Application of Machine Learning and Mathematical Programming in the Optimization of the Energy Management System for Hybrid-Electric Vessels Having Cyclic Operations

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Synopsis

Shipping contributes today to 2.1% of global anthropogenic greenhouse gas emissions and its share is expected to grow in the coming years. At the same time, fuel prices are increasing and companies of the related increase in operational costs. This demands for higher efficiency in ship operations. In these regards, battery-powered vessels are often regarded as a promising solution. The existence of an energy storage element in the system, however, introduces additional challenges in its efficient control.

This paper presents the application of machine learning and mathematical programming to the optimization of the energy management system of Diesel-electric vessels with an energy storage system operating according to a cyclical operational profile.

The proposed energy management system uses unsupervised exclusive machine learning algorithms, k-means or k-medoids, to learn from prior operations. Then mathematical programming based on mixed-integer linear programming is used to address the problem of the optimal unit commitment by means of optimizing the system's operations for minimizing fuel consumption. The calculated optimal state of charge of the energy storage system is used as the reference value for a proportional-integral controller during the real-time operations.

The proposed energy management system is evaluated through its application to a case study corresponding to a hybrid-electric ferry operating in a urban area having cyclic operations through several stations. The results show that the efficiency of the control action is high with an accuracy ranging between 87% and 99%, when compared to an ideal controller, even in presence of large variations in the operational profile and the charging stations.

Between the two tested clustering algorithms, k-means showed higher efficiency in the reduction of fuel consumption in presence of charging stations, while in absence of these, k-medoids showed to provide a better performance.

Keywords: Energy management system; hybrid-electric vessel; cyclic operational profiles, unsupervised machine learning algorithms; mathematical programming; energy efficiency

1 Introduction

International and domestic shipping activities are the catalyst of the economic development and have seen a widespread growth during the last century. Today, shipping plays a crucial role in global greenhouse gas emissions due to the wide use of fossil fuels for propulsion [1]. During the last decades, the stringent environmental regulations and the fluctuation of fuel prices have pushed the transportation sector to invest in novel systems for reducing fuel consumption.

Hybrid-electric vessels (HEV) are ship systems where the power demand is provided by the combined use of internal combustion engines and an energy storage system (ESS). Hybrid concepts are proving successful in the automotive industry [2], where they have shown to contribute to a significant reduction of CO_2 emissions in actual operating conditions [3]. More recently, their use is also spreading in the maritime sector as a mean to reduce emissions and fuel consumption [4].

Similarly to most hybrid applications in the automotive industry, the main purpose of a hybrid system in shipping is for peak shaving. In this condition, the Diesel engines are operated as close as possible to their most fuel efficient operating condition, while the ESS takes care of high- and low- power conditions. This also generally results in a decrease of the size of the total installed power [5] [6]. If the installed ESS capacity is increased, HEVs can also be used to provide part of the energy demand from shore, in association with charging stations, hence further reducing local emissions.

Several authors in previous literature have shown the potential for reduced fuel consumption in shipping by means of HEV designs. Dedes et al. identified savings ranging from 0.3% to 28% depending on the ship type

Authors' Biographies

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Nomenclature

a_0, a_1	Linearizing fitting coefficients	w_f	Weighting factor for Diesel engine's fuel consumption
C	Constant	w_t	Weighting factor for Diesel engine's operating hours
D	Traveling distance between harbors	w_{ss}	Weighting factor for the number of start and stop of Diesel engines (-)
$E_{ESS,0}$	ESS initial energy (kWh)	$x_i(k)$	The load on Diesel engine(i)
$E_{ESS,f}$	ESS final energy (kWh)	$x_{max,i}$	Maximum load on the Diesel engine(i) (-)
E_{ESS}^{max}	ESS maximum capacity (>0)(kWh)	$x_{min,i}$	minimum load on the Diesel engine(i) (-)
$E_{ESS}(k)$	ESS available energy (kWh)	$x_{max,gen}$	Maximum load on the generator (-)
$f(k)$	Objective function for time step k	$\dot{x}$	Load variation in the Diesel engine (1/min)
i	Index of diesel engine and generator	$y_i(k)$	On/Off mode for the Diesel engine(i)
k	Time step index	Δt	Operating time step (sec)
K	Constant	η_{ch}	ESS charging efficiency (-)
$\dot{m}_{fuel}$	Fuel mass flow rate (kg/s)	η_{dis}	ESS discharging efficiency (-)
$\dot{m}_{fuel,max}$	Maximum fuel mass flow rate (kg/s)	η_{em}	Electric motor efficiency (-)
N	Number of diesel engines	η_{gen}	Generator efficiency (-)
N_{cycle}	Number of vessel's daily operational cycles	η_{in}	Inverter efficiency (-)
P	Diesel engine power (kW)	η_{rec}	Rectifier efficiency (-)
$P_{Demand}(k)$	Demand power for time step (k) (kW)	$\delta_i^{STA}(k)$	Number of starts for the Diesel engine(i)
$P_{DE,i}^{max}$	Maximum power of Diesel engine(i) (kW)	$\delta_i^{STP}(k)$	Number of stops for the Diesel engine(i)
$P_{DE,i}^{min}$	Minimum power of Diesel engine(i) (kW)		
$P_{ESS}^{Ch}(k)$	ESS charging power (<0)(kW)	*Acronym*	
$P_{ESS}^{Dis}(k)$	ESS discharging power (>0)(kW)	APCA	Adaptive piecewise constant approximation
$P_{ESS}^{max,ch}$	Maximum charging rate (<0)(kW)	CHST	Charging station
$P_{ESS}^{max,dis}$	Maximum discharging rate (>0)(kW)	CHST/ON	Charging station and overnight charging
$P_{Hotel}(k)$	Hotel power demand for time step (k) (kW)	DC	Direct current
P_{max}	Maximum power of Diesel engine (kW)	EMS	Energy management system
P_{Prop}	Propulsive power (kW)	ESS	Energy storage system
$P_{station}(k)$	Power of the charging station (kW)	HEF	Hybrid electric ferry
Q	Fuel power (kW)	HEV	Hybrid electric vessel
Q_{max}	Maximum fuel power (kW)	MILP	Mixed-integer linear programming
SOC_{max}	Maximum state of charge (-)	ON	Overnight charging
SOC_{min}	Minimum state of charge (-)	PI	Proportional integral
$u_c(k)$	ESS charging mode	PMS	Power management system
$u_d(k)$	ESS discharging mode	SOC	State of charge
V	Speed of the vessel (m/sec)		

and on the operational profile, showing a large potential for the implementation of this technology to a wide range of vessel types. Zahedi et al. [7] also came to similar conclusions, while highlighting the synergies resulting from the use of ESS in combination with a direct current (DC) power distribution grid. From a system sizing perspective, Anvari-Moghadam et al. [8] used mixed-integer nonlinear programming approach for optimal sizing of ESS together with economic dispatch of a drill-ship power system so that ship operation cost was minimized.

When dealing with the use of HEVs, the system optimal scheduling and control becomes a relevant challenge. The use of an energy management system (EMS) as a decision support tool on the ship's on-board system can determine the optimal operating points for operating the multiple power sources and support maximization of the efficiency of the power plant in terms of the reduction of fuel consumption and of the environmental impacts [9]. In addition, the use of an EMS can have a positive influence on dynamic performance and service life [10].

Much of the experience in the control of HEVs comes from the automotive sector. Musardo et al. [11] proposed an adaptive algorithm used in an EMS for application to hybrid-electric vehicles. Yu Wang et al. [12] presented a multi-variable control framework for the purpose of splitting demand power among the different power generators in a hybrid-electric vehicle.

