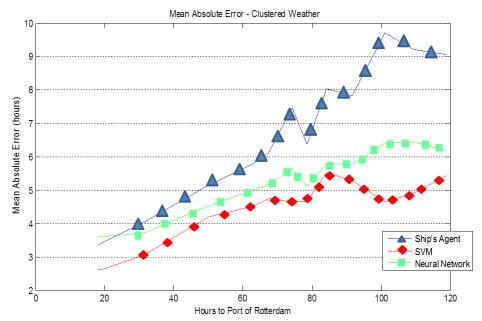


FIGURE 2 MEA on ETA predictions for Ship Agent, SVMs and Neural Networks – clustered weather variable approach.

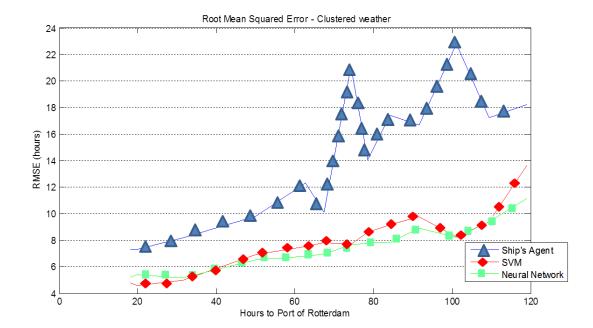


FIGURE 3 RMSE on ETA predictions for Ship Agent, SVMs and Neural Networks – clustered weather variable approach.

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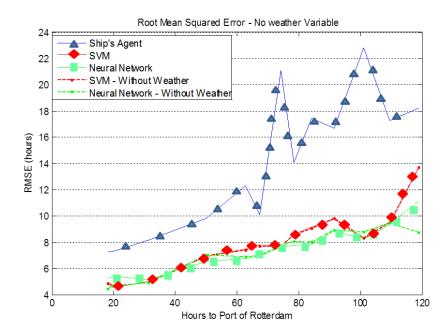
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Both the SVMs and the NN give more accurate predictions compared to the current situation that is based on the ETA provided by the shipping agent. Furthermore, the SVM outperforms the NN for every point in the examined time-horizon. The area where the predictions are significantly improved is between 80 and 120 hours distance from the Port of Rotterdam. For instance in the region 100-120 hours from Rotterdam the MAE is around 5 hours for the SVM, while the ship's agent error is off by more than 9 hours. There is also significant improvement in the variance, as depicted by the RMSE error metrics. In the case of regions that are positioned on average 100 hours from the Port of Rotterdam, prediction errors had an RMSE of 9 hours, while for the ship agent the respective value was 20 hours. This means that in 95% of the cases the prediction error of the proposed SVM was less than 18 hours $(2*\sigma_{SVM}=2*9)$, while for the ship's agent, 95% of the cases were lying within a time interval of 40 hours ($2*\sigma_{agent}=2*20$). Therefore, it is proved the proposed model reduces significantly the uncertainty related to vessels' time of arrival at a port. The regions between 80 and 40 hours away from the Port are characterized by medium improvement on the MAE, but still they present large improvements in the variance. The available online applications presented in the literature review can offer more accurate predictions for these areas and also at that point agents are obliged to update their ETAs, since the information is becoming important for container terminals and the Port of Rotterdam.

FIGURE 4 MEA on ETA predictions for Ship Agent, SVMs and Neural Networks – comparison between initial case and model without weather variables.



 $\textbf{FIGURE 5} \ \ \textbf{RMSE} \ \textbf{on} \ \ \textbf{ETA} \ \textbf{predictions} \ \textbf{for} \ \textbf{Ship} \ \textbf{Agent}, \ \textbf{SVMs} \ \textbf{and} \ \textbf{Neural Networks} - \textbf{comparison} \ \textbf{between} \ \textbf{initial} \ \textbf{case} \ \textbf{and} \ \textbf{model} \ \textbf{without} \ \textbf{weather} \ \textbf{variables}.$

From Figures 4 and 5 it can be deducted that the proposed model including weather conditions has not an impact on predicting the ETA of sea-vessels, since there is no substantial modification between the errors of models with and without weather conditions. The explanation for this is twofold. Firstly, the speeds were obtained from the AIS data, are speeds over ground. This means that they already contain an interpretation of the currents and weather conditions in the area. Specifically, the speed over ground is a function of the

vessel's operating engine power and the currents/weather conditions in the area. Secondly, the captains have a deadline for final arrival at PoR and their failure to meet the deadline will result in penalty costs. They also know that, in case their arrival time is different from the ETA they have provided to the port they may face increased waiting times, because their berthing place may be occupied by another vessel. Therefore, they operate the vessel on a speed mostly influenced by the deadline to reach the port, rather than by the weather conditions. This can explain a very common pattern observed in the data, speeding up in the initial leg, and then, after making sure that the deadline can be easily met, slowing down for the remainder of the route. Although weather conditions definitely have a huge impact on the ship's fuel consumption, they do not seem to influence the final time of arrival, due to the captains' tendency to speed up the vessel in order to arrive at the port on time. It should be noted here that the route examined in this paper took place mostly close to the shore and did not include extreme weather conditions. Weather conditions may have significant impact on the ETA in case routes crossing over oceans are examined.

