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ORIGINAL ARTICLE

Adaptive equivalent consumption minimization strategy for hybrid electric ship

Diju Gao¹  | Haoyang Jiang¹  | Weifeng Shi^{1,2} | Tianzhen Wang^{1,2} | Yide Wang³

¹Key Laboratory of Transport Industry of Marine Technology and Control Engineering, Shanghai Maritime University, Shanghai, China

²Logistics Engineering College, Shanghai Maritime University, Shanghai, China

³Institut d'Électronique et des Technologies du num éRique, UMR CNRS 6164, Université de Nantes, Nantes, France

Correspondence

Haoyang Jiang, Key Laboratory of Transport Industry of Marine Technology and Control Engineering, Shanghai Maritime University, Shanghai 201306, China.
Email: jhy139@foxmail.com

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Abstract

In recent years, with the development of battery technology, hybrid electric ship (HES), as a promising solution to reduce the fuel consumption and emissions, has become a research hotspot. However, frequent use of the battery will accelerate the aging of the battery, and the replacement of scrapped battery will increase the cost of the ship. Therefore, it is necessary to consider delaying battery aging into the energy control strategy of HES. The equivalent consumption minimization strategy (ECMS) is a feasible energy control strategy because it can be implemented in real time. However, under the condition of uncertain initial state of charge (SOC) of the battery, ECMS cannot effectively reduce the fuel consumption unless the equivalent factor (EF) is optimized in real time. In this paper, an adaptive equivalent consumption minimization strategy (A-ECMS) is proposed, which extracts the global optimal EF trajectory from the dynamic programming (DP) solution and uses the back propagation (BP) neural network to adjust the EF in real time. A trade-off between the fuel consumption and battery aging is made in the cost function by introducing a weight coefficient. Finally, the effectiveness and the adaptability of the proposed strategy are verified in MATLAB.

KEYWORDS

adaptive equivalent consumption minimization strategy, battery aging, BP neural network, dynamic programming, hybrid electric ships

1 | INTRODUCTION

With the development of economy, energy crisis and environmental problems have become increasingly prominent. To cope with these challenges, the international maritime organization (IMO) and other bodies put forward higher requirements for energy conservation and

emission reduction in ships.^{1,2} With the development of battery management, charging technology, and power electronics technology, hybrid electric ship (HES) has become a new solution to improve the fuel economy, reduce the pollution emissions and enhance the safety. Although the application of power battery makes HESs to use electric energy to improve the economy and reduce emissions

[Correction added on 08 February 2022 after first online publication: The authors name “Diju Gao” was corrected to read as “Diju Gao”]

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in ships during voyage, coordinating the multiple energy sources to give a full play to their respective advantages makes the control of the HESs more complex than the traditional ships. Energy control strategy is one of the significant issues of HES control.

To ensure the reasonable distribution of energy, many energy management strategies have been proposed. Common energy control strategies for HESs can be divided into rule-based (RB) control strategy and optimization control strategy. The former is easy to be implemented but cannot adapt to various cruising conditions. The latter can be divided into instantaneous optimization and global optimization. Instantaneous optimization includes the model predictive control (MPC) and the equivalent consumption minimization strategy (ECMS). Global optimization includes dynamic programming (DP) and Pontryagin's minimum principle (PMP).³ Global optimization can obtain the global optimal solution, but it cannot be controlled in real time due to the large amount of calculation. Instantaneous optimization can be used in real time, but its optimized performance is not as good as global optimization. In Ref. 4, a ship energy control strategy based on the logic threshold method is proposed, the authors divide the operating mode into two types corresponding to different combinations of energy sources. The proposed strategy does not need to establish a complex mathematical model and has good optimization performance. In Ref. 5, the authors extract the characteristic parameters of various sailing conditions of a ship and establish the standard sailing conditions. The control strategy determines which standard sailing condition the real-time sailing condition belongs to and makes the corresponding adjustment by the established fuzzy pattern recognition model. In Ref. 6, an energy control strategy based on MPC is proposed. The control strategy predicts the future ship load demand every minute and then uses the improved black hole algorithm to obtain the optimal solution to minimize the objective function in the prediction horizons. In Ref. 7, authors propose an energy control strategy based on ECMS and MPC. MPC is utilized to predict the future marine load profile and adjust the equivalent factors in real time. ECMS is used to minimize the total equivalent fuel consumption. In Ref. 8, the multi-objective optimization problem including power-fluctuation compensation and hybrid energy storage system loss minimization is transformed into a single-objective optimization problem by using the weighted-sum method, and then the global optimal solution is obtained by using dynamic programming (DP). The result of dynamic programming can provide a benchmark for the MPC strategy.