Many authors have proposed different approaches to the optimal scheduling problem. Bassam et al. [13] proposed a multi-scheme energy management strategy for a hybrid fuel cell/battery passenger ship to increase the energy efficiency of the ship.

Barklund et al. [14] used linear programming approach in the EMS design for power sharing purpose. Kanellos [15] discussed an optimal power management system (PMS) with greenhouse gas emissions reduced thanks to a dynamic programming approach for an All-Electric ship power systems comprising ESS. Zahedi et al. [16] addressed a detailed efficiency analysis of a shipboard DC hybrid power system and proposed an optimization algorithm to minimize the fuel consumption under various loading condition. They finally proposed an online optimization control for the All-Electric ship power system. Skjong et al. [17] analyzed the load profiles extracted from three different vessels for three different power plant configurations and proposed an EMS used mixed-integer linear programming (MILP) and logic algorithms. All these approaches, while very relevant to the correct analysis of the design and operations of HEVs, limit their work to the offline scheduling of the system given the knowledge of future operations.

In real-life applications, future operations are not known in advance, and the application of optimization-based controllers becomes more challenging. Grimmelius et al. [18] proposed the application of a dynamic computer model of hybrid ship drive systems and compared different system layouts and control strategies using a combination of fuzzy rule based and an optimization algorithm and by means of linear programming approach. More specifically, they proposed the use of equivalent-consumption models in order to eliminate the time-dependence of the problem. Seenumani et al. [19] compared hierarchical controller and a model predictive control for real-time PMS in an All-Electric ship with ESS, fuel cells and gas turbines as power supply systems.

The aforementioned solutions are very effective in a majority of applied cases, and are based on a wide set of experiences from other, more mature sectors such as the automotive industry. In the case of vessels operated according to a cyclical operational pattern, however, information about the past can be used to provide an estimation of future operations.

This study presents an EMS for vessels operated according to cyclical patterns. In this case, learning algorithms can be effectively used to provide a prediction of future operations according to what has occurred in prior cycles.

2 Methodology

2.1 General description

The EMS proposed in this paper is made of an offline and an online control layer. The offline layer refers to the computations which take place before starting any new cycle and is further subdivided into three main interconnected parts:

Clustering Past operational data are used to provide an estimation for the upcoming operation based on the analysis of past measured operational profiles. This is done using clustering algorithms, such as k-means and k-medoids.

Segmentation Clustered data are simplified using an adaptive piecewise constant approximation (APCA) to reduce the dimensionality of the data-set. This is done to reduce the computational time in the optimization section.

Optimization The segmented profile sent to a MILP optimizer with the aim of identifying the optimal power share for the upcoming operational cycle.

In the online layer of the EMS, the information of the optimal state of charge (SOC) of the ESS is sent to the control system of the ESS and used as a reference value in a proportional-integral (PI) controller. The scheme of the proposed EMS is shown in figure (1).

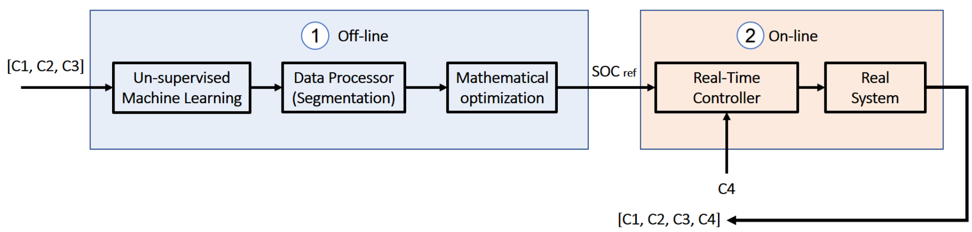

Figure 1: Scheme of proposed EMS

2.2 Offline layer

In the proposed control system, the EMS operates based on the principle of clustering techniques and data analysis processes. After each cycle of operation, the control system is automatically updated by considering the recent operation for the estimation of the next upcoming operation.

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2.2.1 *Clustering*

The proposed EMS is based on the idea of learning from past operations to provide an estimation of the next operating cycle. The implicit assumption is that the future cycle will be similar to the ones previously experienced by the system.

The task of identifying an element that can be used as the most representative of a group of elements is often referred to as clustering [20]. In this specific case, the electric power demand of the vessel, resulting from the sum of the demand for propulsion and for ship auxiliaries, is used as the clustering feature, where the dimensionality of each point in the analysis space is given by the number of time steps of the measured data series. The calculated cluster center is then used as the reference profile for the next operational cycle.

k-means and k-medoids are two plausible unsupervised exclusive machine learning algorithms, both relying on the Euclidean distance. In the k-means approach, the cluster center is evaluated according to the averaging of all past operational performance. In the k-medoids approach, instead, the position of the center is chosen among the past power profiles.

The training data set is continuously updating the control system by means of the last recent measured observation after ending of each cycle of operation and improves its decision making based on the most recent target.

An example of the result of the application of the two clustering algorithms to nine cycles resulting from randomized variations of a reference profile (see section 3) is shown in figure (2), where the difference between the learned profile between the two different algorithms can be observed.

It should be noted that, in presence of charging stations (see section 3) there would be, in theory, two different features to cluster on: the demand power, and the maximum power from the charging station. In this paper, in order to avoid this duplication of the clustering problem, we modify the measured profiles of the demand by assuming a fixed, negative value when the system is connected to a charging station (see figure (3)).

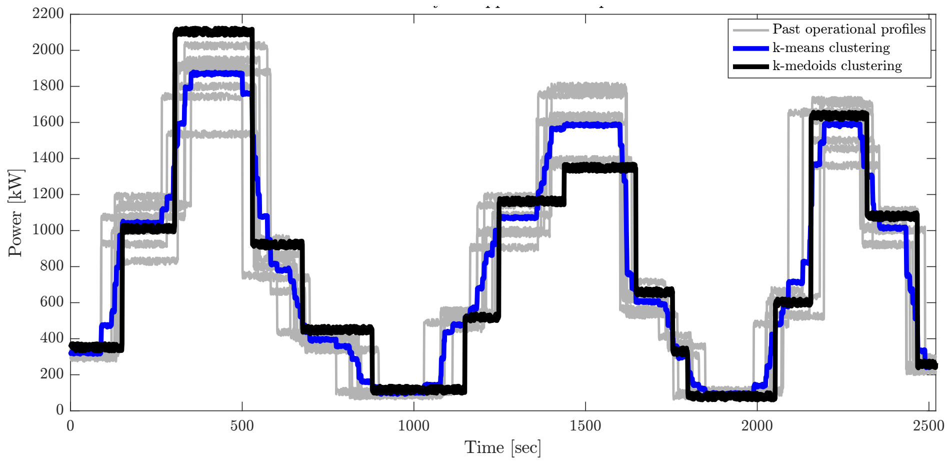

Figure 2: Example of application of clustering techniques to a reference profile.

The distinction between two clustering techniques are also shown in figures (2) and (3). The post-learning profiles obtained by $k-means$ algorithm is less similar to operational profiles because it is based on the average. On the contrary, the $k-medoids$ post-learning profile is selected as one of the past operational profiles and it is more similar to the rest of operations.

2.2.2 *Data processing- segmentation*

The resulting size of the clustered profile reflects the sampling rate of the on-board monitoring system. As a reference example, starting from an on-board monitoring system with a 1 Hz sampling frequency, the clustered profile of a ferry with a one hour long operational cycle would include 3600 points. As the solution time of an optimization problem roughly scales with the number of variables and constraints, using an unnecessary large number of time steps can lead to long computational times.

