2024 European Control Conference (ECC)
June 25-28, 2024. Stockholm, Sweden

Optimizing Cruise Ship Speed Incorporating Weather and Hotel Load Factors*

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***Abstract*— In this paper, real-time weather and ship data will be used for mathematical modeling and cruise ship speed optimization. The ship data will be used for the construction of prediction models for hotel and auxiliary power consumption. Two different prediction model types will be compared: a simple polynomial model with linear parameters, as well as an artificial neural network. The effect of the ship's speed will be predicted using voyage optimization software, which takes into account weather and sea forecasts as well as the ship's hydrodynamic properties, for calculation of the required propulsion power as a function of speed. Total predicted power demand will be finally converted to fuel consumption, using information about the engine efficiencies. Furthermore, the associated cost will be attached to the edges of a graph, from which an optimal speed profile will be selected using dynamic programming. The performance of the models will be compared, and it is found that more than 3% of fuel savings are reported using both model types for the studied voyage.**

I. Introduction

Cruise ship operations are an integral part of the global tourism industry, catering to millions of passengers each year. One of the key challenges faced by the cruise industry is optimizing the operational aspects of cruise ships to ensure efficient fuel consumption and reduce environmental impacts. As sustainability becomes an ever more critical concern, optimizing cruise ship speed as an operational solution takes on increasing significance, not only for cost savings but also for mitigating greenhouse gas emissions [1].

System modeling can be done using several techniques, namely Regression-based Expected behavior models [2], Ensemble learning models [3], Extreme learning machine and neural network [4], and Linear-Parameter-Varying (LPV) modeling [5]. On the other hand, speed profile controlling can be done using various methods: Optimal Control [6], Adaptive Control [7], and Dijkstra Algorithm [8], [9].

*This work was supported by Business Finland under the projects "Integration of Design and Operation of Cruise-Ship Energy Systems" and "Clean Propulsion Technologies"

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Due to stringent regulations set by the International Maritime Organization (IMO) on greenhouse gas (GHG) emissions from ships, there is a growing body of research focused on enhancing ship energy efficiency. For instance, according to [10], convex optimization is proposed for adjusting ship speed based on forecasted environmental conditions, aiming to reduce fuel consumption and carbon emissions. The study demonstrates the efficiency of this approach, particularly for constant conditions, but notes challenges with time-varying scenarios. Other notable studies on this topic include [11], [12], and [13]. However, it's worth noting that there is a lack of research regarding the hotel power system in the literature, highlighting the need for further investigation in this area

This research paper addresses the intricate task of optimizing cruise ship speed with the aim of reducing fuel consumption by integrating weather data and accommodating variations in hotel and auxiliary load factors. To achieve these objectives, we employ polynomial and neural network models and use dynamic programming to find the optimum solution. By doing so, we not only target cost reduction but also contribute to the mitigation of environmental impacts in the shipping industry.

The rest of the paper is organized as follows. In Section II, one-month data is analyzed, and two different models are constructed. In Section III, using the developed models, the optimum speed profile is calculated for the fixed path with different voyage duration. Finally, in Section IV, we summarize the key findings and insights from our study, emphasizing the implications for cruise ship operations and cost reduction.

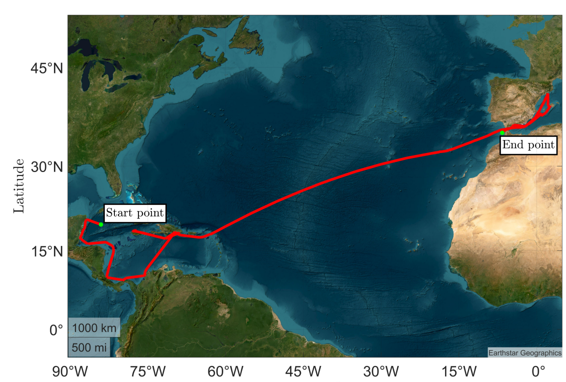

Fig. 1. The studied one-month cruise-ship voyage

II. Modeling

In this study, we have comprehensively analyzed data from a mid-sized cruise ship primarily operating in the Caribbean and Mediterranean Seas, with detailed specifications and characteristics as follows. The tonnage of 100,000 gross tons and dimensions of 295 meters in length and 42 meters in beam. Propelled by a conventional diesel-electric propulsion system, it features a total installed power capacity of 48 MW and was constructed in 2017.