Most of the above energy control strategies only focus on achieving better fuel economy. In reality, excessive use of batteries to meet the load demand will lead to frequent deep charging and discharging of batteries, which may

lead to significant battery degradation.³ In addition, the replacement of scrapped power batteries will increase the usage cost of the ship. It is necessary to consider the battery life when designing the ship energy control strategy. Reference 9 takes the battery aging into account when designing the hybrid power system and energy control strategy and adapts the mixed-integer linear-programming approach and hierarchical method to minimize the fuel cells degradation, the capital expenditure, and the operating expenditure. However, the control strategy includes constraints in the optimization model to limit battery aging and does not propose a specific battery aging model. Reference 10 establishes an accurate Li ion battery performance degradation and life prediction model and applies the established model to optimize the sizes of the hybrid electric powertrain component of a HES. This research forms a foundation for energy management strategy development of HES. In Ref. 11, the depth of discharge (DOD) is defined as key factor of the battery lifetime. A two-step multi-objective energy control strategy is proposed. In the first step of optimization, the hybrid energy storage system including batteries and ultracapacitors capacitor is regarded as a whole, and the optimization goal is to reduce the fuel consumption and emissions. Then in the second step, by optimizing the energy distribution between the batteries and the ultracapacitors capacitor, the lifetime of the battery can be extended. However, using both batteries and ultracapacitors can bring disadvantages to ships, such as reduced cabin capacity, increased cost and weight, and further complex power systems.

It is worth noting that extending the battery life and reducing the fuel consumption are contradictory. Reducing fuel consumption will inevitably accelerate the battery aging, and vice versa. Moreover, the designed energy control strategy should be able to be used in real time, and the control performance should be close to the global optimal solution. From these considerations, an adaptive equivalent consumption minimization strategy based on neural network considering the battery life is proposed in this paper. Firstly, when the initial SOC of the battery is known, the optimal weight coefficient, and the global optimal SOC trajectory of the battery and the global optimal power of the diesel generator (DG) can be obtained by BP. Secondly, extracting the global optimal equivalent factor (EF) trajectory from the global optimal SOC trajectory and the global optimal DG power. Thirdly, the BP neural network is trained with the EF obtained in the second step. The trained BP neural network adjusts the EF in real time, which makes the performance of ECMS close to that of DP.

The main contributions of this paper are as follows:

1. In order to improve the economy of ship operation and reduce the cost of replacing batteries, an adaptive equivalent consumption minimization strategy

(A-ECMS) is proposed to reduce the fuel consumption of HES while reducing the degradation of power battery life.

2. The neural network is used to output the equivalent factor in real time according to the current navigation state of the ship, so that the optimization performance of A-ECMS strategy can be close to that of DP.
3. Compared with the traditional control strategy (diesel engine only), the proposed A-ECMS strategy can save 5% fuel consumption and reduce the total cost by about 3%.

This paper is organized as follows. The HES mathematical model is given in Section 2. In Section 3, the global optimal solution is obtained by DP. The extraction of the global optimal EF is presented in Section 4. Then, A-ECMS is designed and implemented in Section 5. Finally, the conclusion is drawn in Section 6.

2 | HES MODEL DESCRIPTION

In this paper, a series hybrid system is selected to study the energy optimization problem, the system structure of the HES is shown in Figure 1. The power system of the HES is composed of bottom physical system and top energy control system. The bottom physical system is mainly composed of power battery, diesel generator (DG), inverter, transformer, and load. The energy control system controls the power distribution between the power sources by monitoring the power demand, battery SOC, and DG power, then determines the DG power change for the next time step.

For each time step, the power supplied by the power sources satisfies:

$$P_{DG} + P_B = P_L \quad (1)$$

where P_{DG} and P_B are the DG and battery power, respectively, P_L is the HES load demand.