A time series is a temporal database in which the variation of variables are monitored and tracked with respect to time through several observations [21]. Different techniques are commonly used to find of interesting, unexpected, and interpretive valuable structure from data-set [22]. Segmentation is one of the techniques used for compression partitioning analysis in the aim of reducing the dimensionality of the data-set. Segmentation splits up the database into homogeneous and manageable piece-wise information so to ensure to convey the largest amount of information with the least amount of time steps [23]. Among all proposed dimensionality reduction algorithms, in this work we suggest the use of the APCA proposed by Eamonn Keogh et. al [24].

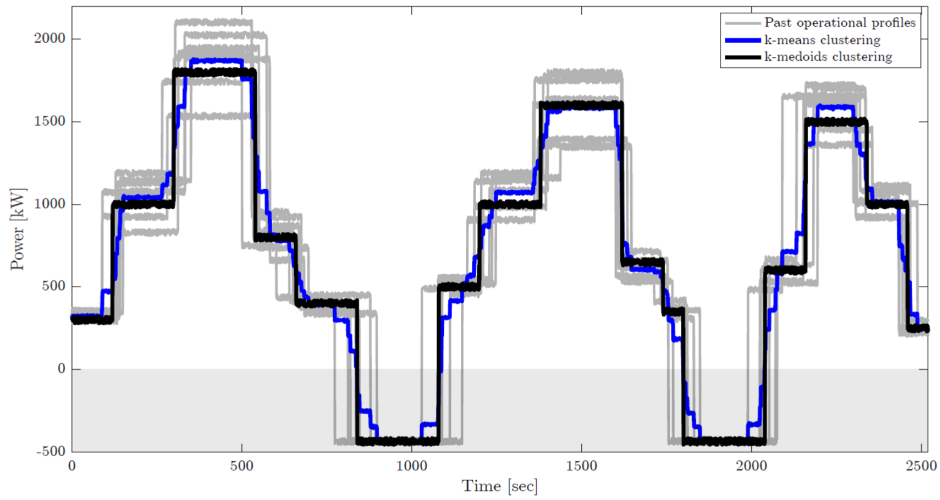

Figure 3: Example of application of clustering techniques to a reference profile, with charging stations.

Figure (4) demonstrates the post-learning and post-segmented profiles in presence charging station. Sub-figures (A) and (B) differ based on the clustering algorithm used in the previous phase ($k-means$ and $k-medoids$, respectively).

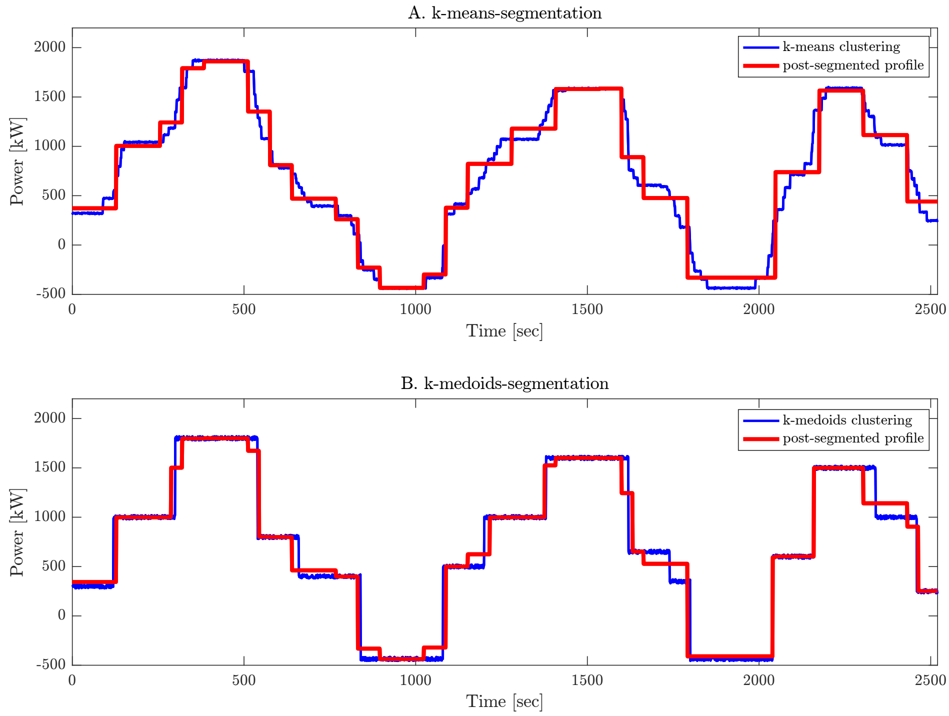

Figure 4: Post-learning and segmentation profiles in the presence of charging stations.

2.2.3 Optimizer- Mathematical programming

The segmented demand is then used in the optimization section to determine the optimal load sharing between ESS and engines for the next cycle of operation. The approach proposed in this section is similar to what proposed by Skjong et al. [17]. In this paper, the optimization is modeled as an MILP problem [25].

The main objective of the optimization stage of the EMS is to minimize the vessel's fuel consumption by acting on the power share between Diesel engines and ESS. The objective function is presented in equation (1):

$$\underset{x_i,y_i,\delta_i}{\text{minimize}} \quad f(k) = w_f \cdot \sum_{i=1}^{N} \Big(a_1 \cdot \mathbf{x_i(k)} + a_0 \cdot \mathbf{y_i(k)}\Big) \cdot \dot{m}_{fuel,max} + w_t \cdot \sum_{i=1}^{N} \Big(\mathbf{y_i(k)} \cdot \Delta t\Big) + w_{ss} \cdot \sum_{i=1}^{N} \Big(\delta_{\mathbf{i}}^{\mathbf{STA}}(\mathbf{k}) + \delta_{\mathbf{i}}^{\mathbf{STP}}(\mathbf{k})\Big) \tag{1}$$

Where i and N are respectively the index and the number of Diesel engines. In the objective function the fuel consumption of the Diesel engines is modelled as a linear function of the engine brake power, as shown in equation (2):

$$\dot{m}_{fuel} = (a_0 + a_1 \cdot \frac{P}{P_{max}}) \cdot \dot{m}_{fuel,max} \tag{2}$$

where $\dot{m}_{fuel}$ is the rate of fuel consumption, P_{max} is the maximum engine power, and a_0 and a_1 are the fitting coefficients. This formulation well represents the behavior of the efficiency of the Diesel engine used in the case study (see Section 3), as shown in figure (5).

