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Model Predictive Control for Energy Management in Hybrid Ferry Grids

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ABSTRACT

High performance and cost-effective ferry boats are of capital interest for customers and marine industry companies. On the other hands, the traditional ferry boats, which are operated by diesel generators, spatter the atmosphere with CO2 emissions and detrimental particles. Hence, more-electric technology revolution in marine applications, especially in ferry vessel systems, has gained a lot of attention during the last decade as a promising technology to decrease fuel consumption and emissions. However, one of the main issues in the electric ferry (E-Ferry) is to keep the voltage and frequency within an acceptable range according to the large dynamic load fluctuations. In order to solve this issue, this paper presents a model predictive energy management based on a modified black hole algorithm (BHA) for the hybrid E-Ferry systems. Finally, to study the efficiency of our proposal, we run a real-time simulation using the d-space simulator and compare the effect of the prediction horizon on the system performance.

1. Introduction

The emission reduction imposed by the international marine organization (IMO) as well as the growing environmental concerns play a significant role in the marine industry's approach to design environment-friendly marine power propulsion system solutions (M. D. A. Al-Falahi et al., 2018; Gheisarnejad et al., 2019; Vafamand et al., 2019b). Furthermore, the fuel price fluctuations force the shipbuilding companies to explore technologically advanced and efficient solutions to decrease operational costs in the marine transportation industry (Shancita et al., 2014). In consequence, by integrating different potential power generation sources (e.g. liquefied natural gas, solar energy, and energy storage devices), marine industry works on finding the best solution for emissions control and energy saving (Khooban et al., 2018; Vafamand et al., 2019a).

Hybrid power sources-based marine vessel systems are boat systems where the energy demand is satisfied by a mixture of diesel power engines, renewable sources like fuel cells, and batteries (Han et al., 2014). In the automotive industry, the concept of hybrid was proven successful and many vehicles have been commercialized. This means that CO2 emissions can be reduced significantly in real operating conditions. Given this achievement, hybrid-energy solutions is also applied in the maritime sector as a high technology tool to decrease emissions and fuel consumption (M. Al-Falahi et al., 2018). Moreover, power recovery approaches are gradually being applied to marine vessel systems to enhance fuel efficiency. For instance, the system of waste heat recovery uses the exhausted fumes for electricity production to improve the main generator efficiency by approximately 5%, hence significantly decreases emissions and the cost of fuel (Skjong et al., 2015).

In general, the complexity of hybridizing marine power grids (e.g. synchronization of each power source) can bring big challenges. Furthermore, AC vessel distribution power systems have disadvantages like reactive power flow, transformers inrush current, the imbalances of the three-phase system, and harmonic currents (Zahedi et al., 2014). In contrast, a DC distribution ship system can deliver efficient electric energy by jointing alternating current and direct current energy supplies through power electronic circuits, which delivers energy flow to the load (Navid Vafamand et al., 2018b; Yousefizadeh et al., 2018a). Nevertheless, owing to non-linear characteristics and switching behavior of power electronic devices, the complexity of DC power systems has increased (N. Vafamand et al., 2018; Vafamand et al., 2019b). However, new advancements in power electronics converters make them more efficient and flexible, by which DC grids become feasible in different power applications. As a result, the utilization of a hybrid power system with a DC grid enables cooler integration of renewable energy sources and energy storage devices (Yousefizadeh et al., 2018b). Also, generation supplies synchronization is not needed which makes the prime movers possible to work at their optimal speeds and providing the fuel consumption and emissions reduction (M. D. A. Al-Falahi et al., 2018). Additionally, the mentioned advantages also provide additional benefits (e.g. saving the space and weight, flexible arrangement of equipment as well as reducing the noise from a conventional diesel power system) in the harbor. Besides, the integration of traditional maritime power plants with RESs and ESSs offers substantial cost and environmental benefits (M. D. A. Al-Falahi et al., 2018). Consequently, by adopting hybrid power systems with DC distribution, we can achieve many gains and benefits.

The optimal scheduling of marine power systems and electric loads (Boudjadar et al., 2016), which are considered as a power management system (PMS), is one of the significant issues in the hybrid marine grids (Kanellos et al., 2016). Particularly, the well-planned function of a marine power grid in the generation side among with optimal scheduling of load demands are able to influence the efficiency of the plant. On top of everything else, for short-run intervals, power energy management in hybrid marine systems plays a significant role in the coordination of controllable power units and electrical loads in a way to satisfy the requirements in the plant's dynamic (Kanellos et al., 2016).

