A Cost-effective and Emission-aware Power Management System for Ships with Integrated Full Electric Propulsion

Kanellos, Fotis D.; Anvari-Moghaddam, Amjad; Guerrero, Josep M.

Published in:
Electric Power Systems Research

DOI (link to publication from Publisher):
10.1016/j.epsr.2017.05.003

Publication date:
2017

Document Version
Publisher's PDF, also known as Version of record

Electric Power Systems Research 150 (2017) 63–75

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

A cost-effective and emission-aware power management system for ships with integrated full electric propulsion

Fotis D. Kanellos [a,*], Amjad Anvari-Moghaddam [b], Josep M. Guerrero [b]

[a] Department of Production Engineering and Management, Technical University of Crete, Chania GR-73100, Greece
[b] Department of Energy Technology, Aalborg University, 9220 Aalborg East, Denmark

ARTICLE INFO

Article history:
Received 1 December 2016
Received in revised form 10 April 2017
Accepted 4 May 2017

Keywords:
Electric propulsion
Energy management
GHG emissions
Particle swarm optimization
Ship energy efficiency

ABSTRACT

The extensive exploitation of electric power in ships enables the development of more efficient and environmentally friendlier ships, as it allows for a more flexible ship power system operation and configuration. In this paper, an optimal power management method for ship electric power systems comprising integrated full electric propulsion, energy storage and shore power supply facility is proposed. The proposed optimization method is exploiting an interactive approach based on particle swarm optimization (PSO) method and a fuzzy mechanism to improve the computational efficiency of the algorithm. The proposed fuzzy-based particle swarm optimization (FPSO) algorithm aims at minimizing the operation cost, limiting the greenhouse gas (GHG) emissions and satisfying the technical and operational constraints of the ship.

1. Introduction

The extensive electrification of large ship power systems by exploiting integrated full electric propulsion system (IFEP) is a very promising solution for ship efficiency improvement and GHG emission limitation [1–8]. In such type of ships, the major part of the electric power produced by ship generator sets is consumed by large propulsion electric motors. IFEP is deemed to be a very promising solution for ship designers as it results in increased sustainability and enables conformity with ship energy efficiency directives [9,10]. Moreover, IFEP provides operation flexibility as a large variety of power plant components can be exploited. The capability of integrating several types of electric power generators also enables conformity with ship energy efficiency directives, not attainable by each single type [11]. On the other hand, the optimized operation of a ship electric power system can lead by its own to fuel consumption reduction and energy efficiency improvement [10–12]. Hence, the deployment of innovative and well-designed power management systems for ships with IFEP that will address all the above issues is becoming a pressing necessity. The major targets of the future ship power management systems will be operation cost minimization and GHG emissions limitation. Especially, the limitation of GHG emissions is expected to be a critical issue in near future. These targets combined with the satisfaction of ship operation constraints render the optimal power management in ships a very complex problem. At the same time, demand side management will also play a key role in the optimal operation of shipboard systems. In ships with IFEP, the major part of the produced electric power is supplied to the propulsion system. Hence, demand side management depends highly on the adjustment of the propulsion power and subsequently ship speed. Furthermore, another factor that has not been exploited adequately in ships and can contribute greatly to operation cost minimization is the optimal scheduling of the operation of the electric power generation system. Optimal power generation scheduling combined with demand side management will result in several positive effects in ship design and operation; like the reduction of the number of the prime movers, further fuel cost reduction, efficient limitation of GHG emissions etc. Some other measures that are examined in the related literature to improve ship power system efficiency are listed in the following: energy management and vessel performance [12–29], route optimization and voyage efficiency [22,23], slow-steaming (reduction of ship cruising speed) [28], effective demand side/load management [11,18,19,23], means of smart electric energy generation [16,25], cold ironing [17,22], and electric energy saving devices and energy storage systems (ESS) [19,20,23].

This paper deals with all issues listed above. A method for optimal power management and GHG emissions limitation suitable for ships employing IFEP, ESS and cold ironing facility is proposed.

* Corresponding author.
E-mail addresses: fkanellos@dpem.tuc.gr (F.D. Kanellos), aam@et.aau.dk (A. Anvari-Moghaddam), joz@et.aau.dk (J.M. Guerrero).

http://dx.doi.org/10.1016/j.epsr.2017.05.003
0378-7796/

The target is to optimize the power generation/storage and the ship speed within ship travel time period. This is achieved by optimally adjusting ship speed and producing power with the lowest possible cost by using optimal generator commitment scheduling. The achievement of these goals is subject to several technical and operational constraints; like power balance, generators' loading, generators' ramp rates and minimum up/down times, ship speed limits, total route length, constraints stemming from calls at intermediate ports, etc. It should be noted at this point, that demand side management and power generation scheduling problems are mutually coupled. Moreover, the optimization objectives are antagonistic. Thus, the problem under examination requires sophisticated solution methods that would be able to tackle with the above challenges. In this regard, an interactive approach based on particle swarm optimization (PSO) method enhanced by a fuzzy mechanism that improves the computational efficiency of the algorithm, is proposed. The algorithm is capable of solving the examined problem in one step while the number of the decision variables is independent of the complexity of the power generation system. The efficiency of the examined method is demonstrated through detailed case studies and compared with that of the dynamic programming method. As a whole, the main contributions of this paper can be summarized as follows:

- Coordinated system-level power generation and demand side management for operation cost minimization and GHG emission limitation,
- Optimal exploitation of energy storage systems and shore-side power supply facilities,
- Design and application of an interactive optimization algorithm based on PSO and fuzzy rule-based approach to improve the computational efficiency.

It is noted that the available relative research in the topic is very limited. Moreover, the existing power management methods for shipboard power systems with IFEP are based mainly on the exploitation of classical optimization techniques that are not able to handle the increased complexity of the system and the multiple antagonistic goals described above. For instance, optimization methods based on dynamic programming [23] are able to provide solution with realistic computation facilities only if the examined problem is divided in two optimization sub-problems.

The rest of this paper is organized as follows: Section 2 deals with the ship energy efficiency assessment. Section 3 introduces the configuration of a ship power system with IFEP and ship power management concept. The mathematical model and formulation of the optimization problem for the examined system is presented in Section 4. The implementation of the proposed optimization method with a Fuzzy-PSO approach is discussed in Section 5. The evaluation of the method for several typical operation scenarios is performed in Section 6 while Section 7 concludes the paper and discusses future works.

2. Ship energy efficiency assessment

According to the International Maritime Organization (IMO) policy, ship operation efficiency indicator (*SOEI*) is defined as the ratio of the produced CO_2 mass (m_{CO_2}) per unit of transport work (TW) [9,10].

$$SOEI = m_{CO_2}/TW \tag{1}$$

So far, ship energy efficiency management plans are focused only on CO_2 emissions and this has been also adopted in this paper. However, the formulation of the problem can be easily generalized by including any other pollutant gas. In this paper, *SOEI* can be slightly modified to facilitate the optimization procedure if it is referred to an arbitrary observation time interval ΔT_j. When ship is in the open sea, *SOEI* can be defined as follows:

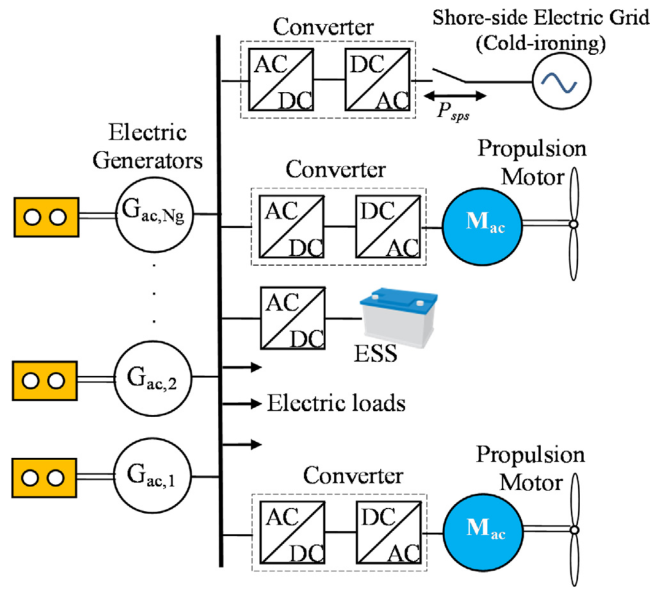

Fig. 1. Generic single-line electric diagram of ship power system with IFEP.

$$SOEI_{1,j} = \left(\varphi \cdot V_j \cdot \Delta T_j\right)^{-1} m_{CO_2} = \left(\varphi \cdot V_j\right)^{-1} \sum_i \sigma_i \cdot P_{ij} \cdot H_i(P_{ij}) \tag{2}$$

where φ is ship loading factor (tns), V_j is ship speed (kn) in the j-th time interval, H_i is the specific fuel consumption (gFuel/kW h) of the i-th power unit, P_{ij} is the power produced by i-th power unit in the j-th time interval ΔT_j and σ_i is a factor used to convert the fuel consumed by the i-th generator to CO_2 mass (gCO_2/gFuel).

When the ship is in port, its speed is zero and previous definition of *SOEI* should be modified as follows:

$$SOEI_{2,j} = \left(\varphi \cdot \Delta T_j\right)^{-1} m_{CO_2} = \frac{1}{\varphi} \sum_i \sigma_i \cdot P_{ij} \cdot H_i(P_{ij}) \tag{3}$$

Ship loading factor φ depends on the type of the examined ship, e.g. passenger ship, RO-PAX ferry, etc. In this study, φ is applied to a RO-PAX ferry and it is calculated as:

$$\varphi = \left(\frac{APL}{NPL}\right) FLD = \left(\frac{0.1 \times NP + NV}{0.1 \times NP_{\max} + NV_{\max}}\right) FLD \tag{4}$$

where *APL* and *NPL* are the actual and the nominal payloads respectively, *NP* is the number of the passengers, NP_{max} is the maximum number of passengers, *NV* is the number of the carried vehicles, NV_{max} is the maximum number of the carried vehicles and *FLD* is the full load displacement of the ship (tns).