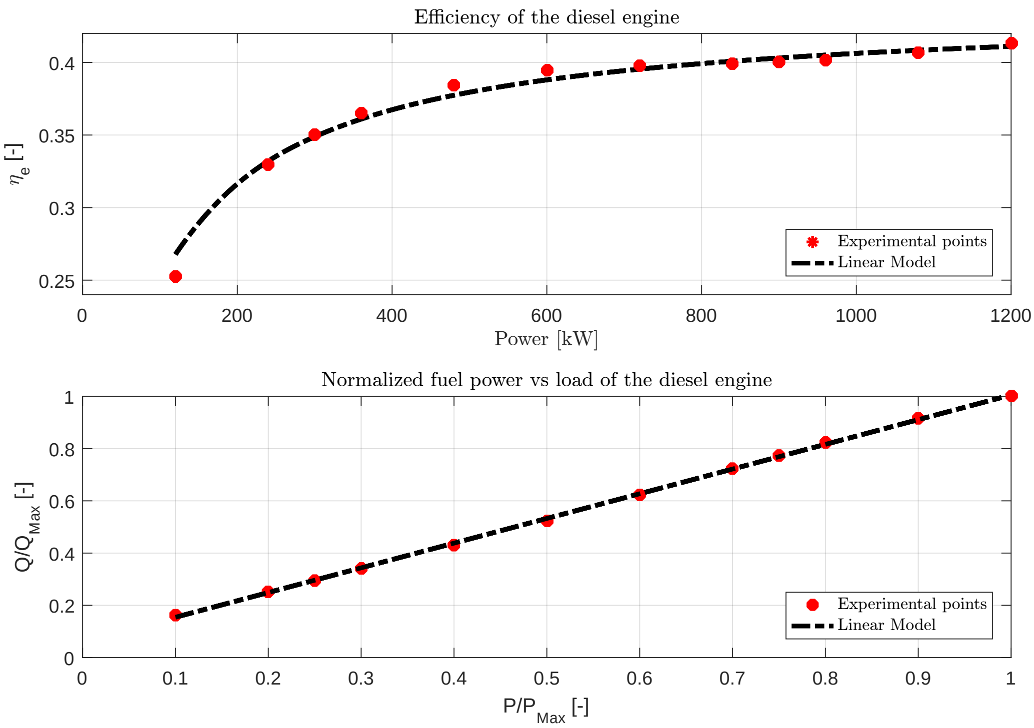

Figure 5: Fuel efficiency and normalized power for the Diesel engine.

The problem is subject to a number of constraints related to the physical behavior of the system and to its operational limits.

To ensure more realistic solutions, the objective function also includes penalties related to the start and stop operations of the Diesel engines and to their operational time. The first contribution is used to prevent solutions where engines are continuously started and stopped with limited benefit to fuel consumption, while the second contribution allows including the effect of maintenance cost.

The energy conservation is expressed in equation (3) ensuring that the demand power is met by the power supply system.

$$\sum_{i=1}^{N} \Big(P_{DE,i}^{max} \cdot \eta_{gen} \cdot \mathbf{x_i(k)}\Big) + \frac{\mathbf{P_{ESS}^{Ch}(k)}}{\eta_{ch}} + \mathbf{P_{ESS}^{Dis}(k)} \cdot \eta_{dis} + \mathbf{P_{station}(k)} = \frac{P_{Demand}(k)}{\eta_{in} \cdot \eta_{em}} + P_{Hotel}(k) \tag{3}$$

In this paper, we assume that there is the possibility of charging the ESS at one or more stops of the vessel at charging stations, represented by the term of $P_{station}(k)$. The absence of the charging station leads to consider $P_{station}(k) = 0$ in this equation.

In order to prevent unrealistic optimization results, the SOC at the beginning and at the end of each cycle need to be related to each other. In this paper, it is considered that the vessel is charged overnight, when it is not employed for normal operations. To make use of the charge accumulated overnight, we assume that, at the end of each cycle, the SOC can be lower than the initial one by a quantity that depends on the ESS capacity and on the expected number of cycles per day. This is represented in equation (4):

$$\mathbf{E_{ESS,0}} - \mathbf{E_{ESS,f}} = \frac{SOC_{max} - SOC_{min}}{N_{cycle}} \cdot E_{ESS}^{max} \tag{4}$$

It should be noted that, in order to increase the ESS's life cycle, it is assumed that the SOC can only vary in the range of 30% to 100% in practical application. This gives the foundation for overnight charging within which vessels start operating off with $SOC = SOC_{max}$ and end up the daily operations with $SOC = SOC_{min}$.

In the absence of overnight charging facilities energy conservation laws require the initial and the final SOC of the ESS are constrained to be equal.

The energy conservation equation for the ESS and the correlation between the number of start/stop with switching condition of the Diesel engine are respectively presented in equations (5) and (6) as equality constraints.

$$\mathbf{E_{ESS}(k)} - \mathbf{E_{ESS}(k-1)} = \left(\mathbf{P_{ESS}^{Ch}(k)} + \mathbf{P_{ESS}^{Dis}(k)}\right) \cdot \Delta t \tag{5}$$

$$\mathbf{y_i(k)} - \mathbf{y_i(k-1)} = \delta_{\mathbf{i}}^{\mathbf{STA}}\mathbf{(k)} + \delta_{\mathbf{i}}^{\mathbf{STP}}\mathbf{(k)} \tag{6}$$

The MILP problem is also subject to some inequality constraints which are used to limit the variation of a decision variable or activate/disactivate the components in the system. The generated load should not be larger than the maximum feasible load that can be generated and sustained by Diesel engines and the generators (see equations (7) and (8)) and should not be lower than the minimum load can be generated by Diesel engines (see equation (9)). There is a conditional constraint regarding on/off status of Diesel engines which represents the fact that the Diesel engine can be either on or off, and that both statuses do not occur simultaneously (see equation (10)). Additionally, a limitation for the load variation of Diesel engines are considered in equation (11).

$$\mathbf{x_i(k)} - x_{max,i} \cdot \mathbf{y_i(k)} \leq 0 \tag{7}$$

$$\mathbf{x_i(k)} - \frac{x_{max,gen}}{\eta_{gen}} \cdot \mathbf{y_i(k)} \leq 0 \tag{8}$$

$$x_{min,i} \cdot \mathbf{y_i(k)} - \mathbf{x_i(k)} \leq 0 \tag{9}$$

$$\delta_{\mathbf{i}}^{\mathbf{STA}}\mathbf{(k)} + \delta_{\mathbf{i}}^{\mathbf{STP}}\mathbf{(k)} \leq 1 \tag{10}$$

$$\mathbf{x_i(k+1)} - \mathbf{x_i(k)} \leq \dot{x} \cdot \Delta t \tag{11}$$

Equation (12) represents the conditional constraint for charging or discharging of the ESS and equations (13) and (14) represent the limits to the charging and discharging rate of the ESS.

$$\mathbf{u_c(k)} + \mathbf{u_d(k)} \leq 1 \tag{12}$$

$$P_{ESS}^{max,ch} \cdot \mathbf{u_c(k)} \leq \mathbf{P_{ESS}^{Ch}(k)} \leq 0 \tag{13}$$

$$0 \leq \mathbf{P_{ESS}^{Dis}(k)} \leq P_{ESS}^{max,dis} \cdot \mathbf{u_d(k)} \tag{14}$$

2.3 Online layer

The online part of the system is made by the actual controller that generates the control input for power share to the ship energy systems. In the proposed control system, the online layer is composed of a feedback PI controller in which the actual value of SOC in the real-time operation tracks the reference value provided by the offline layer. This control configuration allows a high flexibility of the system in meeting the demand, even when there is a large difference between the estimated and the actual values.

It should be noted that when the system detects the connection to a charging station, the control system is "over-ruled" and the system is forced to charge the ESS and to take all available power from the charging station.

2.4 *Ideal and real controller*

In order to provide a reference value to compare the performance of the proposed controller with, an ideal controller is also implemented. In this study, an ideal controller is defined as the one that has access to the knowledge of the upcoming operational demand (see figure (6)), as opposed to a real controller that needs to estimate the future according to the past operations (see figure (7)). The efficiency of the proposed control system is hence calculated as the ratio between the fuel consumption of the system based on an ideal controller and that of the proposed controller.

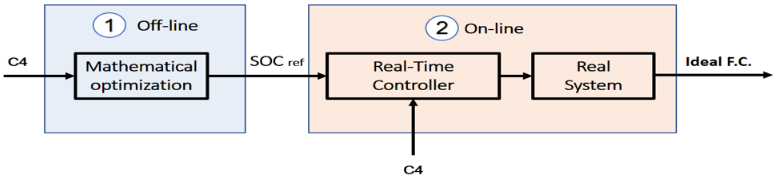

Figure 6: Ideal controller.

