OPTIMISATION OF VOYAGE SPEED USING GENETIC ALGORITHM APPROACH

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SUMMARY

The speed of vessels has long been recognized to have the highest impact on fuel consumption. The aim of this study is to develop a speed optimisation model using a time-constrained genetic algorithm (GA). Subsequent to this, this paper also presents the application of machine learning regression methods in constructing a model to predict the fuel consumption of vessels. The local outlier factor algorithm is used to eliminate outliers in prediction features. In this study, speed is found to be the most significant feature for fuel consumption prediction. On the other hand, GA evaluation results showed that random modifications in the default speed profile could increase GA performance and thus fuel savings more than constant speed limits during voyages. Moreover, at most 6% fuel saving was found using randomly modified voyage speed profiles in GA. Contrary to general opinion, the top speed limits broke the global minimum fuel consumption point searching capability of GA. However, for best results, voyage speed, top speed limit, and expected time of arrival (ETA) delays need to be considered together in a separate optimisation algorithm.

KEYWORDS

Speed optimisation, Fuel consumption, Genetic algorithm, Machine learning, Regression methods

NOMENCLATURE

ADA	*Adaptive Boosting*
AIS	*Automatic Identification System*
ANN	*Artificial Neural Network*
EEDI	*Energy Efficiency Design Index*
ETA	*Expected Time of Arrival*
IMO	*International Maritime Organization*
IQR	*Inter Quartile Range*
GA	*Genetic Algorithm*
GB	*Gradient Boosting*
KNN	*K-Nearest Neighbours*
LR	*Linear Regression*
LOF	*Local Outlier Factor*
ML	*Machine Learning*
RF	*Random Forest*
RMSE	*Root Mean Square Error*
SEEMP	*Ship Energy Efficiency Management Plan*
SR	*Stacking Regressor*
SEEMP	*Ship Energy Efficiency Management Plan*
SVR	*Support Vector Regressor*
VR	*Voting Regressor*
XGB	*Extreme Gradient Boosting*

1. INTRODUCTION

Greenhouse gas emissions (GHG) in maritime transport are one of the main contributors to global warming. Moreover, shipping GHG emissions are projected to increase up to 130% of 2008 values by 2050 (Faber et al., 2020). International Maritime Organization (IMO) aims to decrease the carbon intensity of shipping through the implementation of the energy efficiency design index (EEDI) and so GHG emissions in the initial strategy of IMO. EEDI requires a minimum fuel consumption per tonne-mile for different ship types and size segments. Besides, The Ship Energy Efficiency Management Plan (SEEMP) is an operational measure that enables ship operators to increase fuel efficiency by applying any operational changes such as new voyage planning, weather routing, delay to ports, optimizations of speed, shaft power, trim, ballast, propeller, and waste heat recovery systems, etc. (IMO, 2016).

The new regulations regarding speed restrictions are discussed and new speed reductions are proposed by International Maritime Organization (IMO) at certain times, the shipping industry reduces the speed below the design speed of vessels in order to reduce fuel consumption accordingly emissions, and voyage costs. However, it is still unclear the regulation to apply whether to the maximum speed limits or maximum average speeds. In addition, there exist many oppositions from the industry side to certain speed reductions for each trip. For example, Stena claims that it is not possible to reduce speed by 20% for each trip in high seasons. Also, Terntank thinks it will just penalize the building of new modern ships. Lastly, Swedish Oriented Line opposes speed reduction because they claim that more ships will be required to deliver the same amount of goods (LIGHTHOUSE, 2020).

1.1 RESEARCH PROBLEM

Contrary to popular belief, some ship operators claim that fuel consumption can increase even if the speed is lowered due to the inefficient operation of engines (LIGHTHOUSE, 2020). Moreover, the studies also indicate that an optimum speed profile exists for every voyage, and deviations from the optimum speed can cause more fuel consumption (LIGHTHOUSE, 2020, Psaraftis, 2019, Arslan et al., 2014). Speed optimization is evaluated in order to find the best speed profile resulting in minimum fuel consumption per tonne-mile. According to Ship Energy Efficiency Management Plan (SEEMP), less than optimum speed can cause higher fuel consumption. In addition, slow steaming can be quite overestimated for fuel consumption savings. To support this view, ship companies from the industry describe how they found an optimal speed when they intended to decrease speed due to time chartering or port delaying limitations (LIGHTHOUSE, 2020). Therefore, the optimum speed is not the lowest, and also, it is not constant during the voyage (IMO, 2016, Arslan et al., 2014). Identifying an optimum speed profile also requires solving an optimization problem as well. However, weather and sea environmental variables and market values such as bunker prices, port time windows, delays, etc., have some inconsistencies in real life. On the other hand, the deterministic approaches for solving an optimization of speed and fuel consumption of ships ignore random events. Furthermore, it is assumed that randomly occurring environmental or technical failure events are known in advance (Aydin et al., 2017). In addition, deterministic methods such as convex or cubic functions have been well-studied for speed optimization in recent years in literature. However, the random variables have not been considered yet explicitly for the speed optimization problem (Aydin et al., 2017). For some aspects, many studies in the literature employ a stochastic term for some of the influential factors of fuel consumption, such as weather and sea conditions or engine parameters. It is assumed that the random influential factors of fuel consumption follow a normal distribution (Aydin et al., 2017). It is obvious that using only probabilistic distributions for optimization problems will not produce effective solutions since many more influential factors also exist in fuel consumption.

Therefore, using more random variables can help to get more realistic predictions for fuel consumption. In this study, genetic optimization algorithms are used to search optimum speed profiles for the least fuel consumption. The main reason for the selection of an evolutionary algorithm is to avoid the solution converging in a local optimal point, on the contrary finding the global optimal point of minimum fuel consumption.

On the other hand, a separate fuel consumption prediction model is built by applying machine learning models to predict fuel consumption with a corresponding speed. As a consequence, a fuel consumption prediction model is developed after an initial data preprocessing stage for raw ship data. After that, the prediction function is used as the objective to minimize fuel consumption by randomly selected speed profiles in the genetic algorithm.

1.2 LITERATURE REVIEW

IMO indicates a significant speed reduction can improve the energy efficiency of vessels. Elkafas and Shouman (2021) justify IMO by data analysis of container vessels. The result of their study showed that reducing ship speed by 12.6% will reduce CO2 emissions by about 36%.

In order to show the flexibility potential of speed around the optimal point, Roar et al. (2020) took into account the noon report data of oil tankers. The study showed that the fuel consumption efficiency of speed reduction assessments is overestimated because using cubic methods for speed elasticity results in more fuel savings than regression models for fuel consumption. They also claim that the regression model used in the study was not capable of finding global optima for predictions even though a non-linear model is proposed.