Initially, this section will closely examine the data to filter out irrelevant variables and identify key properties useful for modeling. To model the power consumption of the hotel power system (P_{hotel}) on the cruise ship, we explore two distinct approaches. The first employs a polynomial function in which its parameters are obtained using the least squares method, approximating P_{hotel} as a function of various environmental and operational variables, optimized to minimize a mean squared error cost function. The second approach leverages Artificial Neural Networks (ANN), which adapt their structure during training to capture complex, nonlinear relationships between variables.

The total power consumption can be decomposed as $P_{total}(t) = P_{prop}(t) + P_{aux}(t) + P_{hotel}(t)$, where P_{prop} is the power usage of the propulsors, P_{hotel} is the power needed for serving the passengers, and P_{aux} is the rest (mainly power needed for serving the engines). This decomposition is motivated by the fact that propulsion is largely operator-controlled, with some influence from the weather. Hotel power again relies on passenger activities, which we aim to forecast, and is unrelated to propulsion. Auxiliary power encompasses all other factors, influenced by the former two but not vice versa.

Propulsion power is predicted using the NAPA Voyage Optimization API [14], which employs hydrodynamic models, ship characteristics, and weather data to calculate propulsion power. In our research, as NAPA Voyage Optimization can provide an estimation of propulsion power with specific ship speed, time, and coordinates, our modeling section primarily focuses on hotel and auxiliary power consumption.

Power distribution among various ship systems varies according to the ship's operational state. In the sailing phase, propulsion and non-propulsion are typically distributed about 70:30. This is also true for our data, propulsion systems consume on average 69% of total power. We also choose to split up the 31% non-propulsion service power to hotel services related to the passengers (13%), and all the other non-propulsion (auxiliary) systems (18%). Conversely, when the ship is docked at the harbor, power allocation shifts significantly, with propulsion requiring only 6%, hotel services utilizing 52%, and auxiliary systems 42%. Notably, speed optimization is not applicable during the harboring state, and it falls outside the scope of our research.

A. Data analysis

Our dataset comprised approximately 500 distinct data signals, including variables like ambient temperature, humidity, wind speed, and wind direction. The data was sampled at one-minute intervals over the course of one month. Although transoceanic voyages are infrequent for cruise ships, we have recognized their significance in our modeling process. These extended journeys provide valuable information for a more realistic and accurate model. For this study, we focused on the route shown in Fig. 1.

In this study, we consider ten features for the modeling stage, as listed in Table I. Note that $P_{hotel,avg}$ is the daily average power consumption of the hotel as a function of the local time. In the load distribution process, the hotel power must be determined first before calculating the thrust power. Consequently, the thrust power cannot be used as a feature to estimate the hotel power. Similarly, scrubber power is irrelevant and will also be excluded from the hotel model. Using Neighborhood Component Analysis (NCA), a non-linear, non-parametric method designed for feature selection in regression tasks [15], we calculate and present the importance of these ten features in Table. I.

TABLE I

NEIGHBORHOOD COMPONENT ANALYSIS OF THE MANUALLY SELECTED FEATURES

Features	(notation)	Hotel	Feature wight	Aux-iliary	Feature wight
Ambient temperature	(T_{amb})	$\surd$	8.613	$\surd$	7.793
Ambient humidity	(H_{amb})	$\surd$	8.291	$\times$	6.214
Number of passengers	(N_{psg})	$\times$	1.315	$\times$	0.432
Sea temperature	(T_{sea})	$\surd$	4.969	$\surd$	7.587
Relative wind speed	(V_{wind})	$\surd$	5.433	$\times$	3.156
Ambient pressure	(P_{amb})	$\surd$	5.35	$\times$	4.609
Moist air enthalpy	(H_m)	$\times$	0.007	$\times$	3.503
Hotel average power	$(P_{hotel,avg})$	$\surd$	7.412	$\times$	-
Propulsion power	(P_{prop})	$\times$	-	$\surd$	6.408
Scrubber power	(P_{scrub})	$\times$	-	$\times$	0.028

The low weight assigned to P_{scrub} is due to its strong correlation (Pearson correlation coefficient of 0.87) with P_{prop}. This high correlation indicates a significant positive linear relationship, meaning they tend to increase together. While both H_{amb} and T_{sea} received significant weights in the auxiliary model initially, but in the model fitting stage, it was found that H_{amb} actually worsened the validation performance, and H_{amb} was removed as a feature.