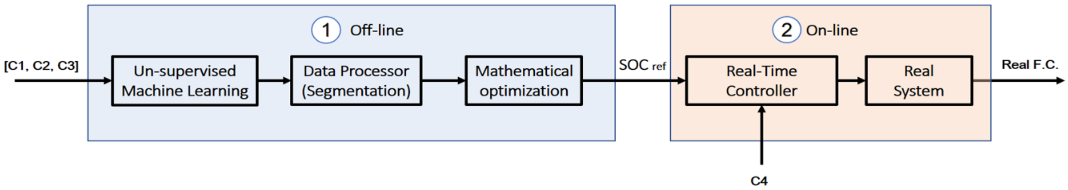

Figure 7: Real controller.

3 Case study

The proposed EMS is applied to a case study. In this case, we propose an urban ferry, as this represent a very typical shipping application subjected to a cyclical operational profile.

3.1 *Urban hybrid-electric ferry (HEF)*

An urban ferry is a vessel operating in urban areas as a part of the public transportation systems as an alternative to the construction of bridges. In this context, the integration of an ESS to the ferry's power plant is highlighted as an interesting solution for operating with high fuel efficiency, low emission, and reduction of transient load from Diesel engines. Thanks to its cyclic operational profile, an urban ferry can be considered as a convenient example for vessels with cyclic operational regimes.

The HEFs in this case study takes 42 minutes of operation to carry out a complete cycle along with two charging stations where the ESS is charged for 4 minutes. The two cases of the ferry being equipped with shore-connection facilities are evaluated separately (see figures (8) and (9)). Tables (1) and (2) respectively present the design data and upper/lower bounds for decision variables.

3.2 *Stochastic artificial data generation*

In absence of measured operational data, in this work, a simplified algorithm is developed to generate stochastic artificial operational profiles to test the proposed control system. The method that was employed in this work is based on the idea of introducing a random variation in the power requirement and operational schedule, starting from a reference profile, that maintains the distance travelled.

In this work, we assume that the propulsive power P_{Prop} against the resistance force of a vessel moving through the water with speed of V can be determined by equation (15) [26].

$$P_{Prop} = K \cdot V^3 \tag{15}$$

Reformulating equation (15) to equation (16) to have the velocity of the vessel with respect to the propulsion power:

$$V = \left(\frac{1}{K} \cdot P_{Prop} \right)^{\frac{1}{3}} \tag{16}$$

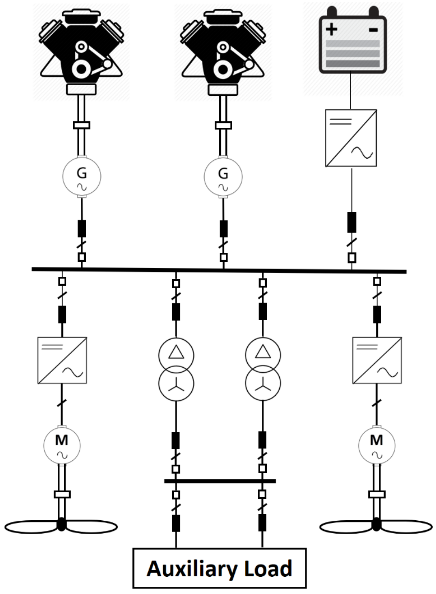

Figure 8: HEF without an external charging circuit.

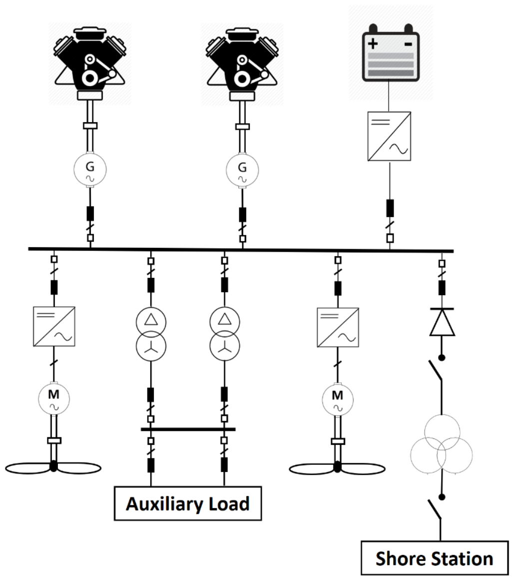

Figure 9: HEF with an external charging circuit.

Table 1: List of design data

Parameter	Value	Unit
Fuel lower heating value	42780	[kJ/kg]
Fuel density	850	[kg/m^3]
Diesel engine maximum power	1200	[kW]
Diesel engine minimum power	120	[kW]
Generator maximum power	1150	[kW]
Generator efficiency	0.95	[-]
Electric motor maximum power	1000	[kW]
Electric motor efficiency	0.96	[-]
Inverter efficiency	0.98	[-]
Rectifier efficiency	0.98	[-]
ESS maximum capacity	400	[kWh]
ESS maximum charging power	400	[kW]
ESS maximum discharging power	400	[kW]
ESS maximum state of charge	100	[%]
ESS minimum state of charge	30	[%]
ESS charging efficiency	0.95	[-]
ESS discharging efficiency	0.98	[-]

Table 2: Decision variables

Lower bound	Variable	Upper bound	Unit
0	$\mathbf{P_{ESS}^{Dis}(k)}$	400	[kW]
-400	$\mathbf{P_{ESS}^{Ch}(k)}$	0	[kW]
{0}	$\mathbf{P_{station}}$	∞	[kW]
120	$\mathbf{E_{ESS,0}}$	400	[kWh]
120	$\mathbf{E_{ESS}(k)}$	400	[kWh]
10%	$\mathbf{x_i(k)}$	100%	[-]
{0}	$\mathbf{y_i(k)}$	{1}	[-]
{0}	$\delta_{\mathbf{i}}^{\mathbf{STA}}\mathbf{(k)}$	{1}	[-]
{0}	$\delta_{\mathbf{i}}^{\mathbf{STP}}\mathbf{(k)}$	{1}	[-]
{0}	$\mathbf{u_c(k)}$	{1}	[-]
{0}	$\mathbf{u_d(k)}$	{1}	[-]

The distance D traveled by a vessel can be easily found by integrating the speed profile over time (see equation (17)):

$$D = \int V \cdot dt = \int \left(\frac{1}{K} \cdot P_{Prop}\right)^{\frac{1}{3}} \cdot dt = \frac{1}{K} \cdot \int \left(P_{Prop}\right)^{\frac{1}{3}} \cdot dt \tag{17}$$

The distance between two harbors D is constant, and we as assume that, not having specific information about the case study and its actual operations, K can also be simplified to a constant. As a consequence, equation (18) is reformulated as:

$$C = D \cdot K = \int \left(P_{Prop}\right)^{\frac{1}{3}} \cdot dt \tag{18}$$

Where C is also a constant. In this study, we assume that operational profiles of the vessel can be considered as discrete patterns. For instance, sailing between two harbors A and B could compose of four steps of operation including a step of docking from the harbor A, a step of a short maneuvering, a step of the main operation, and finally the step of docking to the harbor B. The same for B to A to do a cycle. All these steps can be described by the duration of each step and the average required power. Therefore, the discrete form of equation (18) can be expressed as equation (19).

$$C = \sum_{i=1}^{n} \left(P_i^{\frac{1}{3}} \cdot \Delta t_i \right) \tag{19}$$

Where P_i and Δt_i are respectively the average power and the duration of each step in the load diagram. n is number of steps between two harbors. Equation (19) has a high degree of conformance. It gives the foundation for generating four different types of load diagrams. Four main data generation techniques are discussed in the following.