Diesel generator consists of diesel engine and generator. Under the assumption of rigid connection and without

friction loss between the diesel engine and generator, the fuel consumption (FC) of the diesel generator can be expressed as:

$$FC(t) = SFOC \times P(t) \times \Delta t \quad (2)$$

where t is a t -th time interval, SFOC is the specific fuel oil consumption, P is the DG power, Δt is the time step. The specific fuel oil consumption (SFOC) can be expressed as follows¹²:

$$SFOC(t) = k_1 \times \left(\frac{P(t)}{P_{rated}} \right)^2 - k_2 \times \left(\frac{P(t)}{P_{rated}} \right) + k_3 \quad (3)$$

where P_{rated} is the rated power of DG, k_1 , k_2 , and k_3 are the coefficients of the equation.

Power battery is one of the significant components of HES. The performance of power battery is closely related to the ship energy control strategy based on the battery SOC. The power battery SOC can be expressed as follows:

$$P_B = P_{dcha} \times b_t - P_{cha} \times (1 - b_t) \quad (4)$$

$$E_B(t) = E_B(t-1) + n_B \times P_B(t) \times \Delta t \quad (5)$$

$$SOC(t) = \frac{E_B(t)}{E_{B,max}} \times 100\% \quad (6)$$

where P_B is the battery power, P_{dcha} and P_{cha} are, respectively, the discharging power and charging power of the battery, b_t is the operating variable of the battery ["1" means discharge, "0" means charge]. E_B is the energy capacity of the battery, n_B is the charging/discharging energy efficiency, $E_{B,max}$ is the max energy capacity of the battery, SOC is the state of charge of the battery.

The decline of battery life is mainly manifested by the decrease of capacity and the increase of internal resistance.¹³ In this paper, when studying the battery life, we do not consider the impact of the increase of internal resistance, but only consider the impact of the attenuation of battery capacity. Battery life is generally defined as the

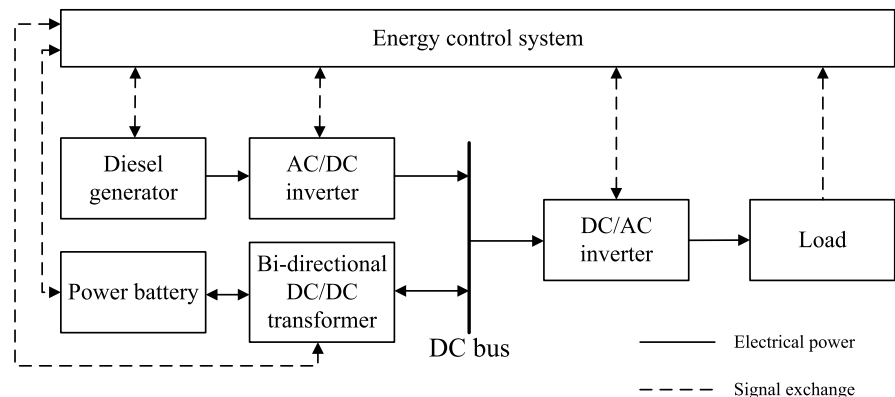


FIGURE 1 System structure of HES

service time from 100% of the rated capacity to only 80% of the rated capacity after one full charge. Battery life is usually categorized as calendar life and cycle life. The loss of battery life during voyage is mainly determined by the loss of cycle life. There are many factors causing the degradation of power battery life, such as Ah-throughput, temperature, and depth of discharge. In order to calculate the effective life depletion due to the charge exchange within the battery, the effective Ah-throughput (Ah_{eff}) is defined as¹⁴:

$$Ah_{\text{eff}}(t) = \int_0^t \sigma(I_c, \theta, \text{SOC}) \times |I(\tau)| d\tau \quad (7)$$

where θ is the battery temperature, I_c is the C-rate defined as the ratio of the current to the nominal charge capacity:

$$I_c = \frac{I}{Q_B} \quad (8)$$

where I is the battery current, Q_B is the capacity of the battery.