Accurate machine learning models for ship fuel consumption predictions require many parameter records by different data sources. Xiaohe et al. (2022) used voyage report data for ship fuel efficiency analyses. However, they noticed the information on the weather and sea conditions is unreliable when the main data source is voyage reports. Therefore, they extended their study as part 2 (Yuquan et al., 2022a) using automatic identification system (AIS) data to obtain the exact trajectory locations of ships and so the weather and sea data. The results showed that using AIS data with voyage reports has improved the accuracy of fuel consumption prediction rates. And finally, they developed another model by adding high-frequency sensor data of sailing speed, draft, trim, weather conditions, and sea conditions as an extended study in part 3 (Yuquan et al., 2022b). So, using 15 minutes of sampled high-frequency sensor and meteorological data has shown the best performance over previous parts.

Kim et al. (2021) analysed ANN or multiple linear regression (MLR) models tested for fuel consumption prediction using main engine RPM, speed over ground, wind speed, rudder angle, draught, trim, wetted surface area, and displacement parameters. Some variables have only a noise effect in the model and nothing for the outcome. Regarding this issue, Andrea et al. (2017) applied Brute Force Method (BFM), which is the most accurate method but shows weak performance, Lasso Regularization, which has a lower computational cost, and Random Forest Method (RFM), which uses decision trees with permutation tests to select the features. Eventually, BF methods ended with better accuracy results. More precisely, the propeller pitch and ship speed parameters had more impact on fuel consumption prediction. On the contrary, the propeller speed is not among them due to being constant long time along the trip. Also, ship draft and shaft power were among the most important parameters for fuel consumption prediction. However, despite assuming to be relevant to fuel consumption, wind speed and its direction were not resulted having a serious impact on output.

In order to avoid overfitting due to overestimated feature selection, using non-parametric models could be a good option. Christos et al. (2019) used parametric and non-parametric ML models together to find the best model performance. Ridge and Lasso regression, MLR, Support Vector Regression (SVR), and ANN are used as parametric models, whereas Decision Tree Regressor (DTR), Extra-Tree Regressor (ETR), K-Nearest Neighbours (KNN) and Random Forest Regressor (RFR) are used as non-parametric models. The assumption of the study was getting higher performance from non-parametric models due to running without parameters assumptions in the beginning.

Hakimzadeh et al. (2018) showed that sea conditions could affect fuel consumption efficiency. In their study, the wind and wave ocean currents caused a 2.2% speed loss relative to a certain longitude axis.

Fuel consumption prediction accuracy is significantly important to calculate fuel consumption in speed optimisation models closest to a real-life scenario. Speed optimisation implements the highest accuracy model between proposed machine learning models. Yang et al. (2020) implemented a genetic algorithm for speed optimisation of an oil tanker. The whole route is divided into several stages, and the speed is corrected considering wind waves and ocean currents. Maximum and minimum sailing speeds and expected time of arrival are applied for genetic optimisation constraints. Moreover, fuel consumption is considered an objective function to be minimized. Eventually, selecting the correct speed for each segment resulted in 2.20% less fuel consumption.

Many unexpected events in maritime shipping can change the expected time of arrival. The waiting and delay in ports can be an extra cost (delaying penalty) in linear shipping. (Aydin et al., 2017) investigated sailing speed with variable ETA delays and bunker prices. Dynamic programming is used to determine sailing speed considering uncertain port times because vessels can prefer sailing at fast or slow speeds by checking the subsequent port congestion and bunkering prices simultaneously. Furthermore, alternatively, a deterministic method is also applied using expected values of random quantities in dynamic programming. However, the average sailing speeds resulted in higher than the dynamic model.

Expected time of arrival and fuel consumption contradict each other. Shortening the ETA causes more fuel consumption and vice versa. (Helong et al., 2021) developed a voyage optimisation model using a genetic algorithm with two different objective functions: Minimizing fuel consumption and increasing arrival punctuality. Planning routes heuristically under harsh sea conditions voluntarily chose low speed and helped fuel consumption by saving up to 3.4% by keeping the same ETAs.

2. MATERIAL AND METHODOLOGY

2.1 DATASET

The data has been stored by Blueflow Energy Management System via centralized Internet servers which monitor and record sensor data information of ships in Sweden about fuel consumption, speed, etc. In this study, the variables shown in Table 1 are considered as the mandatory features for fuel consumption prediction and speed optimization analysis. The data of this paper belongs to a bitumen tanker that carries heated cargo in Sweden. Furthermore, the original recording data resolution is one second.

Table 1: Selected parameters for regression analysis

	Parameter	**Dimension**
1	Speed over ground	knots
2	Consumption	kg/h
3	Ballast	ton
4	Diesel fuel	ton
5	Keel depth	m
6	Aux Generator	kW
7	Freight	ton
8	Water	ton
9	Angle of list	deg
10	Heading	deg
11	Trim	m
12	Tailwind	m/s
13	Wind speed	m/s
14	Wind direction	deg

2.2 DATA PREPROCESSING

It is noticed that the whole voyage starts and ends in the 24-hour interval. More precisely, it is between 9 AM to 6 AM the next day. In this study, fuel consumption analysis focused on more operational and environmental parameters in voyage time intervals than ship maintenance or manoeuvring time intervals. Therefore, low fuel consumption values are excluded in this study.

Also, the original data recording samples have 1 second period. But this time interval causes long running times for our regression models and also restricts the hyperparameter tuning possibilities with more trials. Besides, in order to decrease outliers and avoid regression fit problems, the whole raw data was down-sampled into 30 seconds periods by the averaging method.

On the other hand, The Local Outlier Detection algorithm is applied for outlier detection. Limited to this study, at most five percent of data is removed by setting the contamination ratio as 5. The time range of source data is already limited to 1 day. Moreover, the ship variables can already show different characteristics generally in long time ranges like 1 month or more. Therefore, losing more data or statistical properties from provided raw data is avoided. It can be followed in Figure 1 that an increasing contamination ratio causes many outliers to bring out wrongly between normal green areas. On the other side, increasing k-neighbours results as more desired with many outliers in zero speed regions. For that reason, k-neighbours and contamination parameters are selected as 100 and 5, respectively, and are shown in sub-plot (h) in Figure 1.