1. Variation in duration of time step: considering constant average power associated with each step. The time duration regarding each time step can be stochastically varied so that C in equation (19) is held constant. The total duration of the cycle is also maintained constant.

2. Variation in the power: on the contrary, for this case, considering constant time duration associated with each time step. The average power for each time step can be randomly varied in such a way that C in equation (19) is held constant.

3. Variation in duration of time step and the power: the scope of this case is generating stochastic load profile having variation in both time duration and average power for each step of operating as long as C in equation (19) is held constant.

4. Variation in duration of time step and power in presence of dynamic noise: considering the variation of power around the average power by accounting a noise on the load diagram. This type of data generation is intended to provide the closest representation of how vessels operate in reality.

It should be noted that, while the suggested method for automatic data generation is based on strong simplifications of the actual behavior of a propulsion system, such as the absence of added resistance or the implicit assumption of constant propeller efficiency, it is only used in this study for testing purposes. The proposed control system does not include the artificial data generation, and hence does not depend on it for its correct functioning. The control system proposed in this study focuses on the optimization of the power share between the engines and the ESS, and is hence not concerned by the ships propulsion efficiency.

4 Results

This parts attempts to present and compare the results corresponding to the implementation of the control technique on the various types of HEF. In the first part, the loading conditions of the the Diesel engines and the ESS for different scenarios are presented and the fuel consumption is compared. Subsequently, the results corresponding to the performance of the control system for the ideal and the real controller are visualized and the robustness of the control system is discussed for different types of operation.

4.1 Effect of external charging circuits

In this section, the behavior of the ship power system using the proposed EMS is analyzed for the different potential configurations:

HEF with peak-shaving (HEF) The Diesel engines are the only available source of energy for powering the ship and charging the ESS.

HEF with charging stations (HEF-CHST) The ferry can be connected to the electrical grid during one or more of the stops using charging stations.

HEF with overnight charging (HEF-ON) The ESS of the ferry is fully charged during the night, but not during the day.

HEF with both charging station/overnight charging (HEF-CHST/ON) The ESS of the ferry is fully charged during the night, and can be charged/discharged during the day; plus, having connection to the grid to charge the ESS during its operation.

The results are compared for two scenarios for the ferry, five and ten cycles of operation per day. It is assumed these operations are stochastically varied up to 20% in time and power. A dynamic noise to simulate the real-time conditions is applied on the power.

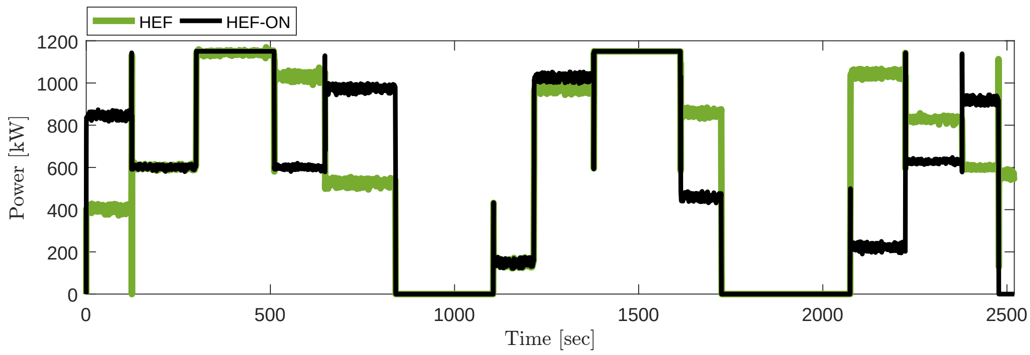

Figure 10: Load on the Diesel engine in presence and absence of overnight charging

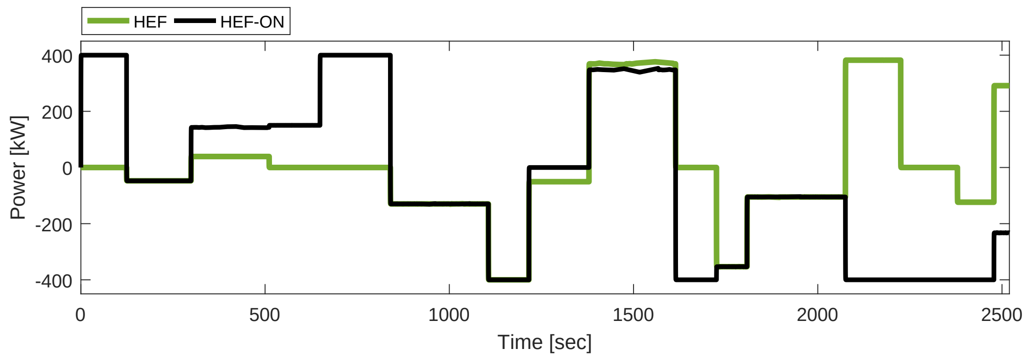

Figure 11: Load on the ESS in presence and absence of overnight charging

The behavior of the system in HEF mode corresponds to what expected from a hybrid system, as shown in figure (10). During low load demand periods the optimizer suggests to switch off the Diesel engines and to supply the demand using the ESS, while during medium-high power operations the Diesel engines are operated at higher load to charge the ESS. It can be noted that this behavior was achieved without pre-setting a rule, and is hence flexible to the application to different ship types, or to different operational patterns for the same ship.

In presence of the peak-shaving function alone, the ESS system is largely underused. This is a consequence of the fact that marine Diesel engines tend to operate at relatively high fuel efficiency also at low load, and of the fact that very low load operations and transients are rare compared to automotive applications. This is also shown by the fact that the ESS is never used to its full potential, neither in terms of energy (ESS capacity), nor of power (maximum C-rate).

In presence of overnight charging, the ESS supplies a larger share of the power demand because it is allowed to discharge a portion of energy for each cycle. In the presence of overnight charging, the ESS is gradually depleted during the daily operation. The contribution of overnight charging to the reduction of the fuel consumption for each cycle of operation for the two cases is reported in table (3).

In presence of charging stations (HEF-CHST), similarly to the HEF-ON case, the average load on the Diesel engines is lower, since part of the energy is provided by charging the ESS when it is connected to the shore (see figure (12)) during the stops. When it is connected to a charging station, not only the ESS is charged, but also the full power demand of the ferry is fulfilled by the power coming from the grid.

It is worth mentioning that this is also a result of the fact that the EMS is aware of the future availability of a charging station, and will consequently allow the use of a larger share of the ESS charge knowing that it will be possible to charge it soon. This behavior, in which operations from past cycles are used to optimize the system in accordance with expected future events, represents one of the main improvements proposed in this work compared to previous literature.

The contribution of charging stations in reduction of fuel consumption for each cycle of operation is reported in the table (3). It should also be noted that when both overnight charging and charging stations are available the savings are improved by more than the sum of the two single contributions, showing the synergy in the combination of the two.

Table 3: Cyclic reduction of fuel consumption on basis of the mean value of five simulation tests in an ideal controller w.r.t HEF when operational profiles have up to 20% variation on time and power in presence of noise.