In the near future, the limitation of *SOEI* will be one of the major targets of ship power management systems. The optimal adjustment of ship speed according to ship electric load variation could lead to efficiency improvement and *SOEI* limitation. This is a further measure proposed in this paper. However, ship speed adjustment is subject to several limitations like, ship speed limits, total route length constraint, traveled distance at intermediate port calls etc.

3. Ship power system configuration and ship power management concept

The generic single-line electrical diagram of ship power systems with IFEP is shown in Fig. 1. In this concept, it is assumed that there exists a main bus/switchboard (SWBD) where all electric generators are connected to. Each generating unit has its own fuel cost function and technical operating constraints. There are also several feeders extended from the main SWBD providing the required electric power to the electric propulsion motors and ship service load through transformers and power converters. In the examined shipboard system, an ESS that regulates any excess or deficit of the produced power and also contributes in vessel energy management is connected to the main bus. It is also assumed that shore-side power supply connection (known as cold ironing) exists in the system aboard. This would allow the vessel to shut down diesel generators and practically eliminate pollution coming directly from shipboard emissions while being at berth. In this regard, the power required for the vessel to continue its activities at berth could be provided by a variety of sources such as port city's power grid, in-port power plants or even via renewable energy sources and energy storage options. It should also be noted that ship propulsion is provided by large electric motors driven by power electronic converters. Power electronics enable continuous variation of shaft speed in a wide range leading to larger operational flexibility and fuel economy. Moreover, the need to use large shafts for the coupling of propellers and prime movers is eliminated.

Ship power systems have some particular operational and technical characteristics that differentiate them from respective shore island electric systems. Some of them are briefly described next. Electric power demand of ships with IFEP mainly depends on the electric power consumption of the electric propulsion motors which also depends on ship travel schedule. Hence, in ships with IFEP a large part of load demand can be adjusted by varying ship speed which however should satisfy travel constraints. The adjustment of a large part of the load is not usually possible in isolated shore electric power systems. To achieve equivalent result in shore electric power systems large ESS should be used. Moreover, ships should comply with strict GHG emissions limitations and operation efficiency targets that are not yet applied to shore electric power systems to similar extent.

Some of the most significant technical differences between ship and shore electric power systems are briefly mentioned next.

- Several different voltage and frequency levels can be used within the same ship electric power system (this happens especially in naval ships).
- Naval ship power systems are divided in autonomous operational zones and comprise very effective reconfiguration systems in order to increase the survivability of the vessel during the battle.
- Due to space and weight limitations imposed to onboard systems special generator configurations are often used.
- In some special ship types comprising IFEP accurate dynamic positioning control is required. In this case, electric power generation system should accommodate very high and fast load variations that usually do not occur in shore autonomous electric power systems.

The fuel consumption (Γ) per time unit of any thermal unit versus its produced power P_i may be accurately approximated by a quadratic function as following:

$$\Gamma_i(P_i) = a_{0i} + a_{1i} \cdot P_i + a_{2i} \cdot P_i^2 \tag{5}$$

The specific fuel consumption of a thermal unit is defined as the amount of the fuel consumption per one produced kW h.

$$H_i(P_i) = P_i^{-1} \cdot \Gamma_i(P_i) \tag{6}$$

The total variable cost of the power plant (C_{tot}) is calculated by taking into account the unit fuel cost ($\rho_{f,i}$), the maintenance cost per power unit (MC_i), the start-up/shut-down cost (SC_{ij}), and the produced active power P_{ij} during the time interval ΔT_j, with the assumption that the generator is running (s_{ij} is equal to 1 otherwise 0). The above quantities are summed for all time intervals and electric generators as following:

$$C_{tot} = \sum_{j=1}^{T}\sum_{i=1}^{N_g}\begin{pmatrix} s_{ij} \cdot \left(\rho_{f,i} \cdot H_i\left(P_{ij}\right) + MC_i\right) \cdot P_{ij} \cdot \Delta T_j \\ +SC_{ij}|s_{ij} - s_{i,j-1}| \end{pmatrix} + PortCall_j \cdot P_{sps,j} \cdot \rho_{sps,j} \cdot \Delta T_j \tag{7}$$

where T is the total time period under study, N_g is the total number of the electric generators, $P_{sps,j}$ is the shore power supply during berthing at the port and $\rho_{sps,j}$ is the price of the shore supplied electricity. *PortCall* is a binary variable which is 1 when ship is at berth otherwise is 0. The supply of electrical power to ships at berth is widely known as cold ironing. Cold ironing can limit drastically local emissions and also reduce the running cost of the ship. When the ship is plugged-in, only the vessel boilers generate emissions as 'hoteling' activities are met by the grid (or other source of electrical power that feeds the port).

It is also assumed that the examined ship power system is equipped with means of energy storage that can optimally store or inject power to the system. The function used to update the state of charge (SOC) of the energy storage system (ESS) is given by:

$$E_{ESS,j} = E_{ESS,j-1} + u_{ESS,j} \cdot P_{ch,j} \cdot \Delta T_j \cdot \eta_{ch} - \left(1 - u_{ESS,j}\right) \cdot \left(\frac{P_{dch,j}}{\eta_{dch}}\right) \cdot \Delta T_j \tag{8}$$

where $E_{ESS,j}$ is the stored electric energy, $P_{ch,j}$ ($P_{dch,j}$) is the charging (discharging) power of the ESS at the j-th time interval and $u_{ESS,j}$ is a binary variable representing the operating mode of the ESS at time j ("1" = charging and "0" = discharging). Likewise, η_{ch} and η_{dch} are the charging and discharging efficiencies of the ESS, respectively.

Propulsion load can be also adjusted so that the optimal points of operation of the power generation units are approached. Furthermore, propulsion load adjustment can contribute to the real time limitation of SOEI.

Ship speed-propulsion power curve depends on hull resistance at specific conditions and can be approximated by the following equation [30]:

$$P_{pro} = \xi_1 \cdot V^{\xi_2} \tag{9}$$

where V is ship velocity, P_{pro} is the required propulsion power to develop velocity V, ξ_1 is a coefficient used for propulsion power and ship velocity matching and ξ_2 is a constant representing hull form effect. If during the time interval ΔT_j the optimal ship speed is $V_{j,opt}$ and the non-optimized speed is V_j then the required adjustment of the propulsion power is:

$$\Delta P_{pro,j} = \left(V_{j,opt}^{\xi_2} - V_j^{\xi_2}\right) \cdot \xi_1 \tag{10}$$

The adjustment of ship speed and consequently propulsion power will result in deviation from the initially scheduled traveled distance. The deviation at the end of the time interval ΔT_j is given by:

$$\Delta_{dev,j} = \sum_{t=1}^{j}\left(V_{t,opt} - V_t\right) \cdot \Delta T_t \tag{11}$$

The optimal adjustment of the propulsion power should be performed jointly with the optimization of the electric power generation. This problem comprises the sub-problems of unit commitment and optimal power dispatch. Unit commitment process defines which generators and when they will be in operation during the examined time period, while the share of load that each generator serves is calculated by the optimal power dispatch process. Well-known methods, like Lagrange method, can be used to define the optimum amounts of the electric power generated by each ship electric generator in order to minimize the operation cost. Moreover, heuristic optimization methods have been proved very efficient in solving unit commitment problem. In this work, a meta-heuristic approach based on PSO method is used to solve the optimal power generation scheduling and demand side management problems. The formulation of the examined optimization problem is provided in the next section.

4. Formulation of the examined problem

The objective function defined in Eq. (7) should be minimized subject to several constraints. In the following, the technical constraints of the examined problem are formulated. Subscripts i, j denote i-th generator and j-th time interval, respectively.

- Power balance constraint:

$$\sum_{i=1}^{N_g} s_{ij} \cdot P_{ij} + P_{dch,j} - P_{ch,j} = \bar{L}_j + \Delta P_{pro,j}; \forall j \notin \Im \tag{12.a}$$

$$\sum_{i=1}^{N_g} s_{ij} \cdot P_{ij} + P_{dch,j} - P_{ch,j} + P_{sps,j} = \bar{L}_j; \forall j \in \Im \tag{12.b}$$

where $\bar{L}_j$ is the average ship electric load in time interval ΔT_j and $\Im$ is the set of the time intervals in which the ship is in port, s_{ij} is a binary variable equal to 1 when i-th generator is running at j-th time interval otherwise 0.

- Minimum and maximum generator loading constraints:

$$P_{ij} \in \left[P_{i,\min}, P_{i,\max}\right]; \forall i, j \tag{13}$$

- Generator ramp rate constraint:

$$\frac{|s_{ij} \cdot P_{ij} - s_{i,j-1} \cdot P_{i,j-1}|}{\Delta T_j \cdot R_{i,\max}} \le 1; \quad \forall i, j \tag{14}$$

where $R_{i,max}$ is the maximum rate of change of the power produced by the i-th generator.

- Minimum operation time of a generator (minimum up-time):

$$\sum_{j \in \Lambda^i} s_{ij} \cdot \Delta t_j \le \mathrm{T_{ON\_min,i}}; \forall \Lambda^i \tag{15}$$

- Minimum out of operation time of a generator (minimum down-time):

$$\sum_{j \in \Sigma^i} \left(1 - s_{ij}\right) \cdot \Delta t_j \le \mathrm{T_{OFF\_min,i}}; \forall \Sigma^i \tag{16}$$

where Λ^i denotes any set of time intervals that the i-th generator operates uninterruptedly, Σ^i denotes any set of time intervals that the i-th generator is out of operation uninterruptedly and $T_{ON\_min,i}$, $T_{OFF\_min,i}$ are the minimum allowable up or down times of the i-th generator, respectively.

- ESS operation limitations:

$$0 \le P_{ch,j} \le P_{ch,j}^{max} \cdot u_{ESS,j} \tag{17.a}$$

$$0 \le P_{dch,j} \le P_{dch,j}^{max} \cdot \left(1 - u_{ESS,j}\right) \tag{17.b}$$

$$0 \le E_{ESS,j} \le E_{ESS}^{max} \tag{17.c}$$

$$E_{ESS,0} = E_{ESS,T} \tag{17.d}$$

where E_{ESS}^{max} is the energy capacity of the ESS and $P_{ch,j}^{max}$ ($P_{dch,j}^{max}$) is the ESS maximum charging (discharging) power. $u_{ESS,j}$ is a binary variable representing the operating mode of the ESS at time j ("1" = charging and "0" = discharging).