We also conducted a backward elimination (removal of one at a time) of the selected features, which showed that ambient humidity, wind speed, and ambient pressure might not be as crucial for the hotel's polynomial model but are essential for the neural network model, indicating that the NCA works well for the ANN model while being less reliable for standard linear regression problems. Since these features did not hinder the performance of the polynomial model, and for the sake of a fair comparison between the two techniques, we used the same inputs for both models. From a physical perspective, the number of passengers is expected to influence the prediction of hotel load. Despite this expectation, our analysis revealed that the inclusion of the number of passengers features did not significantly impact any of the models in our specific case study. However, it is important to note that the lack of significance in our analysis may be attributed to the minimal variation observed in the number of passengers within our dataset. This suggests that while the feature may not be crucial for our specific scenario, its importance could vary in other case studies where the variance in the number of passengers may be more pronounced.

As noted before, the data from when the ship is in port is excluded. The empty areas in Fig. 2 correspond to this data. The speed of the ship is zero at port, so no speed optimization is needed, and thus, the data is irrelevant for this study.

It can be seen in Fig. 2 and Fig. 3 that the ship operates in the Caribbean Sea from 20 March to 6 April and in the Mediterranean Sea from 13 April to 20 April. Figure 1 illustrates the ship's trajectory as it traversed the Atlantic Ocean. This voyage spanned from 06 April at 23:29 to 13 April at 05:20. We used half of this data for training and half for validation. The motivation for this is that the sea and ambient temperature are changing the most during this part. When it comes to other data, about 1/5 of the data is chosen for validation. In all cases, data is divided into 24-hour slots, as the average hotel load is given different values as a function of the day of time. The test data that is actually used for speed optimization is excluded from the model fit.

Two different approaches are employed in the next section to model the power consumption of a cruise ship. The first approach utilizes a polynomial model with linear parameters obtained using a standard least-squares method. The second approach uses a neural network to model the ship's power consumption.

B. Polynomial model

In this section, we create a polynomial model to understand and predict power use in both the hotel and auxiliary systems. We'll explain how we choose the inputs, find the best settings, and see how well the model performs. We'll also share the results and their performances. This model helps us understand and make informed decisions about cruise ship power consumption. Furthermore, we also apply this modeling method to the auxiliary system, showing that it works well with different parts of our study. To simplify, we define the input vectors as $\chi_h = [T_{amb}, H_{amb}, T_{sea}, V_{wind}, P_{amb}, P_{hotel,avg}]$ for the hotel's model and $\chi_a = [T_{amb}, T_{sea}, P_{prop}]$ for the auxiliary model. Using these vectors, the hotel model can be described as $\hat{P}_{hotel} = f_{poly}^{hotel}(\chi_h)$, where $f_{poly}^{hotel}(.) : \mathbb{R}^6 \to \mathbb{R}$ is a generic mapping to be selected as an input design. In this study, $f_{poly}^{hotel}(.)$ is considered as

$$f_{poly}^{hotel}(\chi_h) = \sum_{i\in\mathcal{I}_1} c_{i1}T_{amb}^i + \sum_{i\in\mathcal{I}_2} c_{i2}H_{amb}^i + \sum_{i\in\mathcal{I}_3} c_{i3}T_{sea}^i + \sum_{i\in\mathcal{I}_4} c_{i4}V_{wind}^i + \sum_{i\in\mathcal{I}_5} c_{i5}P_{amb}^i + \sum_{i\in\mathcal{I}_6} c_{i6}P_{hotel,avg}^i$$

wherein $\mathcal{I}_i$'s are the predefined indexing sets, c_{ij} are tuning parameters that would be selected in an optimal manner. This nested optimal problem consists of one outer Integer Optimal Problem and one inner Least-Squares problem. The following Mean Squared Error (MSE) criterion is considered for this problem