In Figure 2, it is noticed at first glance that the correlation coefficient of ship speed over ground and wind speed are 1. Therefore, one can state that collinearity exists between them. However, the speed over ground variable will be used as a control parameter for speed optimisation. So instead of it, the wind speed parameter is excluded from regression analysis. Also, the correlation coefficients of water, freight, and angle of list variables are -0.04, -0.07, and -0.08, respectively. They are so close to zero that these

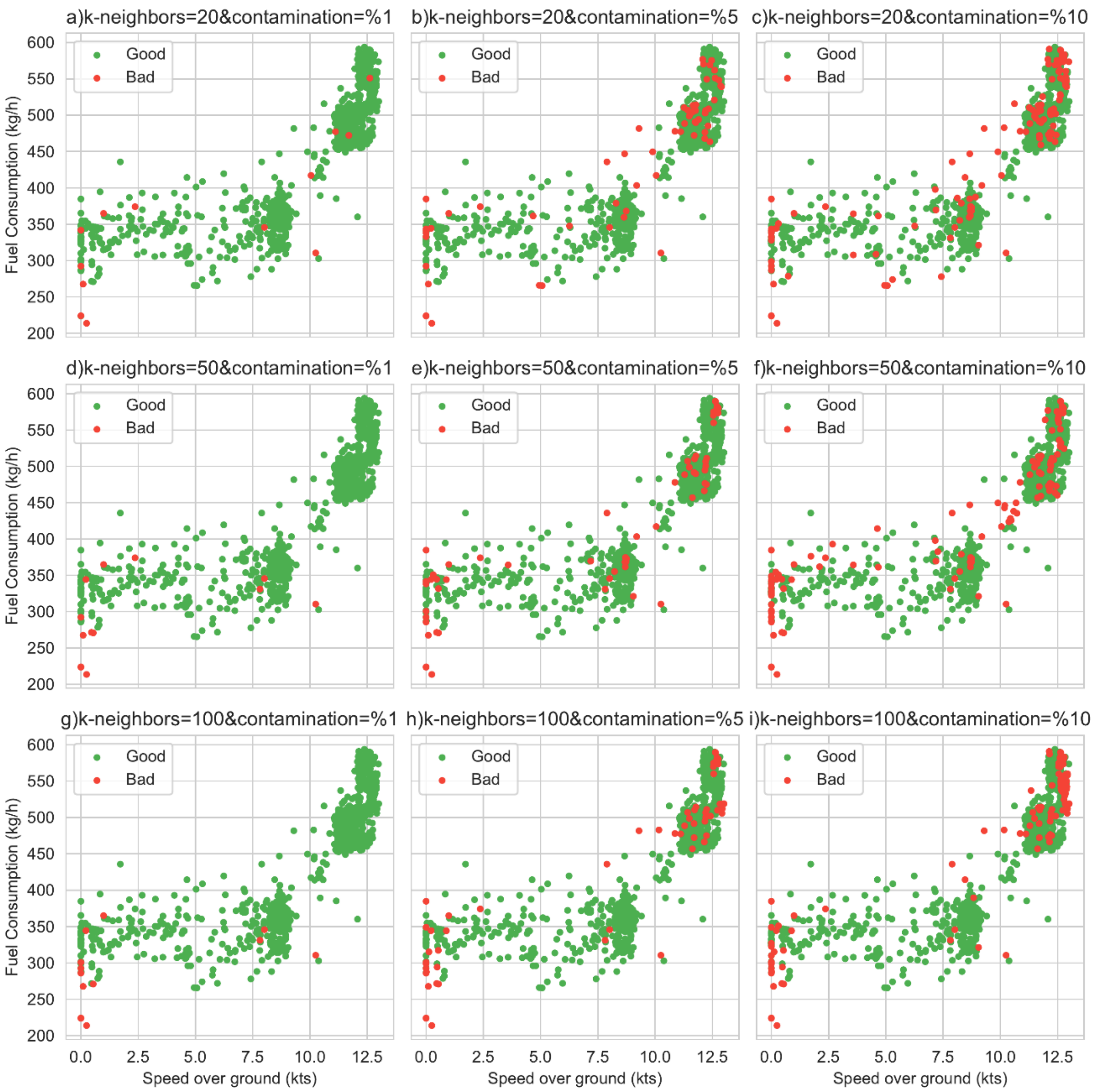

Figure 1. LOF method outlier detection results on various combinations of k-neighbours and contamination parameter values

parameters do not have any expected additivity (Robert, 2022) on fuel consumption prediction. On the other hand, the wind speed variable was already removed from the regression analysis in the previous part. Except for that one, the R-value of ballast vs. diesel and speed over ground vs. trim associations are still high. But trim is another important objective to investigate the effect on fuel consumption in this study. For this reason, they are kept in the analysis.

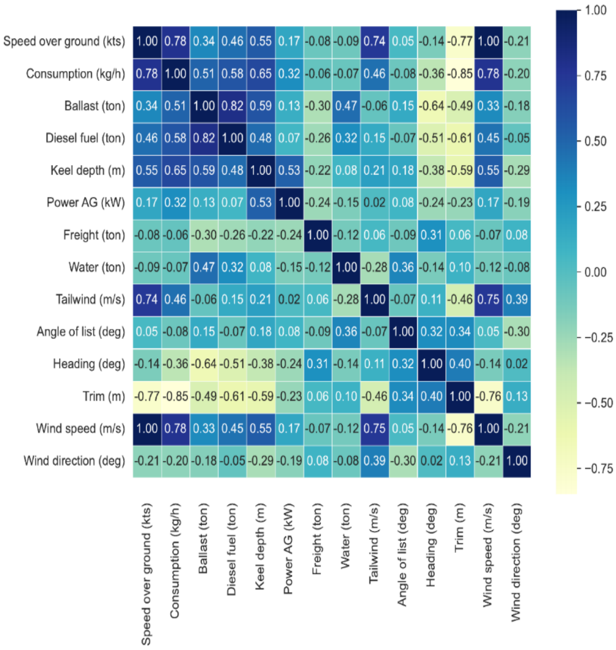

Figure 2. Pearson correlation coefficients between features

3. FUEL CONSUMPTION PREDICTION

Even applied corrective transformations to the features, linear regression results do not show sufficient accuracy and RMSE values. Therefore, fuel consumption predictions using linear regression models are not reliable and feasible depending on the current dataset. Instead of making normal distribution assumptions on features, non-parametric methods can be used for more accurate prediction results. For this reason, Support Vector (SVR), K-Nearest Neighbours (KNN), Random Forest (RF), AdaBoost (ADA), Gradient Boosting (GBR), and XGBoost (XGR) regression models are implemented. Moreover, Grid Search, Randomized Search, and Bayesian Search methods are used to tune their hyperparameters. It can be claimed by using the correlation table that speed over ground and trim variables tend to associate more linearly with dependent variables. However, it's difficult to claim the same thing for other variables.