The relation between the change of the state of charge (E_{ESS}) and the charging/discharging power (P_{ch}, P_{dch}) of the energy storage system is provided in Eq. (8).

- Shore power supply operation limitations:

$$P_{sps,j} \in \left[P_{sps,\min}, P_{sps,\max}\right]; \forall j \in \Im \tag{18}$$

where $P_{sps,min}$ $\left(P_{sps,max}\right)$ is the minimum (maximum) shore power supply.

- Blackout prevention constraint:

$$\sum_i s_{ij} \cdot P_{i,\max} + \left(p_{dch,j}^{max} \cdot \left(1 - u_{ESS,j}\right) - p_{ch,j}^{max} \cdot u_{ESS,j}\right) - \bar{L}_j - \Delta P_{pro,j} \ge \max\left\{P_{i,\max}\right\}; \forall j \tag{19}$$

- GHG emissions constraint:

$$\frac{\sum_{i=1}^{N_g} \sigma_i \cdot s_{ij} \cdot P_{ij} \cdot H_i(P_{ij})}{\varphi \cdot V_j} \le SOEI_{\max,1}; \quad \forall j \notin \Im \tag{20}$$

$$\frac{\sum_{i=1}^{N_g} \sigma_i \cdot s_{ij} \cdot P_{ij} \cdot H_i(P_{ij})}{\varphi} \le SOEI_{\max,2}; \forall j \in \Im \tag{21}$$

where $\mathrm{SOEI}_{max,1}$ is the upper limit of SOEI while ship is traveling and $\mathrm{SOEI}_{max,2}$ is SOEI upper limit while the ship is at berth.

- Minimum–maximum ship speed constraint:

$$V_j \in [V_{\min}, V_{\max}]; \forall j \notin \Im \tag{22}$$

- Initial condition for the deviation of the optimal traveled distance from the non-optimally scheduled:

$$\Delta_{dev,0} = 0 \tag{23}$$

- Final condition for the deviation of the optimal traveled distance from the non-optimally scheduled:

$$\Delta_{dev,T} = 0 \tag{24}$$

- Deviation of the optimal traveled distance from the non-optimally scheduled at the intermediate ports:

$$\Delta_{dev,j} = 0; \forall j \in \Im, \Im - 1 \tag{25}$$

where $\Im - 1$ denotes the set of time intervals before port calls.

- Minimum and maximum deviation of the optimal traveled distance from the non-optimally scheduled:

$$\Delta_{dev,j} \in \left[\Delta_{dev,\min,j}, \Delta_{dev,\max,j}\right]; \forall j \notin \Im \tag{26}$$

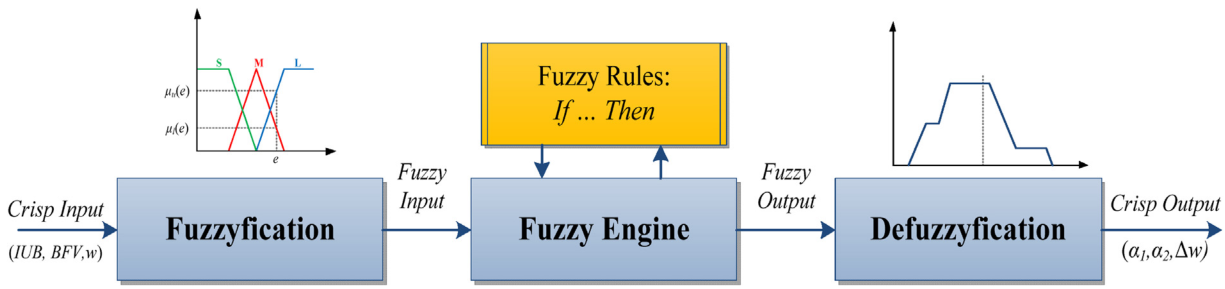

Fig. 2. Fuzzy interface system.

5. Implementation of problem solution with fuzzy PSO

In the previous section, an optimization model for the scheduling of the operation of a shipboard power system with IFEP was developed. There are two main approaches to solve the proposed optimization problem, based on: (1) mathematical methods and (2) evolutionary algorithms. Although, one can hardly say that an optimization algorithm is better than another one without specifying the set of hypothesis and parameters, here particle swarm optimization (PSO) is utilized mainly due to its implementation simplicity and significantly good computational efficiency especially for solving integer and mixed-integer optimization problems [31]. PSO performance depends on a very limited number of parameters and it can prove convergence to optimality (not necessarily global, however local optimality) in many cases [32,33]. Moreover, PSO does not seem to suffer from search stagnation as the aggregate movement of each particle toward its own best position and the best position ever attained by the swarm ensures that particles maintain a position change of proper magnitude during all the optimization process. The behavior of PSO seems also to be stable even for high dimensional problems, exhibiting high success rates even in cases that other mathematical approaches such as Branch & Bound fail [34].

Generally, PSO is a stochastic optimization technique that adjusts properly the trajectories of points “particles” moving in the multidimensional space of the problem [35]. A classic PSO is formulated as following:

$$v_l^{(k+1)} = w \cdot v_l^{(k)} + \alpha_1 \cdot r_1 \left(\Delta x_l^{Pbest} - \Delta x_l^{(k)}\right) + \alpha_2 \cdot r_2 \left(\Delta x^{Gbest} - \Delta x_l^{(k)}\right) \tag{27}$$

$$\Delta x_l^{(k+1)} = \Delta x_l^{(k)} + v_i^{(k)} \tag{28}$$

where $v_l{}^{(k)}$ is the velocity vector of the l-th particle at the k-th iteration, w is the inertia weight factor, α_1 and α_2 are acceleration constants, $r_{1,2}$ are random numbers varying between 0 and 1, $\Delta x_l{}^{Pbest}$ is the best previous solution corresponding to the l-th particle, and Δx^{Gbest} is the best global solution. As it can be seen in Eq. (27) the performance of PSO is affected by a set of parameters previously described as inertia weight and acceleration factors. For example, higher values of the inertia weight factor and lower values of the acceleration coefficients are able to enhance the performance of the algorithm once it faces a local optimum and the fitness function remains unchanged for a long time [36,37]. In order to handle this issue and choose the most appropriate values for achieving a high optimization performance, a self-adaptive mechanism is needed to fine-tune the parameters along the algorithm iterations. Here, a fuzzy interface system (FIS), as depicted in Fig. 2, was developed for this purpose. In the proposed FIS, different rules are used for the adjustment of the acceleration and inertia weight factors where needed, as introduced in Tables 1–2. The normalized best fitness value (BFV; which denotes the relative “*suitability*” of the current particle to the best found) and the normalized number of algorithm iterations for unchanged BFV (IUB) are used as control criteria for the acceleration factors. BFV and current inertia weight value (w) are used to modify the inertia weight factor for the next round. Each fuzzy set corresponds to different linguistic variables as follows: small (S), positive small (PS), medium (M), positive medium (PM), large (L), positive big (PB), positive bigger (PR), negative (NG), zero (ZE) and positive (PT).

Table 1
Fuzzy rules for the adjustment of the acceleration factors α_1, α_2.

α_1 (α_2)		IUB			
		PS	PM	PB	PR
BFV	PS	PR	PB	PB	PM
	PM	PB	PM	PM	PS
	PB	PB	PM	PS	PS
	PR	PM	PM	PS	PS

Table 2
Fuzzy rules for the adjustment of the inertia weight factor.

$\Delta\omega$		ω		
		S	M	L
BFV	S	ZE	NG	NG
	M	PT	ZE	NG
	L	PT	ZE	NG

The membership functions used for the fuzzification phase are depicted in Figs. 3–4. A defuzzification strategy based on centroids (center-of-sums) is also adopted to generate a crispy output for direct use in PSO algorithm.

The main objective of the applied FPSO method is to minimize the operation cost of the ship and limit CO_2 emissions, at the same time. To do so, a vector of decision variables is appropriately defined and assigned to each particle. Each component of the vector corresponds to a coordinate of the PSO search space. Hence, the target of the PSO algorithm is to find the vector corresponding to the optimal scheduling of ship operation. In the examined problem, each particle contains information about the operation state of ship electric generators, the state of charge of the ESS and the deviation of the traveled distance from the non-optimized traveled distance. With the assumption that the optimization horizon is divided in T time intervals the structure of a particle of the swarm is the one shown in Fig. 5.

Where OS_i, ESS_i and $\Delta_{dev,i}$ are variables representing the operation state of ship electric generators, the state of charge of the ESS and the deviation of the traveled distance from the non-optimized one at the i-th time interval, respectively.

As shown in Fig. 5, the first T components (decision variables of the optimization problem) of the particle are denoted by OS_t and used to represent the operation state of ship electric generators. OS_t is an integer whose equivalent in the binary arithmetic system represents the operation states of the generators at the t-th time interval. For instance, if $OS_6 = 5$ then the respective binary number is 101, which means that the first and the third generator operate while the second is switched-off at the sixth time interval.

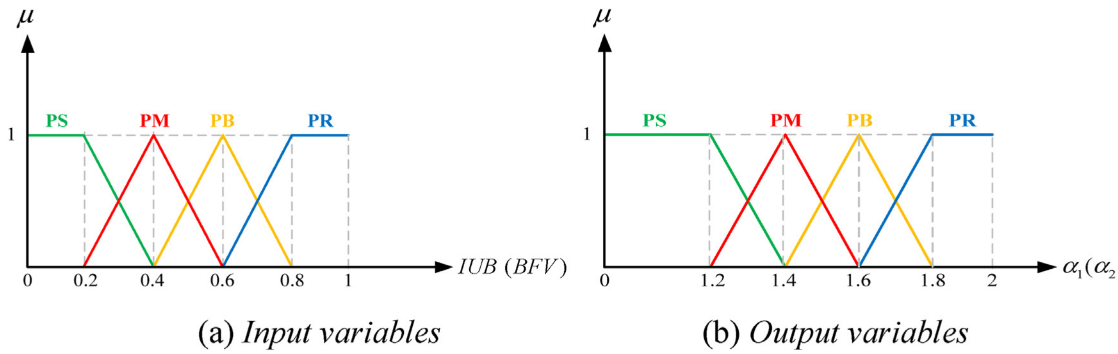

Fig. 3. Fuzzifiers for the acceleration factors.