Up to now, many energy management algorithms with different power grid configurations have been suggested for power systems. For instance, a mixed-integer nonlinear programming (MINLP) algorithm is applied to optimize the energy management problem in shipboard microgrids (Kanellos et al., 2016). The particle swarm optimization algorithm is used to solve the problem. In (Anvari-Moghaddam et al., 2016), the ship power system, which is equipped with solar panels and energy storage devices, is investigated for the economic operation of the whole of the system. The model-predictive control-based optimal energy management is applied in [18], [19]. In these papers, the optimization problem is formulated so that the minimum cost of operation is achieved. In order to enhance the computational efficiency, the real-time optimization problem is described as a simplified two-level optimization model. The examination of experimental ship information , from standard operation to shed light, on the potential for using batteries and optimization based unit commitment is presented in (Park et al., 2015). In [(Banaei and Alizadeh, 2016)], the problem of solving optimum ESSs sizing is modeled as a two-layer optimization problem. In the first step, this paper finds the optimal power generation scheduling for a particular energy storage capacity. Then, the outer layer goes over all possible design configurations (storages capacities) and determines the net saving (saving minus cost) for each configuration.

In this paper, the problem of intelligent model predictive approach for energy management of a hybrid electric-ferry with several generators and batteries is investigated. The practical constraints on the maximum and minimum and the variation rate of power of generators and batteries are considered. To perform the energy management, a nonlinear optimization problem with a polynomial cost function and linear inequalities is presented and the problem is solved by a modified black hole algorithm (BHA). Real-time simulation results show the applicability of the suggested method in handling the highly varying load power. Also, it is shown that higher horizon prediction outperforms the energy management by properly charging and discharging the battery before and during sudden changes in the power demand.

The rest of the paper is organized as follows: In Section 1, the power management for the hybrid electric ferry is discussed. In Section 2, the nonlinear optimization problem is proposed. In Section 3, the black hole algorithm to solve the optimization problem is studied. In Section 4, the real-time simulation results are provided. Finally, in Section 5, conclusion and future works are presented.

2. Illustrations

In general, a marine power system with fuel cell, diesel generator as main sources of the ship power, energy storage systems as a reservation unit, power electronic devices as interfaces for renewable energy systems, and loads like ship motor(s) and navigation system(s) can be considered as a special mobile islanded DC microgrid (see Fig. 1).

Minimizing the fuel consumption of several sources in the case study is the key target of the optimization problem. In this ship system, the powers of generators are assumed as the optimization parameters. The energy management of the fuel cells causes reducing fuel consumption as well as emissions.

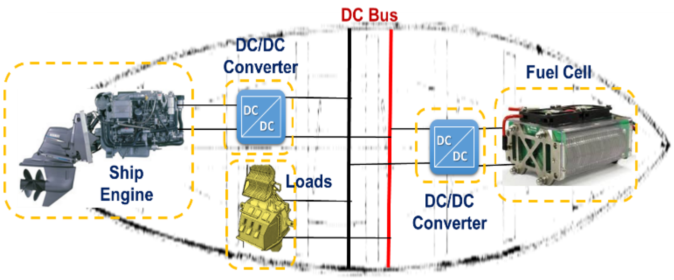

Fig. 1. The scheme of a hybrid electric ferry grid.

This procedure confirms that at least one fuel cell works on the optimum operating condition as well as another renewable source operates in a high-efficiency zone. To achieve this objective, the energy storage device should on accurate scheduling during the entire path. Furthermore, turn off the renewable energy sources is another constraint where it can have a positive effect at a low demand in the reduction of the fuel consumption in marine power systems, in other words the fuel cells should only work in high load demands. As a result, the main objective function of energy management in this study can be formulated as follows:

$$FC_{total}(t) = \sum_{n=1}^{N} (SFOC_n(t) \times P_n(t) \times \Delta t) \tag{1}$$

where the fuel depletion of the ship shows with $\boldsymbol{FC_{total}(t)}$, while $\boldsymbol{P_n(t)}$ is assumed to be the generated power by the $\boldsymbol{n}$-th energy supply at t-th time (KW). The step time of the system is considered as $\boldsymbol{\Delta t}$. Besides, $\boldsymbol{t}$ is a $\boldsymbol{t}$-th time interval, $\boldsymbol{N}$ is the number of fuel cells. The particular fuel oil consumption of the $\boldsymbol{n}$-th energy sources is shown by $\boldsymbol{SFOC_n(t)}$ and written as below:

$$SFOC_n(t) = \left[a\left(\frac{P_n(t)}{P_{n,rated}}\right)^2 - b\left(\frac{P_n(t)}{P_{n,rated}}\right) + c \right] \tag{2}$$

where the rated power of the energy unit is represented by $\boldsymbol{P_{n,rated}}$. Moreover, the parameters $\boldsymbol{a}$, $\boldsymbol{b}$, and $\boldsymbol{c}$ are assumed as the SFOC equation.