$$J = \frac{1}{N}\sum_{k=1}^{N}(P_{hotel}(k) - \hat{P}_{hotel}(k))^2 \tag{1}$$

Therefore, the optimization problem could be formulated as

$$\{c_{ij}, \mathcal{I}_i\} = \arg\min J. \tag{2}$$

The auxiliary system can be effectively modeled using a similar approach employed for hotel modeling. In the context of this paper, the auxiliary model is referenced as $\hat{P}_{aux} = f_{poly}^{aux}(\chi_a)$, where $f_{poly}^{aux}(.) : \mathbb{R}^3 \to \mathbb{R}$ is considered as

$$f_{poly}^{aux}(\chi_a) = \sum_{i\in\mathcal{I}_1} c_{i1}T_{amb}^i + \sum_{i\in\mathcal{I}_2} c_{i2}T_{sea}^i + \sum_{i\in\mathcal{I}_3} c_{i3}P_{prop}^i$$

Figure 2 displays the outcomes of our polynomial modeling. It is evident that both the hotel and auxiliary models accurately represent the daily and monthly power trends. To assess their performance, we focus on the test data, where the hotel model achieves an MSE of 0.027, and the auxiliary model has an MSE of 0.033. These low MSE values confirm the models' effectiveness in capturing the system behaviors.

C. Artificial neural network model

Artificial Neural Networks (ANNs) are computational models inspired by the neural structure of the human brain. They are composed of interconnected layers of artificial neurons, including input, hidden, and output layers. ANNs are renowned for their ability to capture intricate patterns in data.

Mathematically, each neuron computes a weighted sum of its inputs, applies an activation function (e.g., sigmoid or linear), and generates an output. The training of ANNs involves the optimization of weight and bias parameters to align with desired outputs, a process typically achieved through techniques like gradient descent.

In our research, we utilize two distinct neural network models to address the dynamics of power consumption within our study. The first model, tailored for hotel power consumption is $\hat{P}_{hotel} = \mathcal{N}_{hotel}(\chi_h)$, which is an ANN featuring a single hidden layer with 11 neurons. This design aims to capture essential patterns and variations in the context of hotel power consumption. The Levenberg-Marquardt training algorithm (`trainlm`) is applied, optimizing the model's 89 weight elements. The robust training functions of this model make it a powerful tool for modeling hotel