3.1 HYPERPARAMETER OPTIMISATION

Grid Search (GS) has a computational complexity of a cartesian product of k hyperparameter space with n possible values, O() (Yang and Shami, 2020). Therefore, searching for more possible parameter values with GS increases the computational cost exponentially. GS is used for KNN, SVR, ADA, and GBR models in this study. Instead of GS, Random Search (RS) does not search all the input space. Still, it uses only randomly selected values for parameters for the iteration number defined by the user (Yang and Shami, 2020). Increasing the iterative numbers results in better scores for the model, but also computational costs also increase. In this study, the RS is used for RF, XBG, and GBR models. The main disadvantage of both GS and RS methods is the evaluation without memory of previous evaluation results (Yang and Shami, 2020). However, Bayesian methods use past evaluation results of hyperparameters for the next input values. In this study, one of the Bayesian Optimisation techniques, Python HyperOpt library is used to implement hyperparameter optimisation.

Table 2: Model tuning hyperparameters and running times

Model	Tuned Hyper-parameters	Range	Optimal Value	Train Time (min)
LR	None			<1
SVR	None			<1
	Tuner: GridSearchCV			<120
	C	[0.1,1,10,100, 1000]	1000	
	gamma	[1,0.1,0.01,0.001, 0.0001]	0.1	
	kernel	['rbf','poly', 'sigmoid', 'linear']	rbf	
	degree	[1,2,3]	1	
KNN	None			<1
	Tuner: GridSearchCV			<1
	n_neighbours	[5,7,9,11,13,15, 20, 30,50]	5	
	weights	['uniform', 'distance']	distance	
	metric	['minkowski', 'euclidean', 'manhattan']	manhattan	

ADA	None			<1
	Tuner: GridSearchCV			<1
	n_estimators	[2,3,4,5,7,8,9,10, 20,50,100,300]	50	
	learning_rate	[0.97,0.98,0.99,1, 1.01,1.02,1.06]	1.06	
XGB	None			<1
	Tuner: RandomizedSearchCV(iteration:200)			<2
	min_child_weight	[1,3,5,7,10,15]	10	
	gamma	[0.1,0.5,1,1.5,2,5, 8,15]	1	
	subsample	[0.2,0.6,0.8,1.0, 1.5]	0.8	
	colsample_bytree	[0.2,0.6,0.8,1.0, 1.5]	1	
	max_depth	[3,4,5,7,10,15]	15	
	reg_alpha	[50,70,100,120, 150]	50	
	n_estimators	[100,180,300, 1000,1500]	180	
RF	None			<1
	Tuner: RandomizedSearchCV(iteration:200)			<2
	n_estimators	[5,20,50,100,300, 450, 500]	300	
	max_features	['auto', 'sqrt']	auto	
	max_depth	np.linspace(10, 120, num=24)	10	
	min_samples_split	[2, 4, 6, 8, 10]	2	
	min_samples_leaf	[1, 2, 3, 4, 5]	2	
	Tuner: HyperOpt			<15
	n_estimators	uniform(100, 1000)	469	
	max_depth	uniform(5,120)	16	
	min_samples_leaf	uniform(1,5)	2	
	min_samples_split	uniform(2,10)	4	
	max_features	['auto','sqrt','log2', None]	2	
GBR	None			<1
	Tuner: GridSearchCV			<5
	n_estimators	sample(200,1100, step:50)	1050	
	max_features	['auto', 'sqrt']	auto	
	max_depth	sample(4,16, step:2)	12	
	min_samples_split	sample(2,20, step:1)	2	
	min_samples_leaf	sample(5,61, step:5)	5	
	Tuner: RandomizedSearchCV(iteration:200)			<5
	n_estimators	rand(low:100, high:1200)	460	
	max_features	rand(low:5, high:20)	8	
	max_depth	rand(low:2, high:30)	9	
	min_samples_split	rand(low:2, high:100)	55	
	min_samples_leaf	rand(low:2, high:25)	22	
	learning_rate	rand(low:0, high:1)	0.0425	
	subsample	rand(low:0, high:1)	0.823	

3.2 PERFORMANCE RESULTS OF MACHINE LEARNING MODELS

The evaluation process is carried out with the corresponding training and test dataset performance metrics, resulting in Table 3. As a result, the R^2 values of the linear regression model are around 0.8, so the model weakly explains the fuel consumption compared with the studies in the literature (Uyanık et al., 2020, Kee et al., 2018, Christos et al., 2019). Additionally, in Figure 3, the validation and training accuracy scores of LR converge to a value that is quite low with the increasing size of the training data. Thus, it seems not to benefit much from adding more training data.

Also, the R^2 score of the SVR model is worse than the LR model. Also, RMSE values are less than the linear regression model (see Table 3) and R^2 scores are still weakly explain the fuel consumption by comparison to the studies in the literature (Christos et al., 2019, Hu et al., 2021). And, the performance metrics of KNN resulted in better than LR and SVR models. Also, the KNN model in this study explains fuel consumption better compared to the literature (Christos et al., 2019). In addition, SVR and KNN models increase accuracy values by adding new training data (see Figure 3), and the validation and accuracy scores close to each other through adding new data. So, they fit well with the data. On the other hand, after hyperparameter tuning of KNN and SVR, the accuracy and validation scores of learning curves are still high but have some gap between them. Therefore, some overfitting was observed for them. Especially for less training data, the training accuracy score of the SVM is much greater than the validation score. And, adding new training data seems to increase generalization.

Gradient boosting models (GBR and XGBR) also resulted in overfitting problems after tuning hyperparameters with grid and random search tuners.

Table 3: Performance results of all models for test and training datasets

Model	Training RMSE	Training R^2 Score	Test RMSE	Test R^2 Score
SVR	41.37	0.772	41.81	0.753
LR	38.41	0.804	39.63	0.778
KNN	28.31	0.893	29.50	0.877
Tuned KNN (Grid Search)	0.01	1.000	25.57	0.908
Tuned SVR (Grid Search)	15.11	0.970	24.86	0.913
Tuned ADA (Grid Search)	18.53	0.954	23.44	0.923
SR	11.06	0.984	21.41	0.935
Tuned RF (Bayesian)	7.84	0.992	21.07	0.937
Tuned XGB (Random Search)	1.70	0.995	20.78	0.939
Tuned GBR (Random Search)	2.01	0.991	20.75	0.939
ADABoost	15.02	0.970	20.62	0.940
GBR	13.54	0.976	20.44	0.941
RF	12.04	0.981	19.77	0.945
VR	7.87	0.992	19.66	0.946
XGBR	9.85	0.987	19.61	0.946
Tuned GBR (Grid Search)	5.09	0.996	19.58	0.946
Tuned RF (Random Search)	11.00	0.984	19.52	0.946

The accuracies of VR and SR ensemble models are close to each other for training and testing datasets. VR accuracy (0.9455) is slightly higher than SR (0.9353) for the test dataset. But, VR and SR ensemble models still have a gap between training and testing scores and thus have an overfitting problem.