In order to monitor the output of energy units, three kinds of constraints are assumed as follows:
1) the limitations exist in the energy source units
2) the constraints related to the generator ramp rate
(3) basic bounds for the output power of generator units that should be within a specific range.

The other constraint, generator ramp rate constraint, does not allow very sharp changes in the output power of the generator by defining the maximum allowable ramp rate. Moreover, this point is important that the variations of $\boldsymbol{P_n(t)}$ is represented by (4) in a discrete simulation,

$$P_n^{min} \le P_n(t) \le P_n^{Max} \tag{3}$$

$$\left| \frac{P_n(t) - P_n(t-1)}{\Delta t} \right| < R_i \tag{4}$$

The maximum and minimum acceptable stored power in the batteries is the only constraint, which is assumed in this optimization problem. Hence, in (5), this battery constraint is represented as:

$$E^{min} \le E(n) \le E^{Max} \tag{5}$$

Dynamic equations are necessitated for each dynamic optimization problem. Similar to other optimization problems, this study uses equation (6) as the dynamics of the understudy system. Generally, dynamic equations introduce the relationship between the system states at each time to the earlier state(s). The applied dynamic equation in this paper is based on the stored power of the battery at the end of the current time step. In other words, the energy at the previous time step plus the alteration between the overall power generation and the demanded loads, which are multiplied by the time step length, is equal to the stored power of the battery at the end of the current time step.

$$E(n) = E(n-1) + \Delta t \times \left[\sum_{n=1}^{N} (P_n(t)) - P_L(t) \right] \tag{6}$$

where the load power is defined by $\boldsymbol{P_L(t)}$.

3. Nonlinear Model Predictive Control Approach

The objective function defined in (1) is based on fuel consumption at time $\boldsymbol{t}$. If it is minimized, the consumption of fuel without considering the future behavior of the load demand will be reduced. However, if the load demand changes faster than the variation power rate of the generators, then the optimization problem degrades. Thereby, it is necessary to involve the future behavior of the load profile to improve the energy management especially when the load varies roughly. It is shown that the model predictive method outperforms the other approaches from the cost function minimization viewpoint (Mardani et al., 2018; Navid Vafamand et al., 2018a; Vafamand et al., n.d.; Vafamand and Khayatian, 2018).

Based on the above-mentioned reasoning, the following optimization problem is suggested:

For the given generator powers $\boldsymbol{P_n(t_k - 1)}$, battery power $\boldsymbol{E(t_k - 1)}$ at $\boldsymbol{t = t_k - 1}$, and the future power demand $\boldsymbol{P_L(t)}$ for $\boldsymbol{t_k \le t \le t_k + T}$, we define the following optimization problem

$$\min_{P_n(t)\ for\ t_k \le t < t_k + T} \gamma \tag{7}$$

Subject to

$$\sum_{t=t_k}^{t_k+T} \sum_{n=1}^{N} (SFOC_n(t) \times P_n(t) \times \Delta t) < \gamma \tag{8}$$

and for $\boldsymbol{t_k \le t < t_k + T}$,

$$P_n^{min} \le P_n(t) \le P_n^{Max} \tag{9}$$

$$-\Delta t R_i \le P_n(t) - P_n(t-1) \le \Delta t R_i \tag{10}$$

$$E^{min} \le E(t) \le E^{Max} \tag{11}$$

$$E(t) = E(t-1) + \Delta t \left[\sum_{n=1}^{N} \left(P_n(t)\right) - P_L(t) \right] \tag{12}$$

Then, the generators' powers $\boldsymbol{P_n(t)}$ for $\boldsymbol{t_k \le t < t_k + T}$ is obtained.

4. Black Hole Optimization

In general, the black hole algorithm (BHA) is a population-based algorithm. The main concept of a BHA is simply an area of space that has huge mass centralized in it where there is no path for a close object to flee its gravitational pull. The formal movement of stars towards the black hole can be described as follows (Hatamlou, 2013; Khooban et al., 2018):

$$X_{m,\ new}^{iter} = X_m^{iter} + rand(.)(Best^{iter} - X_m^{iter}); \quad m = 1, \dots, N_{Pop} \tag{13}$$

where X_m^{iter} presents the target position, while $X_{m,\ new}^{iter}$ shows the updated agent in iteration $iter$. Furthermore, $Best^{iter}$ denotes the best solution. More information about the formulation and structure of the BHA is discussed in (Khooban et al., 2018).