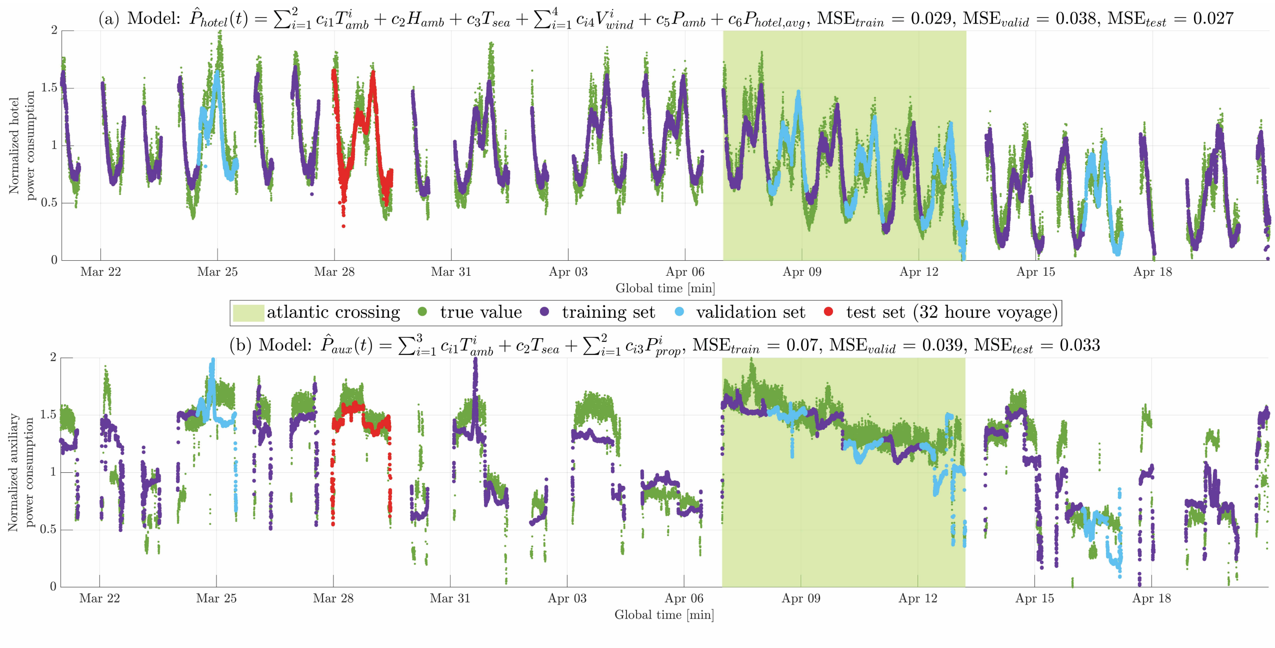

Fig. 2. Model fits for the polynomial models

power consumption, demonstrating its adaptability and high performance.

For modeling auxiliary power consumption, we extend the same approach used for the hotel system, employing an ANN with increased complexity and is noted by $\hat{P}_{aux} = \mathcal{N}_{aux}(\chi_a)$. This ANN architecture features two hidden layers, with 15 neurons in the input layer and three neurons in each hidden layer. This enhanced design allows us to capture intricate relationships within the three input data parameters considered previously, providing deeper insights into auxiliary power consumption dynamics.

With a total of 124 weight elements and utilizing the `trainlm` algorithm, this neural network serves as a crucial tool in modeling auxiliary power consumption. Its adaptability and strong performance underscore its significance in our research.

The performance of our modeling process is visually demonstrated in Fig. 2 and Fig. 3. To facilitate a comprehensive comparison of the models, we present the results in Tab. II. This table evaluates the models using two distinct metrics: MSE and the Correlation Coefficient ($\mathcal{R}$). Our findings clearly indicate that the ANN model surpasses the Polynomial model in performance, as reflected in both evaluation metrics.

In the forthcoming section, we present an optimization problem that aims to identify the optimal cruise ship speed profile with the primary objective of minimizing fuel consumption.

III. Speed Optimization

Cruise ship speed optimization involves advanced technologies and operational practices to enhance efficiency. These include state-of-the-art propulsion systems, weather routing, navigation tech, and eco-friendly practices, all aimed at reducing fuel consumption and emissions to align with sustainability goals.

TABLE II

Model Performance Comparison using MSE and Correlation Coefficient Metrics

	MSE			$\mathcal{R}$		
Model	**train**	**valid**	**test**	**train**	**valid**	**test**
			Hotel System			
Poly	0.029	0.038	0.027	0.89	0.86	0.9
ANN	0.025	0.032	0.022	0.91	0.88	0.93
			Auxiliary System			
Poly	0.070	0.039	0.033	0.78	0.91	0.74
ANN	0.049	0.025	0.022	0.86	0.93	0.83

We leverage NAPA's API to construct a unidirectional graph that plays a pivotal role in our study. The nodes in this graph are defined by the relevant attributes, encompassing local/global time, distance from the initial point, geographical coordinates, weather data, average hotel power consumption, and engine configuration. The edges connecting these nodes carry weights that symbolize fuel consumption during transitions between nodes. This graph can be used for minimization of fuel consumption using dynamic programming.

These node attributes are employed to predict both hotel and auxiliary power consumption, as computed in the preceding section. Propulsion power is forecasted using the NAPA API. Consequently, we integrate this propulsion power prediction into an auxiliary model. This integrated model allows us to predict the total power required for the cruise ship.

In summary, by utilizing NAPA's API and considering the node attributes within our graph, we estimate hotel and