Eventually, RF has improved the training accuracy value from 0.9807 to 0.9839 after tuning the hyperparameters with a random search optimizer (see Table 3). Also, testing accuracy has been improved from 0.9448 to 0.9463 and it seems to be no overfitting occurred for RF. Therefore, RF is selected for speed optimisation evaluation which is discussed in Section 4.

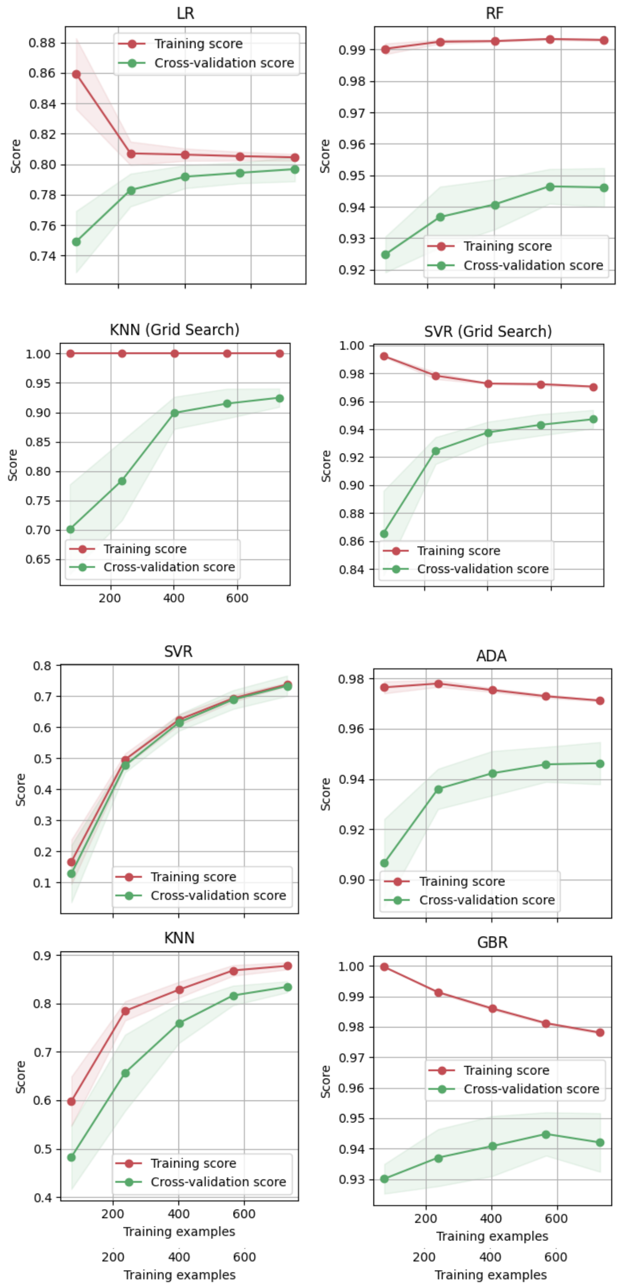

Figure 3. Learning curves of ML models

4. GENETIC ALGORITHM MODELLING FOR SPEED OPTIMISATION

Speed optimisation is evaluated in order to find the best speed profile resulting in minimum fuel consumption per tonne-mile. Because according to Ship Energy Efficiency Management Plan (SEEMP), less than optimum speed can cause higher fuel consumption (Psaraftis, 2019, IMO, 2016). Therefore, the optimum speed is not the lowest and is not constant during the voyage (Arslan et al., 2014, IMO, 2016). Genetic optimisation algorithms are used to search optimum speed profiles for the least fuel consumption. The main reason for the selection of an evolutionary algorithm is to avoid converging in a local optimal point, contrary to finding the global optimal point of minimum fuel consumption.

4.1 A MATHEMATICAL MODEL OF SPEED OPTIMISATION

A speed optimisation mathematical model is developed for a single route between two ports. The notations of the model are given in Table 4.

Table 4: Notations of the speed optimisation model

Parameters	Description
ETA	The ETA at destination port (h)
d	Sailing distance (mile)
d^{new}	Sailing distance of modified speed (mile)
t	Voyage time (h)
T^R	Additional time for selected remaining speed (h)
V^R	Remaining distance speed (mile/h)
V^{new}	Modified speed profile (mile/h)
F_{total}	Total fuel consumption normal speed (kg)
F^R	Fuel consumption rate of remaining speed (kg/h)

If the modified speed profile reaches less distance than normal speed profile, there will be a remaining distance gap to complete normal distance in a time delay. The equation 1 represents the distance to reach of modified speed profile:

$$d^{new} = \sum_{i=0}^{n} V_i^{new} \times t \tag{1}$$

The gap between the distance of the modified speed profile and the normal distance will be closed with the selected remaining speed by the ship operator. The required extra time for the new speed profile to complete the trip represents in Equation 2.

$$T^R = (d - d^{new}) / V^R \tag{2}$$

The total fuel consumption shown in Equation 3 is the sum of the corresponding fuel consumptions of the prediction model using all the speeds until the voyage distance is reached.

$$\min \sum F_{total} + T^R \times F^R \tag{3}$$

Subject to

$$t + T^R < ETA \tag{4}$$

$$V^{new} = \left\{ \begin{array}{c} V^{new}, ifV^{new} < V^{top} \\ V^{top}, diger \end{array} \right\} \tag{5}$$

The objective function in Equation 3 is used to calculate the fitness values of individuals by GA. The main purpose of GA is to find minimum fitness-valued individuals. Therefore, the speed profile uses the constraints in Equation 4 and 5 by ensuring that the ship arrival time will not be longer than ETA. In addition, the maximum allowed speed constraint used for individual modification stages ensures no over speed above it.