In order to improve the exploration properties of the BHA, a new approach is applied to the collapsing process. In the first step, a new updating mechanism for the modified BHA design process is presented as follows:

$$X_{m,\ new}^{iter} = X_m^{iter} + rand_1(.)(Best^{iter} - X_m^{iter}) + rand_2(.)(X_r^{iter} - X_m^{iter}) \tag{14}$$

where $r \in [1, N_{Pop}]$ and ($r \ne m$). In the following, for improving the optimal utilization of data, which is acquired by the members of the population in producing new candidates, the Absorption Capacity is applied for the utilized optimization algorithm. In this regard, a modification should be conducted for the event horizon R^{iter} based on distribution and collection of stars, as:

$$R_{m,\ Mean}^{iter} = \left\| X_{m,\ new}^{iter} - Mean^{iter} \right\|; \quad m = 1, \dots, N_{Pop} \tag{15}$$

$$R^{iter} = 0.1 \sum_{m=1}^{N_{Pop}} \frac{R_{m,\ Mean}^{iter}}{N_{Pop}} \tag{16}$$

where $Mean^{iter}$ is the mean population vector in the iteration. If the difference value between each of $X_{m,\ new}^{iter}$ and $Best^{iter}$ is less than R^{iter}, then the corresponding solution is replaced by a new randomly created one. By using the modification (16), the event horizon is able to control the number of collapsed stars as well as avoid the high scattering of the best solution. So, (17) and (18) are used to overcome the mentioned difficulty.

$$X_{m,\ new}^{iter} = Best^{iter} + \frac{\max_m R_{m,\ Best}^{iter}}{N}(2rand(1,N) - 1) \tag{17}$$

$$R_{m,\ Best}^{iter} = \left\| X_{m,\ new}^{iter} - Best^{iter} \right\|; \quad m = 1, \dots, N_{Pop} \tag{18}$$

Based on the above explanations, the main steps of the modified BHA are presented in Table I.

Table I: The application of the modified BHA for the model predictive energy management.

1. Augment the unknown powers $P_n(t)\ for\ \ t_k \le t < t_k + T$ in the vector $X^* = [P_{1,1}\ \ P_{1,2} \dots P_{1,T}\ \ P_{2,1}\ \ P_{2,2} \dots P_{2,T}]$.
2. Initialize a population of N_{Pop} stars $X_m^{iter}\big|_{iter=1}$ with random locations in the search space.

Loop

3. For each star X_m^{iter}, evaluate the objective function (8).
4. Select the corresponding star that provides the least objective function value as the black hole (i.e. $Best^{iter}$).
5. Change the location of each star based on the modified updating law (13).
6. If a star reaches a location with a lower cost than the black hole, exchange their locations.
7. If the distance of a star to the black hole is less than (16), that star replaced by a new one based on (17).
8. If a termination criterion (a maximum number of iterations or a sufficiently good fitness) is met, exit the loop.

End loop

9. The optimum solution is $X^* = Best^{iter}\big|_{iter=end}$.

5. Real-Time Simulation Results

In this section, the proposed approach is applied to a hybrid ferry grid with two diesel engines and one battery. The parameters of the generators and energy storage unit are provided in Table II. Also, the ramp rate constraint of both generators is assumed to be a maximum ramp rate of 30% per minute, as (Mashayekh et al., 2012)

$$\left(\frac{\Delta P_n(t)}{\Delta t}\right) \le 0.3 P_{n,rated} \left(\frac{KW}{\min}\right) \tag{19}$$

Table II: The parameters of the generators and the battery.

Generator 1		**Generator 2**	
a	0.1691	a	0.1591
b	−0.2924	b	0.2473
c	0.3929	c	0.3507
P_n^{min}	20 KW	P_n^{min}	10 KW
P_n^{max}	320 KW	P_n^{max}	280 KW
Battery		**Load**	
P_{rated}	165 KW	P_L^{Max}	640 KW
E_B^{min}	15 KW	P_L^{ave}	320 KW
E_B^{min}	150 KW	P_L^{Min}	67 KW

The SFOC of each generator based on its normalized generated power is presented in Fig. 2. As can be seen in Fig. 2, the least SFOC for the generators 1 and 2 can be obtained as the $P_1(n)/P_{1,rated} = 0.8646$ and $P_2(n)/P_{2,rated} = 0.6832$, respectively. However, for the non-optimum points of the SFOC, for which less power than its optimum value is generated, the overall fuel consumption cost can be reduced. So, by incorporating the battery, the optimization problem may choose the best power that is not equal to that of the optimum value of the SFOC.