Cycles	HEF-ON	HEF-CHST	HEF-CHST/ON
5	7.61%	10.1%	18.98%
10	4.07%	9.75%	14.87%

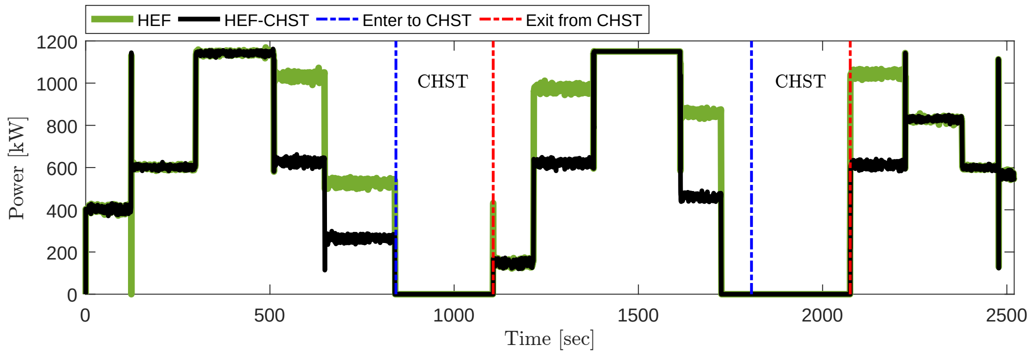

Figure 12: Load on the Diesel engine in presence and absence of charging stations

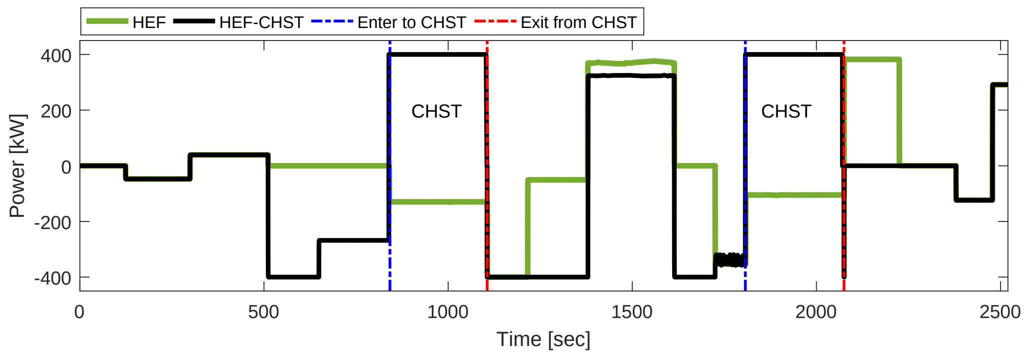

Figure 13: Load on the ESS in presence and absence of charging stations

4.2 Controller performance

The results presented in this section focus on the online part of the controller. The ideal controller can appropriately track the reference SOC coming from the offline layer, since its prediction of future operations coincides with the actual power demand. Moreover, the ESS is monitored by the PI controller and the rest of demand power is supplied by the Diesel engines. This is valid for all configurations and any types of variation for operational profiles.

On the contrary, the real controller does not know the future. In the proposed control system, $k-means$ or $k-medoids$ learning algorithms are adopted in the real controller to estimate the forthcoming operation based on past operational profiles. The results of the simulations suggest that in absence of charging stations (configurations HEF and HEF-ON) the controller can appropriately follow the reference, regardless of the type of clustering algorithm used.

In the case of presence of charging stations, however, the situation is different, as shown in figure (14).

This is primarily caused by the decision of over-ruling the PI controller of the ESS when the system is connected to shore, and by the fact that the timing at which this happens can vary compared to the future reference cycle estimated by the clustering algorithm. The persistence of an error between reference and measured SOC after the charging stations is due to the limitation of discharging power in ESS.

The cause of this disturbance in the real controller lies in the variation of operational profile in terms of the duration of the time steps, and not in variations of the average power.

It should also be noted that, in presence of charging stations, there is a significant difference in the performance of the EMS depending on the chosen learning algorithm. In particular, it was observed that the $k-means$ approach performs better than the $k-medoids$ if the operational profiles are widely different in time duration (See figure (14)).

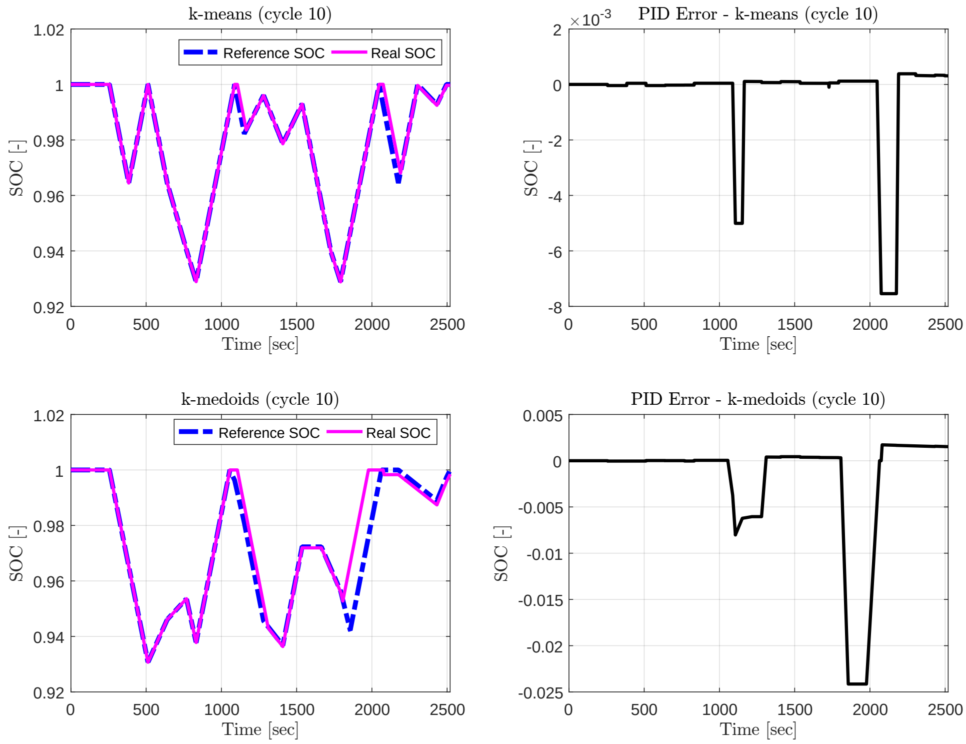

Figure 14: SOC in the real controller for HEF-CHST

4.3 Efficiency of $k-means$ and $k-medoids$ algorithms

In the previous section, it was qualitatively observed that the $k-means$ algorithm behaves better than $k-medoids$ in some scenarios. To make a decision on which of the two clustering algorithms, we performed a series of tests with varying conditions of power, time step duration and in presence of noise. The analysis is based on a total of 120 tests. The clustering algorithms are then compared based on their achieved reduction of fuel consumption when compared to an ideal controller.

The results of these tests are summarized in table (4). They suggest that the application of the $k-means$ learning package is closer to the ideal controller for the ferry in presence of charging stations and for large variations in the operational profile, while the $k-medoids$ approach works better in absence of charging stations.

4.4 Analysis of weight factors in the objective function

In the proposed EMS, the objective function that is minimized within the optimizer section is made of the contribution of three elements: the fuel consumption, the number of engine starts and stops, and the running hours. As these contributions originally have different units, the problem would result into a multi-objective optimization. In order to treat it as a single-objective problem, we used weight factors. The choice of the value assigned to weight factors is hence to be discussed based on their influence on the system behavior.

The influence of the weight factors of the number of start and stops (w_{ss}) and of the running hours (w_t) on the number of engine start and stops in a cycle is shown in figure (15). It can be observed that even a small w_{ss} is enough to reduce the number of engine starts from 16 ($w_t = 0$) to 10 or 12. It can also be shown that having a non-zero value for the w_t helps in making the system more resilient against an inaccurate choice of w_{ss}.