σ is a severity factor, characterizing the relative life of a battery under rating conditions, which is defined as¹⁴:

$$\sigma(I_c, \theta, \text{SOC}) = \frac{\Gamma}{\gamma(I_c, \theta, \text{SOC})} = \frac{\int_0^{\text{EOL}} |I_{\text{nom}}(t)| dt}{\int_0^{\text{EOL}} |I(t)| dt} \quad (9)$$

where $\gamma(I_c, \theta, \text{SOC})$ is the total Ah-throughput corresponding to a given sequence of current, temperature, and SOC. Γ is the total Ah-throughput when the battery is subject to its nominal load cycle, which is expressed as:

$$\Gamma = \int_0^{\text{EOL}} |I_{\text{nom}}(t)| dt \quad (10)$$

where I_{nom} is the current profile under nominal conditions and *EOL* indicates the battery end of life. When Ah_{eff} is equal to Γ , it means that the battery will reach its end of life. Therefore, reducing Ah_{eff} is equivalent to reducing the degradation of battery life. It is important to note that the severity factor $\sigma(I_c, \theta, \text{SOC})$ in this paper is obtained by the same method as in Ref. 15.

3 | OPTIMIZATION PROBLEM FORMULATION AND SOLUTION

3.1 | Problem formulation

The energy control strategy for HESs is actually an optimization problem. When the load demand is known, the battery power is taken as the control variable u . By adjusting

the battery power, the diesel generator can operate in the range of high efficiency, and the optimal operating range of the diesel generator is determined by the SFOC curve. In this paper, the proposed strategy considers minimizing the fuel consumption and prolonging the battery life as the optimization objective and discretizes the given voyage condition into N stages. Therefore, the essence of the proposed strategy is a multi-stage control problem with discrete time as the stage.

In order to make Equation (7) suitable for global optimization, it is discretized as:

$$Ah_{\text{eff}} = \sum_{k=1}^N \sigma(I_c, \theta, \text{SOC}) \times |I(k)| \quad (11)$$

Taking P_{DG} as control variable x , SOC as state variable u , and introducing a weight coefficient λ , the whole objective function can be expressed as:

$$J = \sum_{k=1}^N [L(x(k), u(k))] \quad (12)$$

$$L(x(k), u(k)) = (1 - \lambda) \times C_E(x(k), u(k)) + \lambda \times \frac{C_B(x(k), u(k))}{\Gamma} \times C_a \quad (13)$$

$$C_E(x(k), u(k)) = \text{FC} \quad (14)$$

$$C_B(x(k), u(k)) = \sigma(I_c, \theta, \text{SOC}) \times |I_c(k)| \quad (15)$$

where C_E is the fuel consumption of the HES, which is determined by equation (2), C_B is the accumulated Ah-throughput, λ is the weight coefficient, Γ is the battery life which is subject to the nominal load cycle, C_a is the conversion factor, which is defined as the ratio of battery replacement cost and 1 L gasoline cost.

The constraints are as follows:

$$P_{\text{DG}}^{\min} \leq P_{\text{DG}} \leq P_{\text{DG}}^{\max} \quad (16)$$

$$\left| \frac{P_{\text{DG}}(k) - P_{\text{DG}}(k-1)}{\Delta k} \right| \leq H \quad (17)$$

$$P_{\text{cha}}^{\min} \leq P_{\text{cha}} \leq P_{\text{cha}}^{\max} \quad (18)$$

$$P_{\text{dcha}}^{\min} \leq P_{\text{dcha}} \leq P_{\text{dcha}}^{\max} \quad (19)$$

$$\text{SOC}^{\min} \leq \text{SOC} \leq \text{SOC}^{\max} \quad (20)$$

where P_{DG}^{\min} and P_{DG}^{\max} are the minimum and maximum output power of the diesel generator, and H is the maximum change rate of diesel generator power, which is set to prevent

the drastic change of diesel generator power within short time,⁶ in this paper, $H = 1\text{ kW/s}$. P_{cha}^{\min} and P_{cha}^{\max} are, respectively, the minimum and maximum charging powers of the battery, P_{dcha}^{\min} and P_{dcha}^{\max} are the minimum and maximum discharging powers of the battery, respectively, SOC^{\min} and SOC^{\max} are, respectively, the minimum and maximum states of charge of the power battery, which are set to protect the power battery from being used at too high or too low SOC.