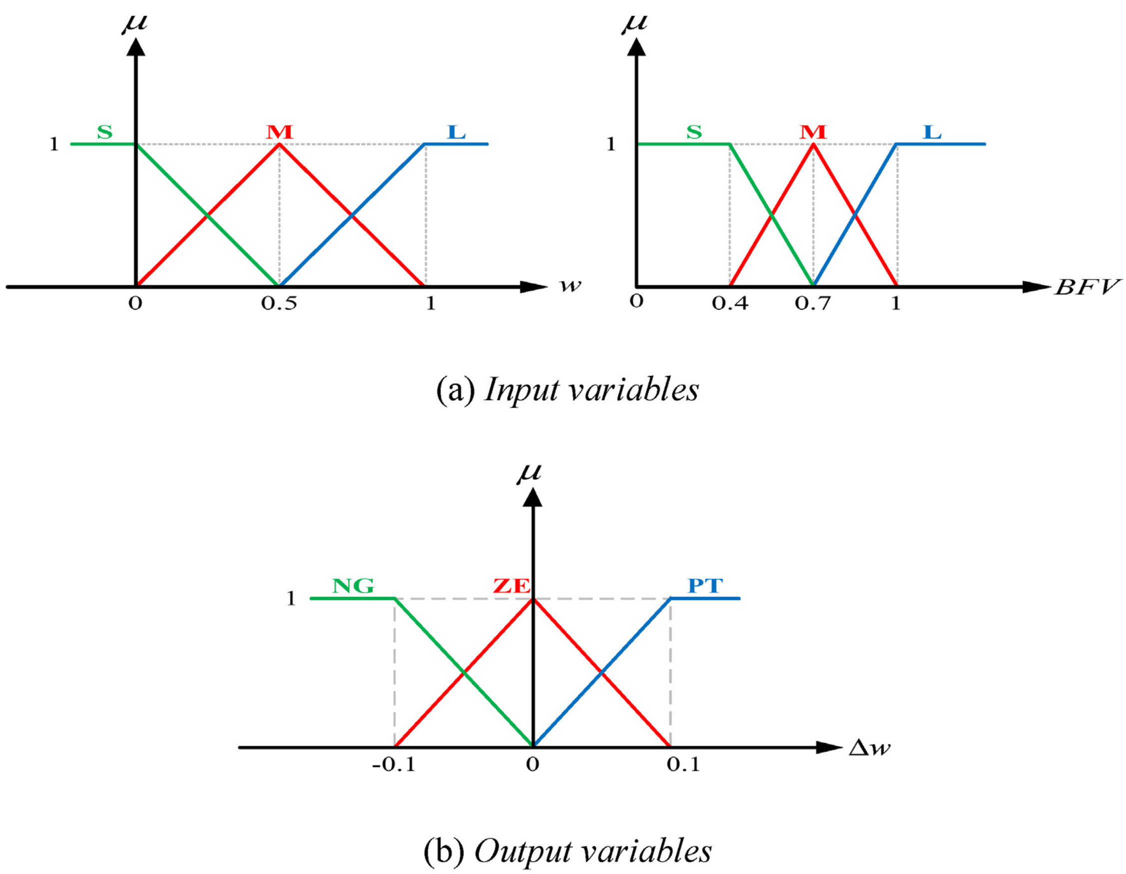

Fig. 4. Fuzzifiers for the inertia weight correction factor.

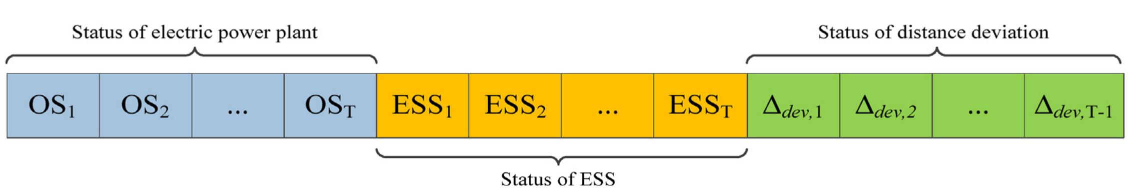

Fig. 5. Particle structure.

The next T components (decision variables) of the particle are denoted by ESS_t and used to represent the state of charge of the energy storage system. For instance, if $ESS_6 = 3.5$ then 3.5 MW h are stored in the ESS at the end of the sixth time interval.

The last T-1 components (decision variables) of the particle are denoted by $\Delta_{dev,t}$ and used to represent the deviation of the traveled distance from the non-optimized one at the t-th time interval. For instance, if $\Delta_{dev,3} = 1.2$ then the ship has traveled until the end of the third time interval 1.2 km more than the distance of the non-optimized schedule.

According to the above formulation, the complexity of the ship power system (number of generators) does not affect the total number of the components of the particle (decision variables). However, it should be noted that the number of ship generators affects the

Table 3
Ship power system data and ship parameters.

Electric power plant parameters						
	Gen 1		Gen 2	Gen 3	Gen 4	Gen 5
Nom. power (MW)	15		15	15	9	9
Minimum up/down time (h)	1/1		1/1	1/1	1/1	1/1
Diesel-electric generator startup[a]/shut-down cost (m.u.[b])	$0.2\times\rho_{Nf,1}/0$		$0.2\times\rho_{Nf,2}/0$	$0.2\times\rho_{Nf,3}/0$	$0.2\times\rho_{Nf,4}/0$	$0.2\times\rho_{Nf,5}/0$
Diesel-electric generator cost function coefficients	a_{0i}	390	400	420	430	450
	a_{1i}	61.5	63	65	12	10
	a_{2i}	5.4	5.4	5.6	13.1	13.5
CO_2 emissions (gCO_2/g fuel)		3.20	3.20	3.20	2.50	2.50
Fuel cost (m.u./kg)		0.50	0.50	0.50	0.70	0.70
Technical min. (MW)		3	3	3	2	2
Technical max. (MW)		15	15	15	9	9

Energy storage system parameters			
Energy capacity (MW h)	6	SOC range (%)	10–90
Max. charge/Discharge power (MW)	2.5, 2.5	Charge/Discharge efficiency (%)	90, 95

Ship parameters			
Type	RO-PAX ferry	No. of vehicles (n_v)	750
Nominal speed (kn)	24	$SOEI_{max1}$ (gCO_2/tn kn)	27 (1st op. scenario) 24 (2nd op. scenario)
Max. number of passengers	2800	$SOEI_{max2}$ (gCO_2/tn h)	165 (1st op. scenario) 135 (2nd op. scenario)
Full load displacement (tns)	75,000	$\xi_1 = 0.0025$; $\xi_2 = 3$	

[a] Diesel electric generators with start-up cost equal to 20% of their nominal hourly fuel consumption cost ($\rho_{Nf,i}$) and zero shut-down cost, are used.
[b] m.u.: Monetary unit.

range of values of *OS* decision variables. For instance, if the ship comprises 7 generators then the equivalent binary numbers of *OS* should comprise 7 digits and the range of *OS* is $[1\ 2^7-1]$. Similarly, if the ship comprises only 3 generators then the range of *OS* is reduced to $[1\ 2^3-1]$. Hence, the more complex the ship power system is the larger the search space becomes; but the number of the decision variables remains the same.

$\Delta_{dev,i}$ is defined as follows:

$$\Delta_{dev,i} = DEV_{i,opt} - DEV_i \tag{29}$$

where $DEV_{i,opt}$ and DEV_i are defined in Eq. (30):

$$DEV_{i,opt} = \sum_{t=1}^{i} V_{t,opt}; DEV_i = \sum_{t=1}^{i} V_t \tag{30}$$

V_i is the initial non-optimized ship speed while $V_{i,opt}$ is the optimized ship speed at the *t*-th time interval.

A simplified block diagram of solution process of the examined problem is shown in Fig. 6.

It should be noted here that when the constraints of the problem are not satisfied then respective penalty terms are applied to the objective function of Eq. (7). Some of the constraints are handled as "soft" constraints e.g. traveled distance, ship speed while the rest as "hard" constraints e.g. minimum up/down time of the generators. In case of hard constraints violation, a large number is added to the total variable operation cost calculated in Eq. (7). While for soft constraints violation, the total variable operation cost is multiplied with a suitable penalty factor. This penalty factor equals unity if the respective constraint is satisfied, while in the opposite case, it increases linearly to the difference of the constrained variable value from its upper or lower limit.

A process for an initial guess of the best particle is also proposed in this paper. The aim is to initially guide the algorithm to a suitable area of the search space. In this way, a number of epochs dedicated to move the particles from their initial random locations to better ones are avoided. The initialization process is described next.

- *Calculation of the status of the electric power plant*

The least number of the more economical generators needed to securely supply the load are used in each time interval.

- *Calculation of ESS states and traveled distance deviation*
  - The threshold entering high-load zone is defined and the loads being larger than this threshold are considered as large loads. Respectively, the low-load zone threshold is defined.
  - The energy content of each load zone is calculated.
  - If the energy contents of high and low-load zones differ considerably, or they cannot be provided by means of propulsion adjustment and/or ESS dispatching, then different thresholds are selected through a recursive process and steps 1–2 are repeated.
  - The difference of the non-optimized high-load values from the lower threshold of the high-load zone is estimated in all time intervals. A percentage of the estimated difference is considered as decrease of the propulsion power while the rest is considered as discharging power of the ESS. The respective process is applied to the low-load zone.
  - Taking into account the above calculated quantities the respective parts of the initial particle are easily calculated. The rest of the particles are created randomly.

6. Simulation results and discussion

The proposed method is applied to the electric power system of a RO-PAX ferry with full electric propulsion. The examined ship comprises 2 large electric propulsion motors supplied by a set of five diesel-electric generators. The examined configuration is typical for a relatively large ship of this type. The single-line diagram of the integrated full electric propulsion system is shown in Fig. 1. The technical parameters of the ship and the onboard power system are presented in Table 3.