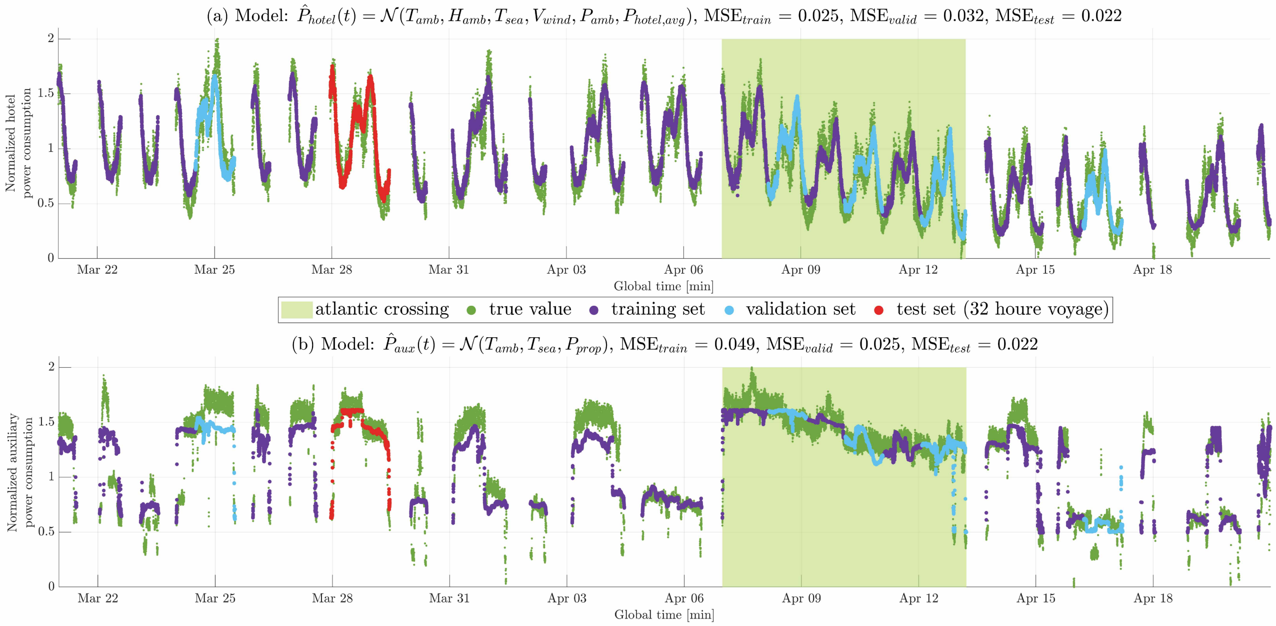

Fig. 3. Model fits for the ANN models

auxiliary power consumption. Coupled with the propulsion power prediction from NAPA, we compute the total power needed for the vessel.

On the ship under investigation, there are four engines available for propulsion. These engines consist of two larger ones of the same size and two smaller ones of the same size. It is worth noting that, on the sea, one avoids using only one engine and all four engines, but all other five combinations are considered in this study (S: small engine, L: large engine): SS, LS, LL, LSS, and LLS.

To accurately predict the fuel consumption for each edge, it is imperative to consider the Specific Fuel Oil Consumption (SFOC) of the ship's engines, as depicted in Fig. 4. SFOC is a critical measure of engine efficiency, quantifying the amount of fuel required to generate a unit of power. Lower SFOC values correspond to higher engine efficiency. Fig. 4 illustrates that a transition to the most efficient engine load is at 85%. No higher loads than that are allowed, so abrupt shifts in the total SFOC curve are obtained at this point, the engine combination is changed, and the combined engine load adjusts to a less efficient level. For the sake of simplicity, we have not accounted for the costs associated with engine switches in Fig. 4.

In summary, by incorporating the relevant attributes into the graph, we can determine the fuel consumption for traveling between specific coordinates at a designated speed. To identify the optimal speed profile within this graph, we employ Dijkstra's algorithm [16].

In this study, we address the speed profile optimization problem, focusing on a 32-hour voyage that serves as our test data in the modeling section. The optimization results are presented in Fig. 5. Notably, each node in the graph is connected to nine edges, with the right-side edges featuring higher speeds compared to their left-side counterparts. This

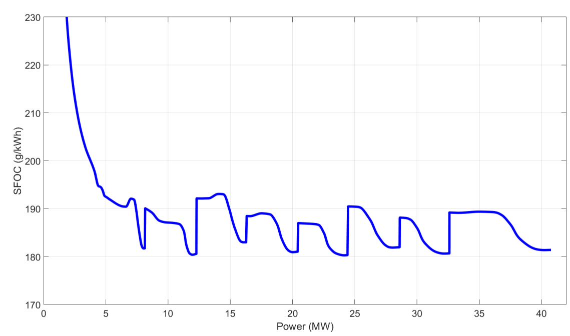

Fig. 4. Total SFOC as a function of power generated when the engine load is distributed equally between engines. Loads up to 85% are utilized

distinction is evident when examining the normalized ship speed in Fig. 5.