4.2 THE IMPLEMENTATION STEPS OF THE GENETIC ALGORITHM

The workflow of the proposed speed optimisation model is shown in Figure 5. The implementation steps shown in the workflow can be explained as follows:

4.2 (a) Individual And Population Initialization

The initialization of the proposed speed optimisation method can cause convergence and robustness problems in speed optimisation (Helong et al., 2021). A special effort was exerted to create a high-level genetic diversity for the individuals to overcome these problems. For those reasons, a modification to the speed profile was applied to create different initial speed profiles for new individuals by making a random change in a randomly selected part of the original speed profile (see Figure 4). The randomly selected amount of speed reduction and time interval change was applied to the original speed profiles.

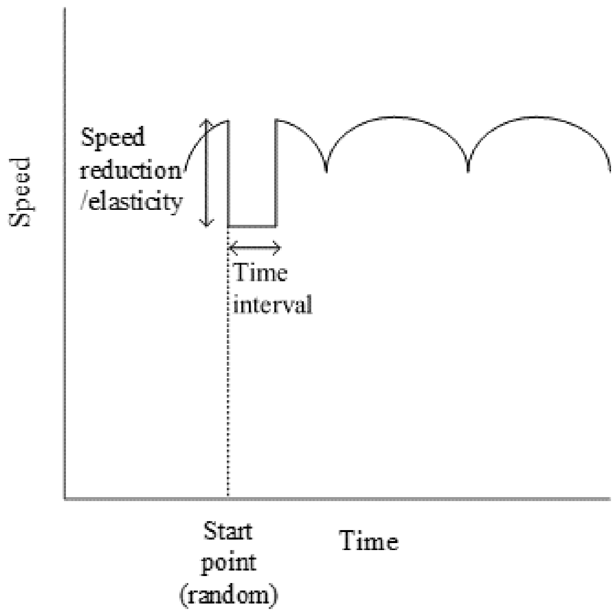

Figure 4. A random modification for initializing individuals

4.2 (b) Fitness Values

Fitness is an objective function that has the goal of minimizing fuel consumption. Random reductions, crossovers, and mutations can cause a delay in time or overtime for voyages. The evaluation algorithm first calculates the new total voyage time by including the remaining speed. And a penalty fitness score assigns to the overtime profiles to inhibit their selection by GA.

The corresponding fuel consumption values are also evaluated by the best prediction model using new speed profiles, including the remaining speed. The total fuel consumption defines as the fitness score of individuals.

4.3 (c) Selection

After all the individuals are evaluated in a population, they are ranked with fitness values in increasing order because the purpose of the fitness function is to minimize fuel consumption in this study.

The first step in a generation is the selection of offspring. K-Tournament selection method with 3 tournament size and k (1) time is used in this study. Every time, the best two individuals are selected for the crossover step.

4.2 (d) Crossover

Best individuals are paired and mated according to crossover probability ratios (De Andrade, 2014). The individual with the minimum fitness value defines the offspring of the current generation. Two-point crossover is used in this study.

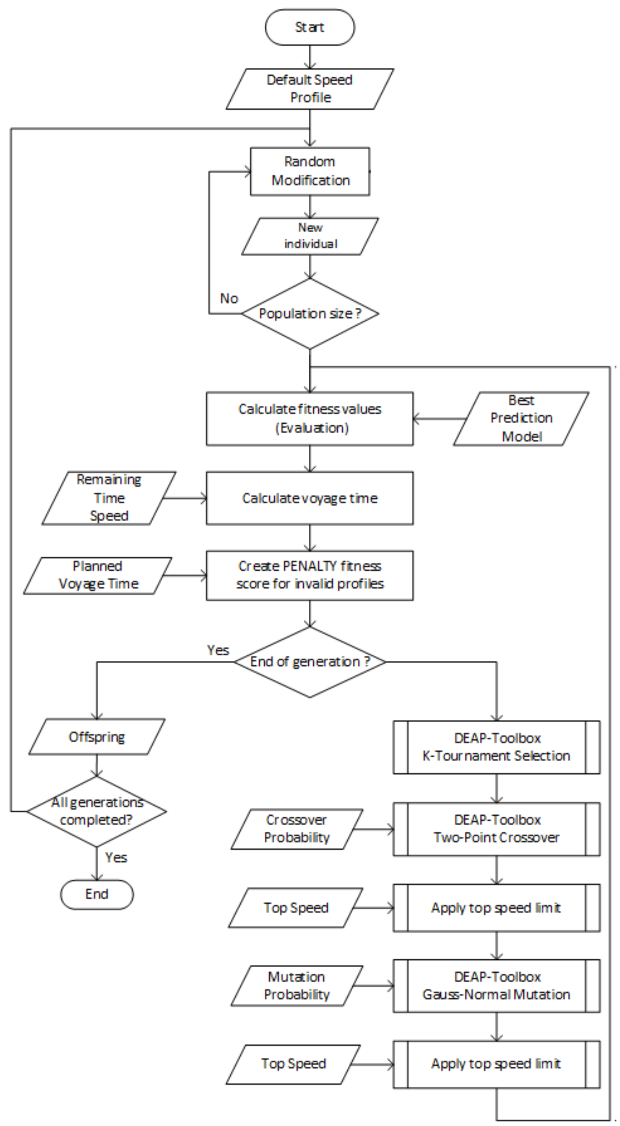

Figure 5. Flowchart of the speed optimisation problem

After each crossover step has been completed, top speed is checked, and speed limit values are applied if any speed value exceeds the top speed limit.

4.2 (e) Mutation

Mutation is another important step for increasing genetic variability. Mutations are required to continue searching for the best results as long as possible. Otherwise, the optimisation wrongly assumes a local minimum or maximum point as global. In order to reduce the risk of such wrong assumptions, using a certain amount of mutation rate is benefitable (Helong et al., 2021). Randomly selected values in individuals mutated in gauss-normal distribution range defined with zero mean and a standard deviation. After the mutation step is completed, evaluation steps are run to create new fitness values of only modifications that occurred to individuals. All five steps above repeat until the end of all the generations completed. By nature of genetic optimisation, generation size is defined as approximately 99.

5 HYPERPARAMETER OPTIMISATION RESULTS

The data belongs to a bitumen tanker in Sweden carrying heated cargo in Northern Europe. The ports of call are located in a wide area between Iceland, United Kingdom, Ireland, Norway, Denmark, Sweden, Poland, and Finland. The routes can be seen in Figure 6. Incidentally, the AIS data was not available for this tanker and the route information couldn't be provided from an available data source.

Figure 6. Area of operation of data-logged bitumen tanker (Hüffmeier et al., 2020)

All the tuning parameters used in GA are listed in Table 5. Speed decrease is initialized with a random number between 2 and 6 knots, and speed decrease time is also initialized with another random number between 30 and 300 minutes.