Two operation scenarios are considered regarding GHG emissions limitation. In the first scenario, upper limits of $SOEI_1$ and $SOEI_2$ are considered equal to 27 gCO_2/tn kn and 165 gCO_2/tn h, respectively. In this case and for the examined travel conditions, SOEI limits are not activated. In order to evaluate the efficiency of the

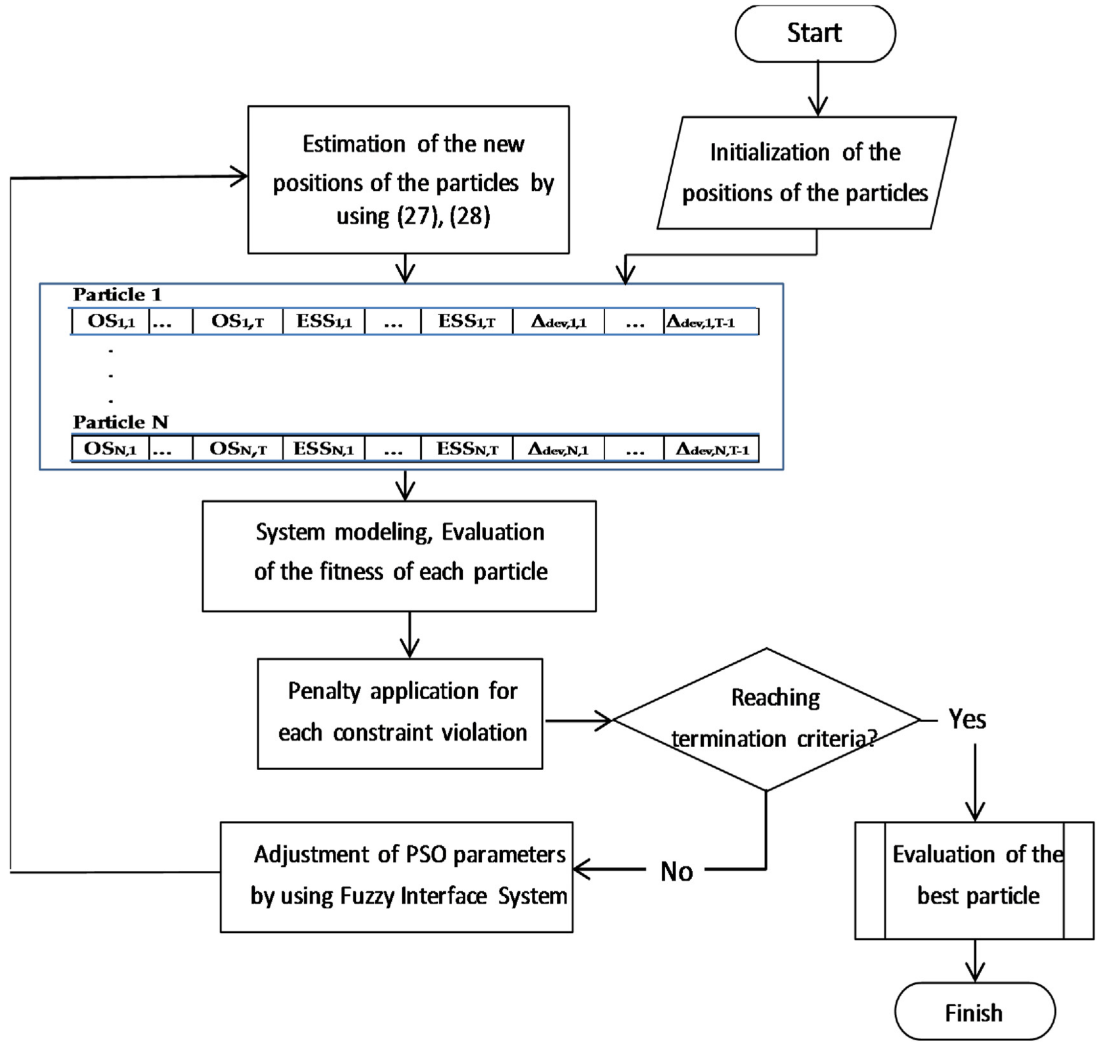

Fig. 6. Block diagram of solution process with the FPSO method.

proposed method in limiting the GHG emissions during the ship travel a second operation scenario with lower SOEI limits is also examined. In this scenario, $SOEI_1$ and $SOEI_2$ upper limits are considered equal to 24 gCO_2/tn kn and 135 gCO_2/tn h, respectively. As it will be shown next, SOEI constraints are activated in the second operation scenario and the proposed optimization algorithm manages to maintain $SOEI_1$ and $SOEI_2$ below their upper limits throughout all ship travel.

According to Eq. (1) SOEI contains GHG emissions in its nominator and transport work in its denominator. Hence, SOEI can be adjusted by adjusting either GHG emissions or the produced transport work (proportional to ship velocity). When SOEI limits are low the GHG emissions should be limited by producing more power from the cleaner generators or by using the energy stored in ESS. If both of the two above measures are not enough then ship velocity can be increased to the extent possible. It is noted that when the ship is at berth it can use cold ironing facility to limit GHG emissions but cannot exploit the traveling speed. In case of using very high SOEI limits then there is no concern about the GHG emissions and the major target is to minimize ship power system operation cost. Consequently, the less expensive generators (which are usually more pollutant) will be used and higher SOEI values will be obtained. In conclusion, it is expected that low SOEI limits will lead to cleaner operation and possibly higher operation cost (as it will be proved next by the obtained simulation results).

A 174 nm total-length route is used for both operation scenarios with the ship stopping at one intermediate port. Cold ironing facility is available at the intermediate and the destination port. The maximum power exchange between the shore and the ship is assumed 6 MW at a price of 100 m.u./MW h. The number of the passengers, the vehicles and the corresponding ship loading factors for the two parts of the examined route are shown in Table 4. The non-optimized total power generation, propulsion power and ship service load for this trip are shown in Fig. 7. In case of non-optimized operation, propulsion is not adjusted and ESS and cold ironing are not used. Hence, no optimization is applied to the system. It is assumed that the initial non-optimized schedule of ship speed is deployed by the captain according to his experience. The proposed optimization technique is then applied to find the optimal deviations from this non-optimal schedule of ship speed and the optimal operation schedule of power generation/storage and cold ironing facility that lead to minimum operation cost and satisfaction of all technical constraints.

The problem of the optimal ship power generation scheduling and demand side management is solved in two ways; by using the proposed method and dynamic programming [23,35]. In both cases, the above described objectives and constraints are used. It is noted that the method of dynamic programming could take forever to find a solution for this problem due to the large number of the obtained states. However, this issue can be handled by solving the problem in

Table 4
Data for ship payload.

Part of examined route	Number of passengers (NP)	Number of vehicles (NV)	Ship loading factor (φ (tns))
Departure–intermediate port	2150	590	58.617
Intermediate port–final destination	1950	570	55.704

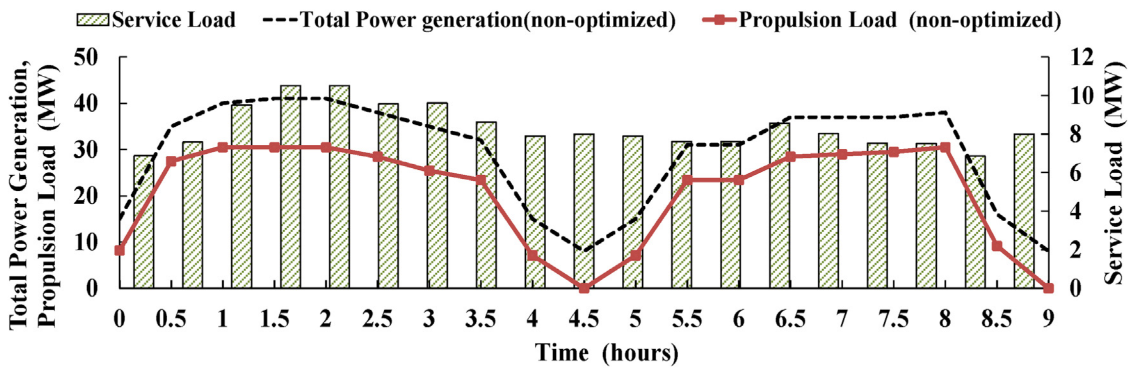

Fig. 7. Total power generation, propulsion power and ship service load (non-optimized operation).

two stages. First, propulsion adjustment is applied and then ESS and cold ironing are exploited taking into account the results obtained in the first step. In case of fuzzy PSO (FPSO), it was shown after several trials that a maximum number of 40 epochs and 500 particles ensure satisfactory convergence characteristics. The initial position of one particle is obtained by the initialization process described in Section 5 while the initial positions of the remaining particles are generated randomly.

The evolution of the performance of the best particle along the algorithm epochs for the first operation scenario is shown in Fig. 8. It is observed that after almost 30 epochs of training the performance of the FPSO algorithm does not present significant change. Moreover, it is evident that simple PSO exhibits slower convergence characteristics. It is noted that the capability of the proposed method to ensure convergence to feasible solutions under different conditions has been tested by executing the optimization algorithm 50 times with random initial conditions. The maximum deviation of the obtained solutions from the best was less than 1.2%.

The results obtained for the first operation scenario are shown in Figs. 9–14 . The power produced by the electric generators for the two examined optimization methods (FPSO and dynamic programming) are shown in stack form in Figs. 9 and 10. The sum of the powers produced by each generator and the provided one by the shore connection are also compared with the non-optimized total electric power generation, in the same figures.

The evolution of ship speed, the state of charge of the ESS, SOEI and operation cost, are shown in Figs. 11–14 for both examined optimization methods. In Fig. 13, SOEI value when ship is at berth is divided by 10 in order to be comparable with SOEI values in open sea.

From simulation results included in Figs. 9–11, it can be observed that both algorithms adjust properly propulsion power and smaller deviations of total electric load occur. Generators 1–2 are operated continuously, while generators 3 and 4 are operated only during high load periods.