The speed profiles optimized using the two different models, namely ANN and Poly, are compared with the actual speed profile of the ship. A closer examination of the normalized fuel consumption (as depicted in Fig. 5) reveals that the actual system consumes more fuel during the middle part of the voyage, where the operators utilize the LLS combination. The ANN speed profile results in fuel savings of 3.08%, while the Poly speed profile results in 3.23% fuel savings, as shown in Tab. III. For a fair comparison between the speed profiles, the total power consumption was in all cases recalculated using the VO propulsion and the ANN hotel and auxiliary power consumption. The obtained total consumption was furthermore converted to fuel consumption using the SFOC curve. Table III shows fuel savings and used engine combinations. Apart from the actual 32-hour journey, longer and shorter voyage durations are also considered. The comparisons are then against the actual voyage. It comes as no surprise that longer voyage durations save fuel, but one can also see that speed optimization is useful for cases where one needs to catch up in time.

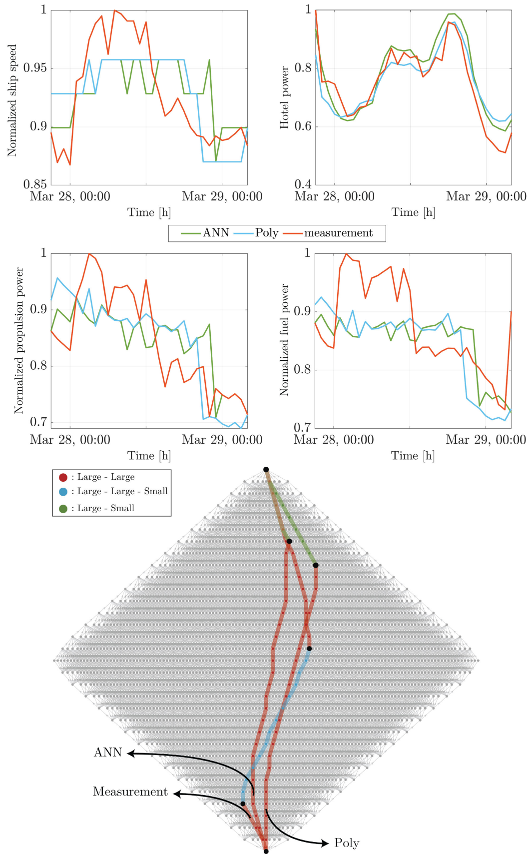

Fig. 5. Optimized and actual speed profiles

TABLE III

FUEL CONSUMPTION AND SAVING ANALYSIS. VD: VOYAGE DURATION, EC: ENGINE COMBINATION, OPT: OPTIMAL, AND FS: FUEL SAVING

Model	VD (h)	EC average speed	EC Opt. speed	Optimal vs actual FS (%)	Optimal vs average FS (%)
Poly	30	LLS-LSS	LLS-LL	-1.30	0.98
	31	LLS-LSS-LL	LSS-LL	1.44	1.62
	32	LLS-LL	LL-LS	3.32	1.29
	33	LLS-LL	LL-LS	4.78	2.27
	34	LL-LS	LL-LS	6.08	2.04
ANN	30	LL	LL-LS	0.40	0.36
	31	LL-LS	LL-LS	2.61	0.49
	32	LL-LS	LSS-LS	4.34	0.09
	33	LL-LS	LS	5.80	0.18
	34	LS	LS-SS	6.97	0.15

IV. CONCLUSIONS

Ship and weather data were used for cruise-ship speed optimization. The ship data was used for the construction of prediction models for hotel and auxiliary power consumption. Two different prediction model types were compared: a polynomial model with linear parameters, as well as a neural network. The effect of the ship speed was predicted using voyage optimization software, which took into account weather and sea forecasts as well as the ship's hydrodynamic properties, for calculation of the required propulsion power as a function of speed. Total predicted power demand was finally converted to fuel consumption, using information about the engine efficiencies. All this information was stored in a graph, from which an optimal speed profile was selected using dynamic programming. Both considered modeling techniques perform well on both tasks, the more complex neural network slightly better. Higher than 3% fuel savings were reported in both cases for the studied journey. As a potential avenue for future research, enhancing the model's performance could involve developing an adaptive framework for generating the hotel's average power feature. Additionally, integrating battery storage alongside engine systems to store surplus power for improving fuel efficiency warrants consideration.

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