It can be concluded that the use of a weighting factor for the number of engine start and stops helps in avoiding an excessively high, and unjustified, number of engine starts and stops, and that a use of the weighting factor for the running hours make it easier to adopt a reasonable value for the w_t.

5 Discussion

As highlighted in the previous section, the method proposed in this paper for the optimal control of hybrid vessels shows a positive performance in optimizing the energy efficiency of these systems. However, it should be noted that the method has limitations, some of which are intrinsic to the proposed approach.

First of all, this approach is specifically designed for vessels having a repetitive, cyclical operational profile. This hypothesis is the basis for using previous operations in order to predict future ones, and is central to the functioning of the method. The method is hence most suitable for ships operating in short cycles repeated with

Table 4: Efficiency of learning algorithms with respect to ideal controller, HEF-CHST/ON

Variation	5 cycles k-means	5 cycles k-medoids	10 cycles k-means	10 cycles k-medoids
Time variation				
5%	97.6%	96.6%	98.7%	96.7%
10%	96.4%	94.0%	98.0%	96.3%
20%	93.3%	94.2%	97.2%	90.2%
Power variation				
5%	98.7%	99.3%	95.9%	96.5%
10%	97.8%	97.5%	99.2%	99.2%
20%	98.2%	96.4%	98.1%	98.9%
Time and power variation				
5%	96.2%	94.5%	97.3%	96.1%
10%	96.0%	91.8%	97.8%	95.1%
20%	97.4%	93.8%	98.0%	87.5%
Time and power variation in presence of noise				
5%	95.5%	95.0%	99.0%	94.7%
10%	97.0%	93.8%	98.6%	93.7%
20%	96.3%	89.7%	99.0%	98.0%

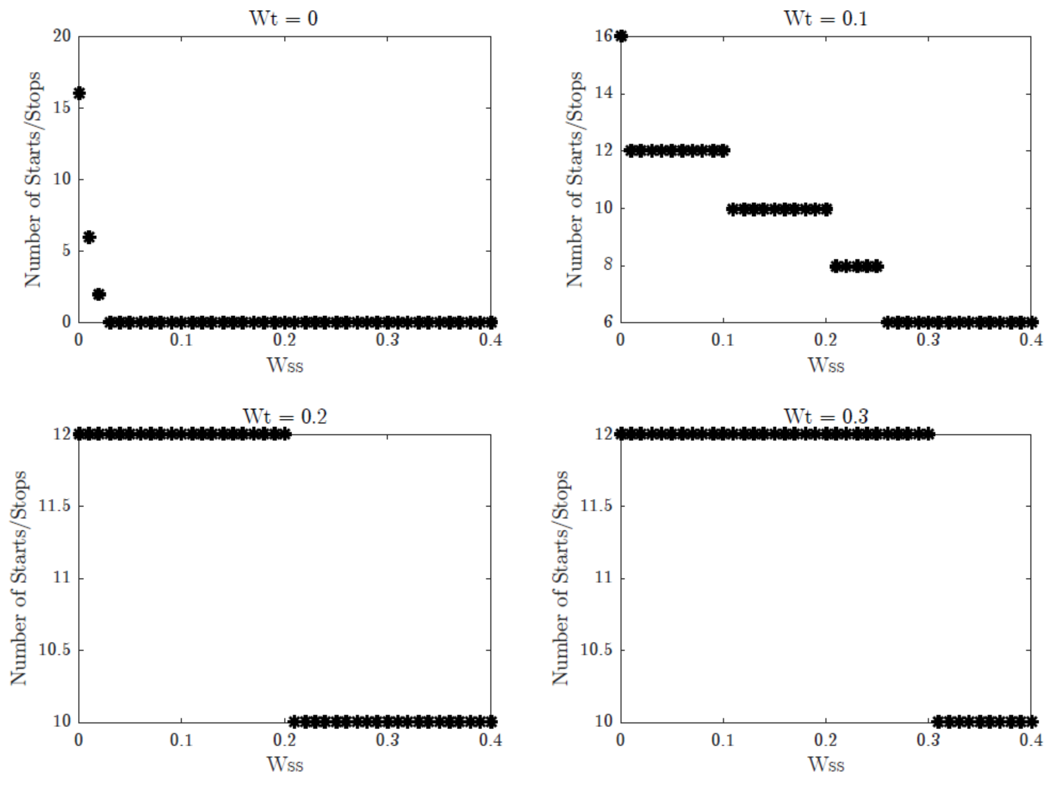

Figure 15: Effect of weight factors on the number of engine starts and stops

high frequency, as short-sea ferries operated in towns or between close islands, where operational cycles last between a few minutes and a few hours, as it was tested in the case study proposed in this paper. We expect that the proposed method could be extended, after appropriate test phases, to vessels with regular services on longer routes, such as ferries, cruise ships, fishing vessels and container-ships. We expect, on the other hand, this approach to be inappropriate for ships with inherently irregular patterns, such as those operated in tramp trade.

In addition, the model presented in this paper for the system optimization was tailored to the case study in different parts, and the validity of the model for other types of systems can be questioned.

As a first point, it is worth mentioning that in many types of marine Diesel engines the maximum efficiency is determined around 80% of maximum load. However, the experimental points provided by the manufacturer for the specific engine used in this study (see figure 5), demonstrate a different behavior of the selected engine, with the peak efficiency located at the 100% of the engine load. This provides the ground for the choice of a simple linear modeling assumption for this specific case. It should be noted, however, that the standard case with peak efficiency at intermediate loads can be dealt with using a piece-wise linearization approach.

Furthermore, for this specific case, the Diesel engines are operated in generator mode at constant speed, hence making the engine efficiency to be independent from the engine speed. In cases where mechanical propulsion is used, and hence the influence of engine speed is non-negligible, the method should be revised accordingly, and is expected to perform with lower accuracy.

As highlighted in the text, in this paper we assume that all the efficiency of electro-mechanical components (electric generators and motors) and of the ESS are constant. This assumption is justified by its common application in previous literature in the subject [18, 17], but certainly introduces a simplification of the ship model. It should be noted, however, that this can be partly solved by using additional integer variables, with limited loss in solution speed.

6 Conclusions

This study aimed to assess the effect of learning algorithms in improving the efficiency of the control system in a specific category of HEVs having cyclic operational profiles. The challenge of the optimization of the load sharing on different power sources was addressed. The proposed EMS was trained by means of past operations to deduce a new prediction for the upcoming operation. Having processed the post-learned profiles by means of segmentation technique, the information is used in the MILP optimizer to evaluate the optimal status of charging and discharging of the ESS. This information is then used in a PI controller to monitor the real SOC in the real-time operation of the vessel.

The control system is applied to different configurations for a HEF through a case study. The effects of presenting external charging circuits on the control system is analyzed under the assumption of random variations of operational profiles up to 20% with respect to a reference operational profile.

In this study, it is concluded that the proposed EMS works efficiently even in presence of large variations in the operational profile. The efficiency of the control action, with respect to an ideal, optimal controller, is high even in presence of charging stations, with an accuracy ranging between 87% and 99% (when compared to an ideal controller) depending on the clustering algorithm, on the size of the variations in the operational profile, and on the availability of charging stations. The system showed to have close to ideal performance even with large variations in the operational profile, hence showing the robustness of this approach.

Of the two tested clustering algorithms, $k-means$ showed higher efficiency in the reduction of fuel consumption in presence of charging stations, while in absence of these, $k-medoids$ showed to provide a better performance.

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