This is expected to happen, as generators 1 and 2 have lower operation costs than generators 3 and 4. In both optimization methods, ship speed is decreased when ship is in open sea while it is increased significantly when the ship is approaching or leaving from a port. In this way, ship speed profile becomes less volatile and traveled distance constraints are satisfied. Also, it is apparent from Figs. 9 to 10 that less energy is required to run the system compared to the non-optimized case. In other words, the optimal management of generation units and ESS as well as the optimal demand side management could save energy and decrease the operating cost of the shipboard power system. In case of non-optimized operation (propulsion is not adjusted, optimal power generation scheduling, ESS and cold ironing are not used), the total running cost of the ship power system is 45.904 m.u., while it is decreased to 42.986 m.u. in case of using FPSO and about to 43.096 m.u. in case of dynamic programming. Hence, the total operation cost of the system is decreased by 6.36% and 6.14% if the optimal solution obtained by FPSO and dynamic programming is adopted, respectively. In case of using simple PSO, the total operation cost is 43.091 m.u., which happens to be very close to that obtained by dynamic programming. It should be noted that the inferior performance of dynamic programming is a result of the fact that this algorithm needs to be implemented in two stages in our study. Thus, its ability to locate the global minimum with zero error is limited compared to FPSO.

SOEI is maintained well below its upper limit all the way long in both optimization methods, i.e., it is less than 27 gCO_2/kn tn for traveling in the open sea and 160 gCO_2/tn h at berth. Moreover, ship speed deviations from the initially scheduled values are within the allowed range and the upper speed limit is not violated along the mission profile. The conditions of the traveled distance at the intermediate ports and the destination as well as those of initial and final SOC are well-satisfied.

Next, the proposed method has been evaluated in limiting the SOEI while the ship is traveling and being at berth. To do so, lower SOEI upper limits e.g. $\max(SOEI_1) = 24$ gCO_2/tn kn and $\max(SOEI_2) = 135$ gCO_2/tn h, are used. The most indicative results obtained for this operation scenario are shown in Figs. 15–18 and compared with the results of the first operation scenario ($\max(SOEI_1) = 27$ gCO_2/tn kn and $\max(SOEI_2) = 160$ gCO_2/tn h). The powers produced by the electric generators are shown in stack form in Fig. 15. The sum of the powers produced by each generator and the provided one by the shore connection are also compared with the non-optimized total electric power generation, in the same figure.

The evolution of $SOEI_1$, $SOEI_2$, ship speed and the state of charge of the ESS, are shown in Figs. 16–18 . SOEI is well-limited below the new upper limits during all the travel, i.e. it is less than 24 gCO_2/kn tn for traveling in the open sea and 135 gCO_2/tn h at berth as shown in Fig. 16. For comparison reasons, SOEI values obtained by FPSO in the first operation scenario are also shown in the same figure. It is apparent that in the first operation scenario

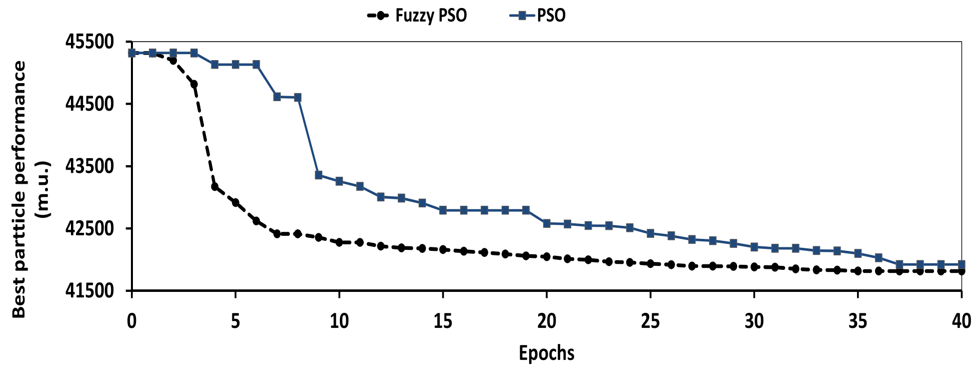

Fig. 8. Evolution of the best particle along the algorithm epochs.

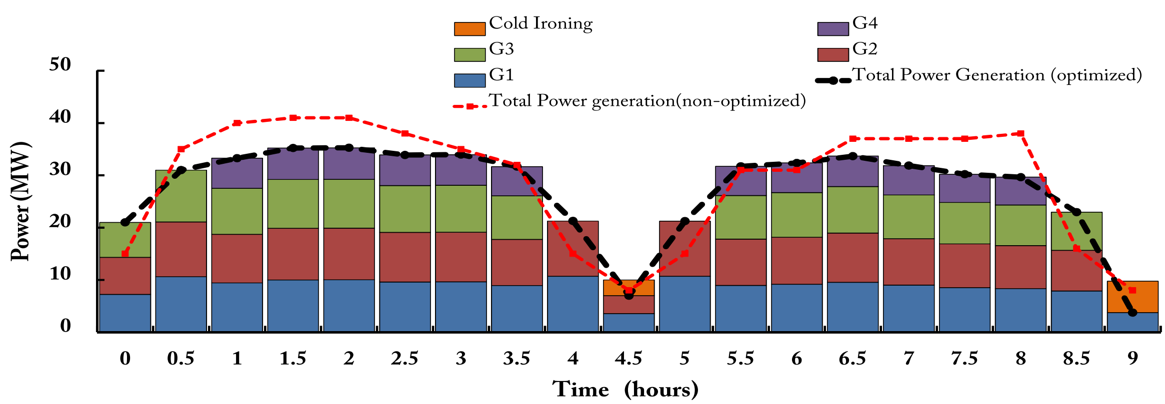

Fig. 9. Optimal power generation scheduling by using FPSO algorithm.

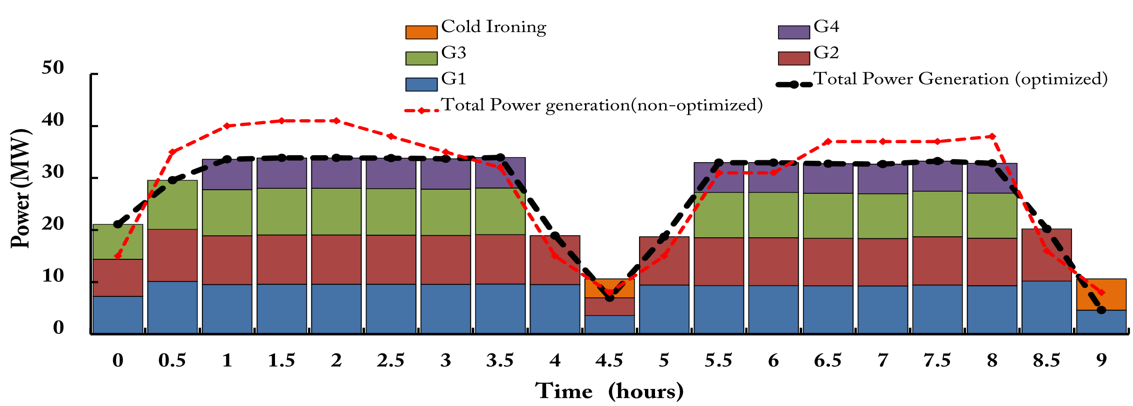

Fig. 10. Optimal power generation scheduling by using dynamic programming.

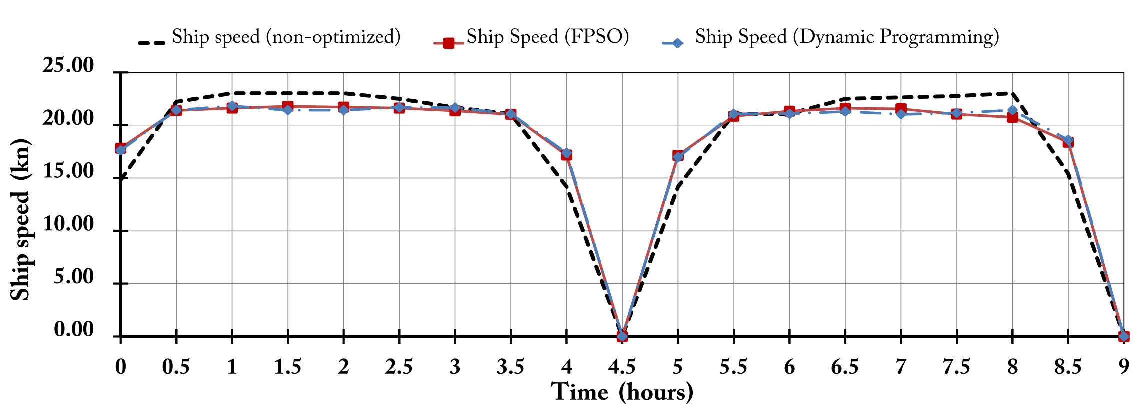

Fig. 11. Ship speed (kn).

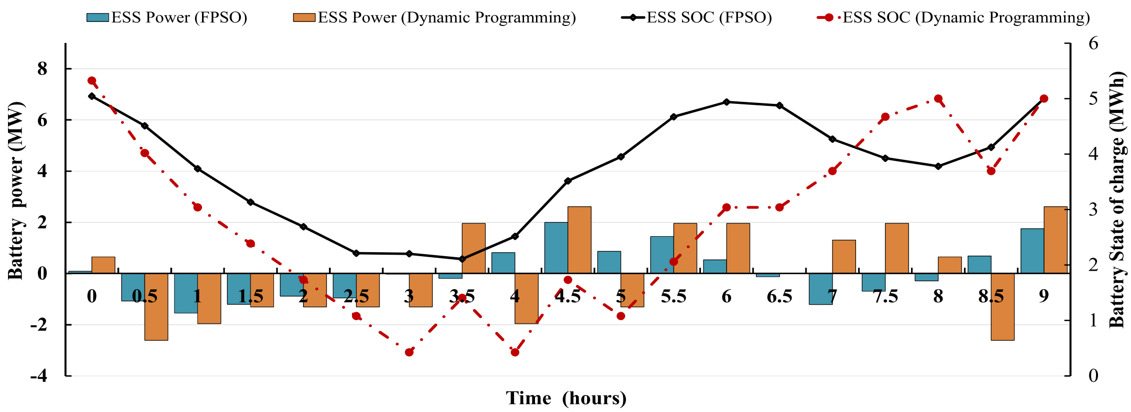

Fig. 12. State of charge of the energy storage system (MW h), and energy storage system power (MW).