5. IMPLICATIONS OF THE RESEARCH

Based on the results presented in the previous section the developed models can improve ETA predictions in long time horizons. The advantages of this information are important for the stakeholders involved in hinterland transportation as summarized below.

- Hinterland Transportation parties (e.g. EGS), logistics service providers and freight forwarders. These parties plan their services long in advance. Every week, they have to decide on how much capacity to book for barge and rail. A deviation in the pre-allocated capacity from the actual cargo to be transported incurs additional costs. These costs can be saved through a more accurate estimation of vessel arrivals. Also, better planning of the barge and train schedules can be achieved, if there is greater certainty over vessel arrivals for a time horizon span of 5 days.
- Container terminals (e.g. ECT): ETA prediction is valuable information for the optimization of equipment allocation and manpower. One of the most important decisions that ETA is expected to assist is berth allocation. Optimal assignment of berths reduces vessels total turn-around time, increases customer satisfaction and meets the contractual obligations to ocean carriers [16, 17].
- **Shipping companies**: The proposed information tool can be used as a competition monitoring tool. By aggregating the ETAs of all the vessels in the examined area, it is possible to know how many ships will be arriving during the next days and in which time slots. This information can increase the bargaining power of a shipping company when negotiating for cargo transportation. Apart from that, there is the indirect benefit of lower handling times for the vessel, due to the optimization in container terminal operations.
- **Port authorities**: One of the direct benefits is the ability to plan better for pilot availability to guide the vessels to the terminals, as well as reduction of traffic congestion around the areas of the port. On the indirect benefits, the competitive position of the port compared to other ports in the area will be enhanced, due to the increased efficiency and decreased handling time of vessels at container terminals.

Finally, this information is expected to promote synchromodal transportation. Synchromodality is defined as "the creation of the most efficient and sustainable transportation plan for all orders in an entire network of different modes and route, by using the available flexibility"[3] and is expected to increase the performance of the entire container hinterland transportation. Specifically, the early identification of delays in vessel arrivals is key to the synchromodal planning activities of hinterland transportation parties.

This is because the whole process has to be updated depending on early/late arrival of containers, in the first step of the inland transportation that of the vessel arrival in the port. A late arrival of a vessel may result in unavailability of capacity in barges or trains, thus assigning more containers to trucks.

6. CONCLUSIONS AND FURTHER RESEARCH

Uncertainty over vessel arrival times is a major hindrance towards the planning activities of the stakeholders involved in container transport. Currently a vessel's ETA is declared to the terminal by the shipping agent. However, this ETA is not frequently updated and contains large deviations from reality, especially for long time-horizons. In this paper SVM and NN models were used to estimate the ETA of containerships at the port of Rotterdam, accounting for a middle time horizon. The SVM models were found to outperform the NNs when comparing MAE of the models in all cases. This can be attributed to the fact that through the principle of similarity, on which SVMs function, they were better able to generalize on unseen data. The NNs would need more data available for achieving the same results, since their training requires more examples to generalize well.

Both models achieved significantly better predictions compared to the current situation, where the ETA is based on the ship's agent estimations. In the best results obtained, when using different SVMs for each region, the mean absolute error reduced from 9 hours to less than 5 for areas positioned above 100 hours from the Port of Rotterdam (Western Mediterranean) and in the case Gibraltar (80 hours from the Port of Rotterdam) the error was reduced to 4 hours, while the ship's agent error is 7.5 hours.

Regarding the influence of weather conditions on predicting the ETA, it was found that they do not play a crucial role for estimating ETA on the examined route. Nevertheless, it cannot be concluded that weather conditions and currents have no impact on the time of vessel arrival to the Port. However, even if a weather modelling approach could yield somewhat better results in predictions, the extra effort of acquiring and using the data for the model development would probably be more time-consuming than the additional value created. It can be concluded that for ETA prediction positional and speed data, as provided by the AIS database, are sufficient.

An interesting topic for further research would be to try and expand the ETA predictions time horizon and to make efforts to apply the models in additional routes. It is expected that for routes that travel over the Atlantic, the weather variables may have more impact on estimating the ETA. In addition, given that additional data will be collected, the models can be applied and to other vessel types such as such as tankers. With enough data gathered from past voyages, it is possible to train neural networks and support vector machines in predicting vessel arrival times given the same inputs as in the current study. Then, the accuracy of the models can be checked for different time horizons, to determine in which range they perform sufficiently. In addition the model could be applied to other container terminals. The possibility of creating a customized model that can apply to other terminals than those in Rotterdam will be investigated.

Another proposed area for further research is considering the waiting time of vessels at previous European ports, such as Antwerp and Felixstowe. The uncertainty related to the vessel's service time in those ports causes significant deviations in the final ETA at the Port of Rotterdam. In this case, variables such as the terminal berth utilization rates and the number of containers that the vessel loads and unloads at the terminal can be used as input. Additional cost and terminal productivity data can be acquired in order to perform a Cost Benefit Analysis (CBA) on the improvement of terminal operations when applying the proposed model.

Finally, we propose the development of a decision support system for vessel-speed estimation. The proposed system will calculate the impact of weather conditions on the vessel's speed and will help captains keep a relatively steady engine power that would guarantee the on-time arrival at the port, while saving on fuel consumption.

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