In the random initialization approach, firstly, the speed profile modification parameters (see Figure 7) are randomly selected to investigate better global optimal points. Speed decrease is selected randomly at a value between 1 and 6 knots, and speed decrease time is between 30 and 300 minutes. This random process has been repeated at the beginning of every generation for all individuals of the belonging generation. So, a high level of genetic diversity is produced before the genetic algorithm is executed.

Afterward, the different numbers of mutation and crossover probabilities, standard deviation, top speeds, and individual numbers are used as control parameters while others are constant. Finally, the fuel consumption results are compared visually.

GA parameter tuning is applied manually in four steps. In Table 5, all the control and constant parameters are listed for every step. In the first step, mutation and crossover probability control parameters are changed, and the GA repeatedly run for 7 different combinations of them in between 10% and 90% of probabilities. Second, the best parameters of mutation and crossover probabilities are used, and mutation standard deviation (sigma) values are changed four times from 0.2 to 1.5. Third, individual numbers are changed to 150, 300, and 500. Finally, the speed limit and remaining speed parameters have changed in six different combinations.

In this study, GA was run repeatedly after changing control parameters. The objective function of minimizing the fitness values of GA simulations is the fuel consumption variable. The parameter tuning simulations have been completed in four steps, and the results are presented in Figure 7.

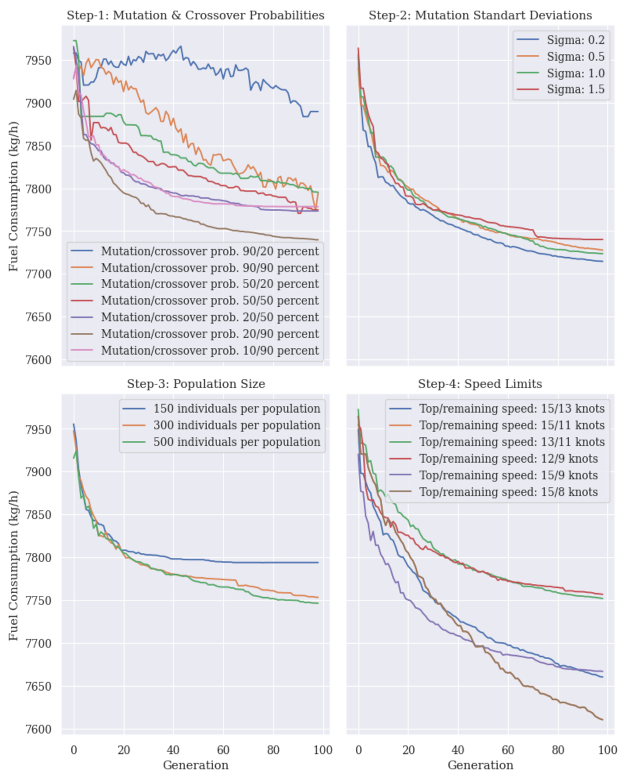

Figure 7. Parameter tuning results of random approach

Table 5: Control parameters and constants in randomly initialized GA

Steps	Mutation probability	Crossover probability	Sigma	Population size	Speed limit (mile/h)	Remaining speed (mile/h)
1	variable	variable	1.5	300	13	13
2	20%	90%	variable	300	13	13
3	20%	90%	1	variable	13	13
4	20%	90%	1	500	variable	variable

5.1 MUTATION AND CROSSOVER PROBABILITIES

In Figure 7, low mutation rates are observed to show better performance together with high crossover rates. Anyway, too low mutation rates have caused more fuel consumption. In addition, by referencing Figure 88b, it is observed that increasing the mutation rate causes unstable speed profiles. On the contrary, a higher crossover rate keeps the speed profile stable during the search for a global minimum point. Furthermore, the crossover operator searches all over the speed profile with equal probability (see Figure 88a). So, 20% mutation and 90% crossover rates are chosen in a random approach for the next tuning iterations.

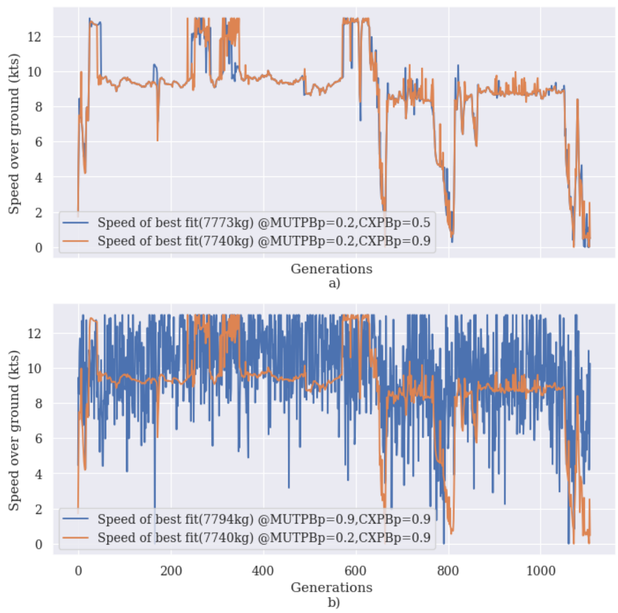

Figure 8. Speed profiles of best fits in random approach step-1, a) crossovers and b) mutations

5.2 MUTATION STANDARD DEVIATION (SIGMA)

Although it doesn't affect the results significantly, increasing the spread of ship speed (inverse of sigma) resulted in higher performances. The sigma parameter does not have the same effect every time. Some cases shown in Figure resulted in the opposite direction. So, for the next tunings, the sigma parameter has been assigned to 1.

Besides, in Figure 99, the speed profiles of best-fitted individuals of populations with different sigma values and actual voyage speed profiles are represented together. It is observed that increasing the sigma values makes the genetic algorithm more eager to look forward to more fuel savings by changing speed values more drastically. Furthermore, as seen in the gray line window frame in Figure 9, with increasing the sigma values, the genetic algorithm gives up seeking a solution for fuel consumption saving via small changes in speed. Thus, the optimisation study has overcome being stacked in a local minimum point and continues to search for the global minimum point.

Figure 9. Speed profiles of best fits in random approach step-2, mutation standard deviations

Besides, the speed signals of the best individuals have a lot of noise for practical usage. Therefore, a low-pass filter is required to eliminate the high-frequency signals. And, an exponentially weighted moving average mean filter in Python Pandas library is applied with a very low smoothing factor (α) of 0.1 for the following figures.

5.3 POPULATION SIZE

By referring to Figure 7, increasing the number of individuals in a population always shows better GA performance in this study, and 500 individuals showed the most efficient results.