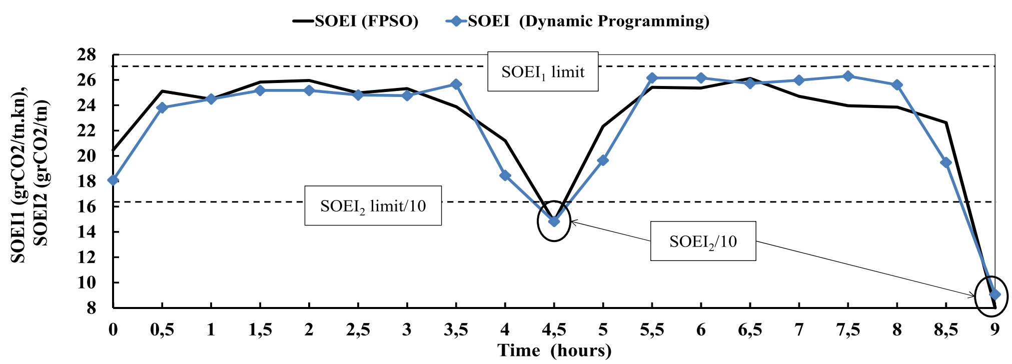

Fig. 13. Ship energy efficiency operation index (SOEI).

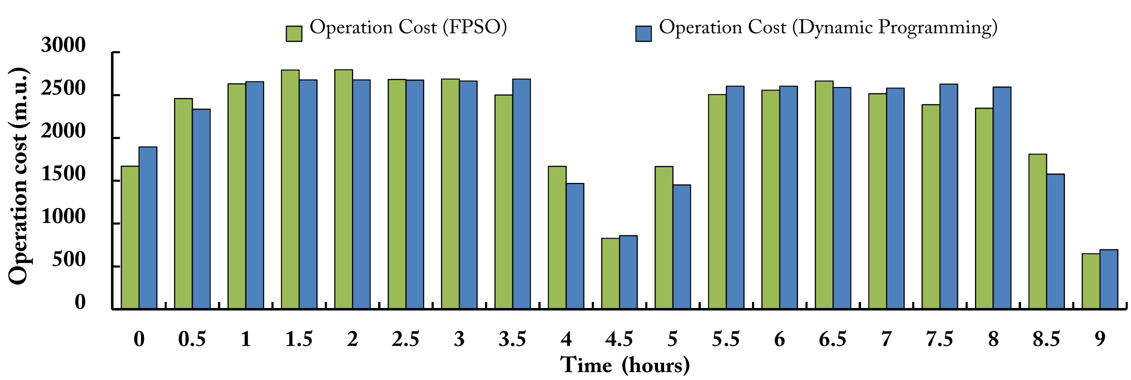

Fig. 14. Ship power system operation cost.

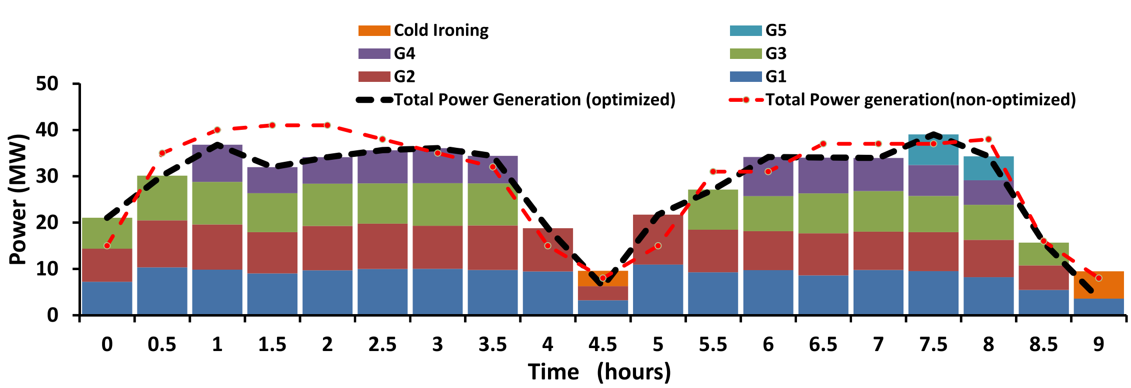

Fig. 15. Optimal power generation scheduling by using FPSO algorithm.

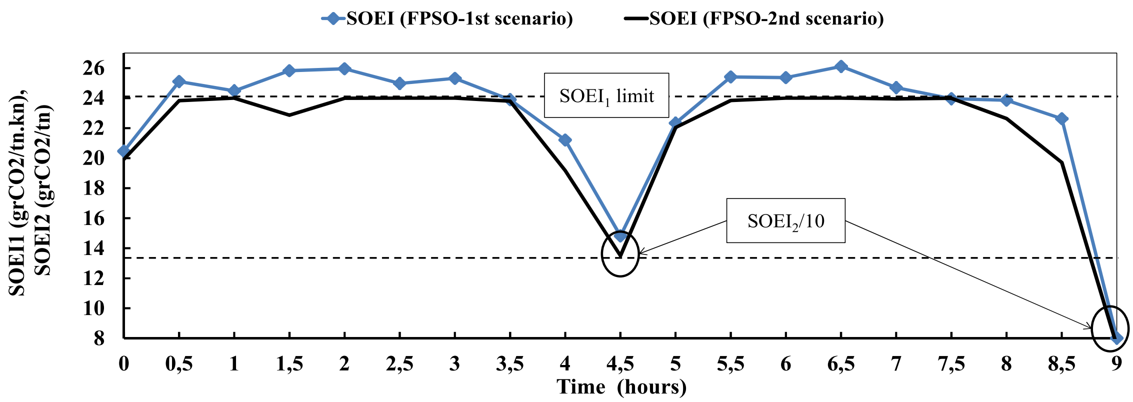

Fig. 16. Ship energy efficiency operation index (SOEI).

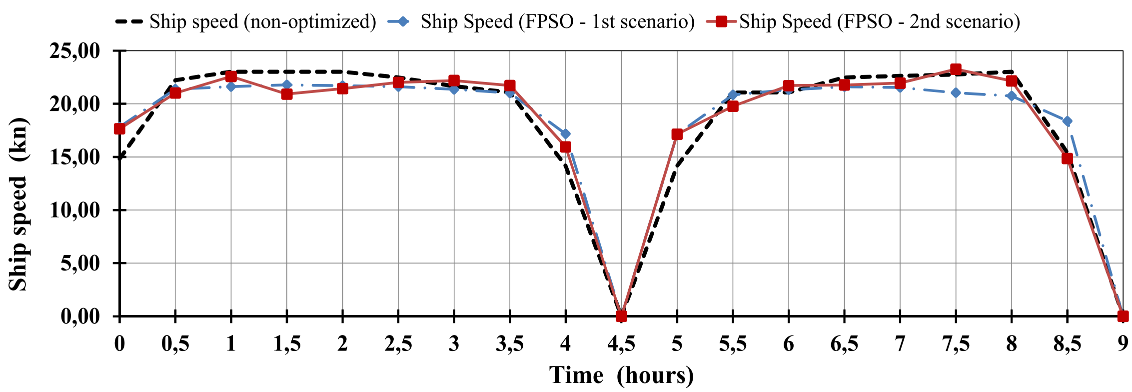

Fig. 17. Ship speed (kn).

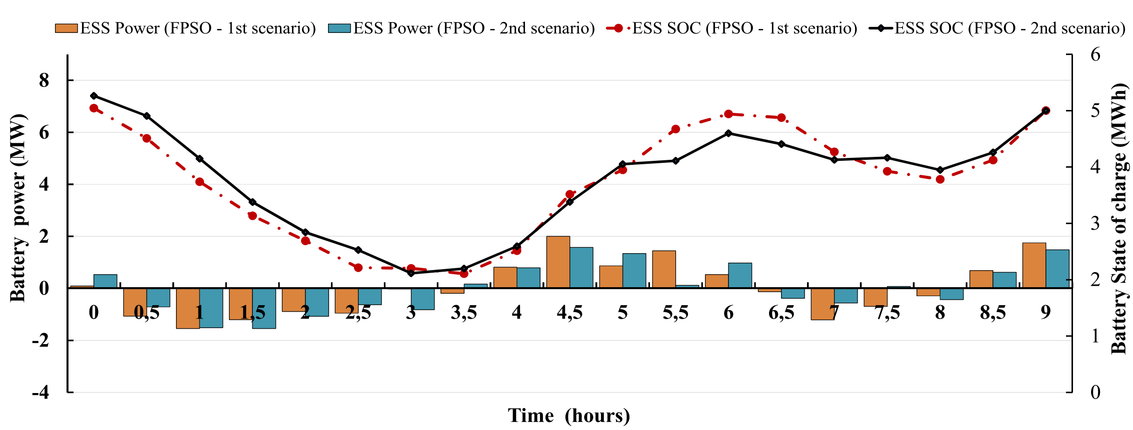

Fig. 18. State of charge of the energy storage system (MW h), and energy storage system power (MW).

$SOEI_1$ is almost always above the new limit of 24 gCO_2/kn tn while this does not happen in the second operation scenario; thus proving the efficiency of the method in limiting GHG emissions. In Fig. 17, the evolution of ship speed is shown for the two operation scenarios and the case that no optimization is applied. In the second operation scenario, the algorithm leads to ship speed increase at several time intervals in order to achieve SOEI limitation. Moreover, it can be seen in Fig. 15 that generator 5 is used only in second operation scenario as it produces lower emissions but with higher operation cost. The evolution of the state of charge of the ESS for both operation scenarios is shown in Fig. 18. It is observed that similar ESS charging profiles are obtained for both cases.