The load demand profile is shown in Fig. 3. As can be seen in Fig. 3, the considered load profile has smooth and rough power changes.

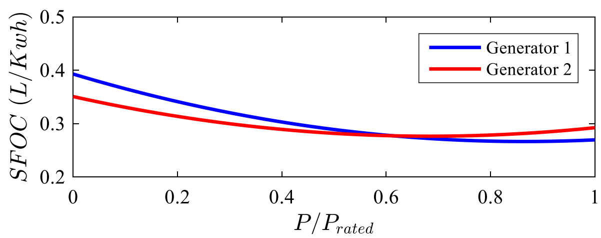

Fig. 2: The SFOC of each generator.

The simulation is performed based on the parameters given in Table II, the rate constraint (19), and the load demand profile provided in Fig. 3. Furthermore, it is assumed that the battery is initially charged by 20 KW. For the real-time simulations, the dSPACE 1202 board has been selected as the rapid prototyping solution. More details can be found in (Vafamand et al., 2019b). To show the merits of the proposed approach, two prediction horizons $T = 3$ and $N = 10$ are considered, and the optimization problem is performed for every one minute.

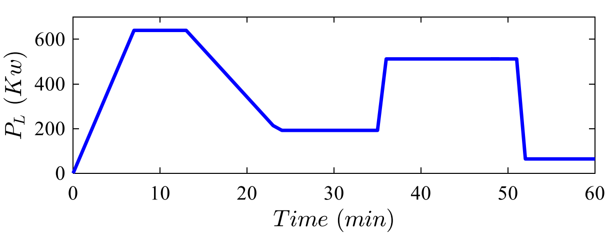

Fig. 3: Power load profile of the hybrid ferry.

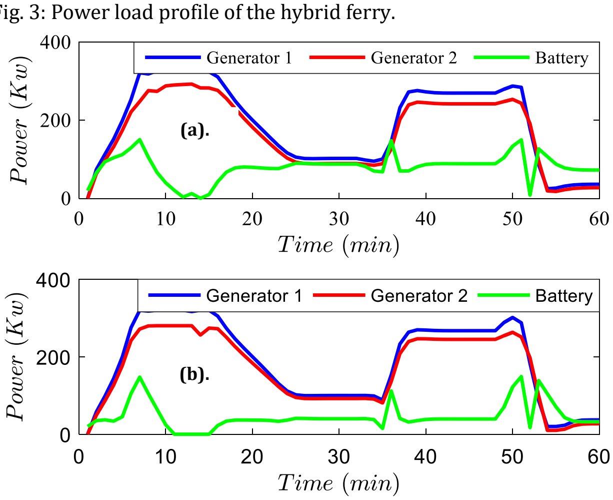

Fig. 4. **(a):** The prediction horizon 10. **(b):** The prediction horizon 3.

As can be seen in Fig. 4, the proposed approach with horizon 10 is able to feed the demanded load for all time points. However, by choosing the prediction horizon 3, the generated power is not sufficient in the time interval $t \in [10\ 16]\ min$. The reason is that the total power of the generators 1 and 2 is not enough and it is needed that the battery is fully charged before the high demand load. Since the optimization algorithm with the prediction horizon 10 senses the high demand 10 mins before it occurs, the battery is smoothly charged to its maximum value. However, the optimization algorithm with prediction horizon 3 only senses the high demand 3 mins before it occurs and because of the constraint on the power generation rate, the battery is not fully charged. Consequently, when the load is increased, the ferry experiences lack of power for a short period of time. This fact shows the importance of considering predictive approaches to predict the future behavior of the load profile and use such information in the optimization problem.

6. Conclusion

The main target in this research was to introduce an efficient and cost-effective energy management algorithm for all-electric ferry ships. In order to achieve the key goal, a new intelligent model predictive energy management was presented. Moreover, an improved heuristic optimization algorithm, the so-called Black Hole, was applied to tune the unknown variables of the model predictive control approach. The assumed cost function in this study was based on reducing fuel consumption as well as decreasing emissions. Finally, simulation results showed that the proposed method can effectively reduce fuel consumption as well as increase the performance of the whole of the electric ferry vessel. For future works, other renewable energy sources can be considered in the energy management system of the ferry ship. Moreover, the optimal sizing and placing of the energy storage systems among with renewable energy units can be formulated in the optimization problem.

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