5.4 TOP AND REMAINING SPEEDS

By referencing Figure 7, it is observed that increasing the speed limit of the voyage while lowering the results of the remaining speed in more fuel savings. Also, increasing both the speed limit and the remaining speed results in less fuel consumption than decreasing the speed limit.

Besides, it is required to define a speed for the remaining distance in GA. Because making random modifications to the speed profile can extend or shorten the distance, longer distances are eliminated in GA. So, the remaining distances can be zero or more at the end of the evaluation step of GA.

The speed of these additional distances and the top speed limit affect each other. The speed profile outputs of different combinations that belonged to step 4 are represented in

Figure 1010. Reducing the top speed limit while fixing the remaining speeds causes fewer fuel savings (see Figure 1010a). On the other hand, the same behaviour is not valid or vice versa. For example, while the top speed limit is fixed to 15 knots, 15 or 9 knots remaining speed causes more fuel consumption than 11 knots. In brief, the top speed limit is nonlinearly correlated with the remaining voyage speed in GA, and another optimisation routine is required to find the best combination.

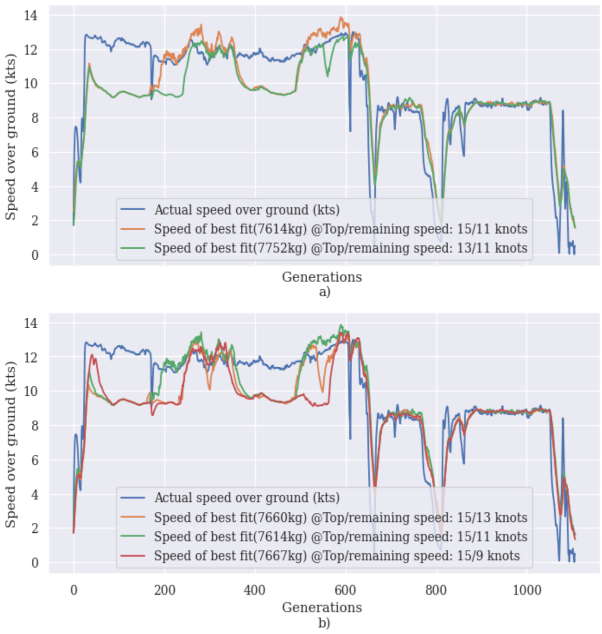

Figure 10. Speed profiles of best fits in random approach step-4, changing speed limit (a) and voyage speed for remaining distance (b)

5.5 ETA DELAYING CASES

Many studies in maritime literature use a certain time window for voyages and investigate optimum speed only for trips without any delay of arrival. But in real life, delays are very common, and voyage speeds are affected by delay penalties. Moreover, except for weather conditions, extra detouring due to inconsistencies of bunkering costs, waiting costs due to port congestion, etc., cause cost inefficiency for ship operators (Aydin et al., 2017). However, hitting the two targets with one arrow is possible if a delay in ETA is used. Time delays in port arrival times can help avoid these problems and save a significant amount of fuel consumption.

For these purposes, in this study, one and two hours delays of ETA are applied in the optimisation routine. The GA simulated 1 and 2 hours delays under 15 knots fixed top speed limit conditions and different amounts of remaining speed values are taken into account to show their effect on fuel consumption. The fuel consumption results are given in Table 6 and briefly, decreasing the remaining speed had always increased fuel savings up to 6% at the end of GA generations completed for 1-hour delay conditions of ETA (see Figure 51). However, it is not valid for 2 hours delaying conditions, the minimum fuel consumption occurred not for the lowest remaining speed condition. GA implementation successfully searches for minimum fuel consumption point by decreasing the voyage speed for the remaining distance at the same time so that the remaining speed, top speed limit, and delaying of ETA need to be considered in another optimisation algorithm to find the best combination of them.

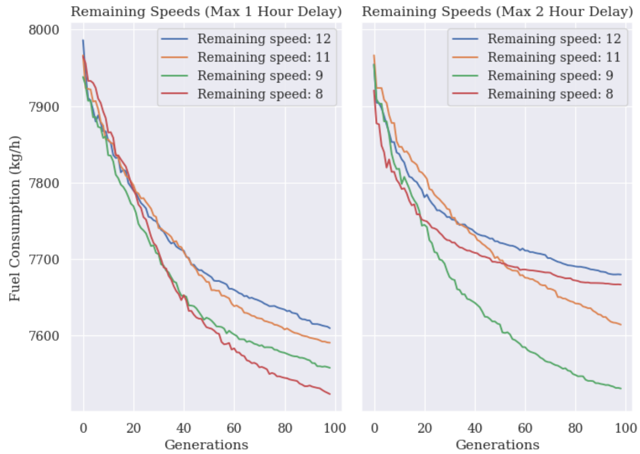

Figure 11. Fuel consumption results for 1 hour (a) and 2 hours (b) ETA delays

Table 6: Fuel consumption saving results in percent using different ETA delays

Remaining distance speed (knots)	1 hour delay	2 hour delays
12	% 4,78	% 4,18
11	% 5,12	% 4,88
9	% 5,52	**% 5,90**
8	**% 6,00**	% 4,22

6. CONCLUSIONS

This study aimed to explore fuel consumption efficiency potential by speed optimisation for vessels. By analyzing linear and non-linear machine learning regression models for fuel consumption prediction, this thesis has shown how fuel consumption can be predictable using various environmental, operational, and voyage real data logs of vessels. LR, SVR, and KNN fuel consumption models resulted in the lowest training accuracy, respectively, below 90%. On the contrary, gradient boosting-based prediction models have shown the highest accuracies but highly included overfitting.

This study also challenged the random speed profile initialization of genetic algorithm for speed optimisation of ships which is not well studied in the literature. Although some random distributions are used in recent studies for stochastic terms of GA individuals, our approach will improve the searching capability of GA for the best individual, i.e., speed profile for minimum fuel consumption during voyages. In addition, the optimum speed profile resulted in less amount of voyage distance in normal voyage time, so a remaining distance with a time delay requires to complete with another predefined speed. In this study, no linear relationship was found between time delay and the speed at the remaining distance. At most 6% fuel consumption resulted in a 1-hour delay and 8 knots voyage speed.

Besides, high crossover rates, population sizes, speed limits, and low mutation rates observed better performance results in GA. However, the speed limits depend on the preferred voyage speed used in GA. So, defining speed limits without considering voyage speed profiles can cause less fuel savings in GA. Therefore, the remaining distance speed, top speed limit, and delaying of ETA need to be considered in a separate optimisation algorithm to find the best combination of them in a future study.

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