Finally, it is noted that the operation cost obtained for the second operation scenario amounts to 43.467 m.u., which is slightly increased to that of 42.986 m.u. obtained in the first operation scenario.

Computation time required by FPSO was 2320 s and 2281 s by simple PSO. The computation time required by the dynamic programming method was 3166 s. Although FPSO and simple PSO algorithms required almost the same computation time, the performance of FPSO was superior as understood from the training profiles of Fig. 8, (i.e., FPSO converges earlier and more smoothly). It is noteworthy that all simulations were carried out in a computer with a CPU at 2.5 GHz and 4 GB RAM. It is reminded that the problem is practically unsolvable with a common computer if dynamic programming is not applied in two stages.

7. Conclusion

In this paper, an effective optimal operation method for IFEP-driven ships supplemented by energy storage system and shore-side power supply facility is proposed. An interactive approach based on a fuzzy self-adaptive meta-heuristic algorithm is proposed and applied accordingly, to solve the examined optimization problem considering economic and environmental objectives. In order to achieve the optimization goals and satisfy the existing technical and operational constraints, different power management strategies at demand and supply sides (such as propulsion power adjustment, energy storage dispatching and shore power supply management) are applied. Simulation results showed that the proposed method can ensure not only minimum operation cost but also reduced GHG emissions. Moreover, the proposed optimal power management method demonstrated superiority in finding the optimal solution and better convergence characteristics than conventional methods such as PSO and dynamic programming.

Future work will mainly aim at developing complementary optimal real-time control methods that will adjust the operation of lower-level devices based on the results obtained by the system-level optimizer proposed in this paper. Moreover, accurate load forecasting techniques suitable for ship power systems should be developed.

References

[1] S.D. Sudhoff, Currents of change, IEEE Power Energy Mag. (July–August) (2011) 30–37.
[2] S.A. Gertsos, J.M. Prousalidis, C.A. Frangopoulos, Electric propulsion: from infancy to adolescence, in: Proc. 8th International Marine Design Conference (IMDC), Athens, Greece, 5–8 May, 2003.
[3] M.R. Banaei, R. Alizadeh, Simulation-based modeling and power management of all-electric ships based on renewable energy generation using model predictive control strategy, IEEE Intell. Transp. Syst. Mag. 8 (2) (2016) 90–103.
[4] T.J. McCoy, Trends in ship electric propulsion, in: Proc. IEEE PES meeting, Chicago, USA, 21–25 July, 2002, pp. 343–346.
[5] P.B. Backlund, C.C. Seepersad, T.M. Kiehne, All-electric ship energy system design using classifier-guided sampling, IEEE Trans. Transp. Electrif. 1 (June (1)) (2015) 77–85.
[6] B. Zahedi, L.E. Norum, K.B. Ludvigsen, Optimized efficiency of all-electric ships by dc hybrid power systems, J. Power Sources 255 (2014) 341–354.
[7] E. Skjong, E. Rødskar, M. Molinas, T.A. Johansen, J. Cunningham, The marine vessel's electrical power system: from its birth to present day, Proc. IEEE 103 (December (12)) (2015) 2410–2424.
[8] E. Skjong, R. Volden, E. Rødskar, M. Molinas, T.A. Johansen, J. Cunningham, Past, present, and future challenges of the marine vessel's electrical power system, IEEE Trans. Transp. Electrif. 2 (December (4)) (2016) 522–537.
[9] IMO, Prevention of Air Pollution from Ships, (MARPOL 73/78 Annex VI), Technical Report, IMO, UK, 2004, August.
[10] IMO, Resolution mepc, 213 (63) (2012, March): 2012 Guidelines for the Development of a Ship Energy Efficiency Management Plan (SEEMP). [Online]. Available: http://www.imo.org/OurWork/Environment/PollutionPrevention/AirPollution/Documents/Technical%20and%20Operational%20Measures/MEPC.213%2863%29.pdf.
[11] J.M. Guerrero, Z. Jin, W. Liu, M. Bin-Othman, M. Savaghebi, A. Anvari-Moghaddam, L. Meng, J.C. Vasquez Quintero, Shipboard microgrids: maritime islanded power systems technologies, PCIM ASIA 2016, VDE Verlag GmbH (2016) 135–142.
[12] F.D. Kanellos, G.J. Tsekouras, N.D. Hatziargyriou, Optimal demand side management and power generation scheduling in all electric ship, IEEE Trans. Sustain. Energy 5 (4) (2014) 1166–1175.
[13] A. Anvari-Moghaddam, T. Dragicevic, L. Meng, B. Sun, J.M. Guerrero, Optimal planning and operation management of a ship electrical power system with energy storage system, in: 42nd Annual Conference of the IEEE Industrial Electronics Society (IECON'16), October 24–27, Florence, Italy, 2016.
[14] F.D. Kanellos, J.M. Prousalidis, G.J. Tsekouras, Control system for fuel consumption minimization—gas emission limitation of full electric propulsion ship power systems, J. Eng. Marit. Environ. 228 (I) (2014) 17–28.
[15] X. Feng, T. Zourntos, K.L. Butler-Purry, S. Mashayekh, Dynamic load management for NG IPS ships, in: Proc. 2010 IEEE/PES General Meeting, Minneapolis, MN, July, 2010, pp. 4760–4767.
[16] J.A. Momoh, J.Z. Zhu, S.S. Kaddah, Optimal load shedding study of naval-ship power system using the Everett optimization technique, Electr. Power Syst. Res. 60 (3) (2002) 145–152.
[17] F.D. Kanellos, G.J. Tsekouras, J.M. Prousalidis, Onboard DC grid employing smart grid technology: challenges, state of the art and future prospects, IET Electr. Syst. Transp. 792 (2014) 1–11.
[18] X. Feng, K.L. Butler-Purry, T. Zourntos, A multi-agent system framework for real-time electric load management in MVAC all-electric ship power systems, IEEE Trans. Power Syst. 30 (August (3)) (2015) 1327–1336.
[19] C.R. Lashway, A.T. Elsayed, O.A. Mohammed, Hybrid energy storage management in ship power systems with multiple pulsed loads, Electr. Power Syst. Res. 141 (2016) 50–62.
[20] A.B. Gallo, J.R. Simões-Moreira, H.K.M. Costa, M.M. Santos, E. Moutinho dos Santos, Energy storage in the energy transition context: a technology review, Renew. Sustain. Energy Rev. 65 (2016) 800–822.
[21] S. Mashayekh, Z. Wang, L. Qi, J. Lindtjorn, T.A. Myklebust, Optimum sizing of energy storage for an electric ferry ship, in: IEEE Power and Energy Society General Meeting, San Diego, CA, 2012, pp. 1–8.
[22] J.M. Prousalidis, G.J. Tsekouras, F. Kanellos, New challenges emerged from the development of more efficient electric energy generation units, in: IEEE Electric Ship Technologies Symposium, Alexandria, VA, 2011, pp. 374–381.
[23] F.D. Kanellos, Optimal power management with GHG emissions limitation in all electric ship power systems comprising energy storage systems, IEEE Trans. Power Syst. 29 (January (1)) (2014) 330–339.
[24] G.J. Tsekouras, F.D. Kanellos, J. Prousalidis, Simplified method for the assessment of ship electric power systems operation cost reduction from energy storage and renewable energy sources integration, IET Electr. Syst. Transp. 5 (2) (2015) 61–69, 6.
[25] G.J. Tsekouras, F.D. Kanellos, Optimal operation of ship electrical power system with energy storage system and photovoltaics: analysis and application, WSEAS Trans. Power Syst. 8 (October (4)) (2013) 145–155.
[26] C. Shang, D. Srinivasan, T. Reindl, Economic and environmental generation and voyage scheduling of all-electric ships, IEEE Trans. Power Syst. 31 (September (5)) (2016) 4087–4096.
[27] S. Bose, et al., Shipboard power systems reconfiguration—a cyber-physical framework for response time analysis, IEEE Trans. Ind. Inform. 10 (February (1)) (2014) 439–449.
[28] Andreas Wiesmann, Slow steaming a viable long-term option? WÄRTSILÄ Technical Journal (February) (2010) 49–55. [Online]. Available: http://www.wartsila.com/docs/default-source/Service-catalogue-files/Engine-Services–2-stroke/slow-steaming-a-viable-long-term-option.pdf.
[29] F.D. Kanellos, A. Anvari-Moghaddam, J.M. Guerrero, Smart shipboard power system operation and management, Inventions 1 (4) (2016) 1–14.
[30] Man Diesel & Turbo, Basic Principles of Ship Propulsion. [Online]. Available: http://marine.man.eu/propeller-aft-ship/basic-principles-of-propulsion.
[31] C. Technologies, Use of particle swarm optimization algorithm for solving integer and mixed integer optimization problems, Int. J. Comput. Sci. Commun. Technol. 4 (1) (2011) 4–8.
[32] S. Kitayama, K. Yasuda, A method for mixed integer programming problems by particle swarm optimization, Electr. Eng. Jpn. 157 (2) (2006) 40–49.
[33] M.N. Road, S. Africa, S. Africa, A convergence proof for the particle swarm optimizer, Fundam. Inform. 105 (4) (2010) 341–374.
[34] E.C. Laskari, K.E. Parsopoulos, M.N. Vrahatis, Particle swarm optimization for integer programming, Proc. 2002 Congr. Evol. Comput. CEC'02 (Cat. No.02TH8600) 2 (2002) 2–7.
[35] S.S. Kumar, V. Palanisamy, A dynamic programming based fast computation Hopfield neural network for unit commitment and economic dispatch, Electr. Power Syst. Res. 77 (8) (2007) 917–925.
[36] A. Anvari-Moghaddam, A.R. Seifi, T. Niknam, Multi-operation management of a typical microgrid using particle swarm optimization: a comparative study, Renew. Sustain. Energy Rev. 6 (2) (2012) 1268–1281.
[37] A. Anvari-Moghaddam, A.R. Seifi, T. Niknam, M.R. Alizadeh Pahlavani, Multi-objective operation management of a renewable micro grid with back-up micro turbine/fuel cell/battery hybrid power source, Energy 36 (11) (2011) 6490–6507.