3.2 | Dynamic Programming

Dynamic programming is usually used to solve multi-stage global optimization problems based on the Bellman optimal principle.¹⁶ The DP algorithm calculates the minimum cumulative cost function from each k to the final state by recursive calling.¹⁷

The minimum cost function of the $(N-1)$ -th stage is:

$$J_N^*(x(N-1)) = \min_{u(N)} [L(x(N-1), u(N-1))] \quad (21)$$

The minimum cost function of the k -th stage is:

$$J_k^*(x(k)) = \min_{u(k)} [L(x(k), u(k)) + J_{k+1}^*(x(k+1))] \quad (22)$$

Combining the optimal control from each stage k into a sequence leads to the global optimal control strategy of dynamic programming:

$$u^* = \{u^*(1), u^*(2), \dots, u^*(N-1)\} \quad (23)$$

3.3 | Optimization results under given voyage condition

In this section, the offline global optimization of HES energy control strategy under different initial SOC is realized with the goal of minimizing the weighted sum of the fuel consumption and power battery degradation. The given voyage condition is obtained from the hybrid electric ship experimental platform. The experimental platform is equipped with 16 lithium iron phosphate batteries having a total capacity of 100 Ah, which can be combined freely according to demand, two diesel generators with rated power of 60 kW and two propulsion motors having rated output power of 70 kW, which can meet the simulation of most ship load conditions. The experimental platform is shown in Figure 2. The load power profile of given voyage condition as shown in Figure 3. The simulation parameters are shown in Table 1.

When the initial SOC is 40%, 50%, and 60%, respectively, and the final value SOC is 60%, the optimization results corresponding to different weight coefficients λ are shown in Tables 2–4.

In this section, the total cost is equal to the sum of cumulative fuel consumption multiplied by fuel cost and cumulative battery loss multiplied by battery cost:

$$C_{\text{tol}} = \sum_{k=1}^N C_E(x(k), u(k)) \times W_E + \frac{\sum_{k=1}^N C_B(x(k), u(k))}{\Gamma} \times W_B \quad (24)$$

where C_{tol} is the total cost, C_E is the fuel consumption, W_E is the fuel price of the day, C_B is the Ah-throughput, and W_B is the battery cost.

It can be seen from Tables 2–4 that when the weight coefficient $\lambda = 0$, the control strategy only considers the fuel consumption, so the fuel consumption of the HES is the least under this coefficient, and the effective Ah-throughput is the most important. With the increase of weight coefficient, the control strategy tends to protect the battery, so the effective Ah-throughput gradually decreases and the fuel consumption gradually increases.

When the weight coefficient $\lambda = 1$, the control strategy only considers the battery life, so the effective Ah-throughput is the least important under this coefficient, and the fuel consumption of the HES is the most important. At this time, the power of HES is completely provided by the diesel generator. In addition, it can be inferred from Tables 2–4 that no matter what the initial SOC is, when the weight coefficient $\lambda = 0.4$, the total cost of the HES is the least. Therefore, $\lambda = 0.4$ is taken as the optimal weight coefficient in this paper, and the global optimal SOC trajectory of the battery and the global optimal power of the diesel generator under this coefficient are shown in Figures 4 and 5.

4 | ECMS FOR HES

Although the DP can obtain the global optimal solution, but the DP calculation is complex, cannot be used in real time. The ECMS strategy only considers the current instantaneous cost, so it can be applied to real-time control.

4.1 | ECMS-based optimization problem formulation

The objective of ECMS is to minimize the instantaneous total equivalent fuel consumption (C_{equ}), which is described as the sum of the diesel generator fuel consumption (C_{DG}), and the converted equivalent fuel consumption from battery (C_B). In this paper, since the battery life needs to be considered, the battery life loss (C_{lif}) needs to be converted into the total consumption (C).

$$\begin{aligned} C(t) &= (1-\lambda) \times C_{\text{equ}}(t) + \lambda \times C_{\text{lif}}(t) \\ &= (1-\lambda) \times (C_{\text{DG}}(t) + C_B(t)) + \lambda \times C_{\text{lif}}(t) \end{aligned} \quad (25)$$

where λ is the optimal weight coefficient obtained in Section 3, $\lambda = 0.4$.

The instantaneous fuel consumption of diesel generator can be expressed as:

$$C_{DG}(t) = \frac{SFOC \times P(t)}{3.6 \times 10^{-3}} \quad (26)$$

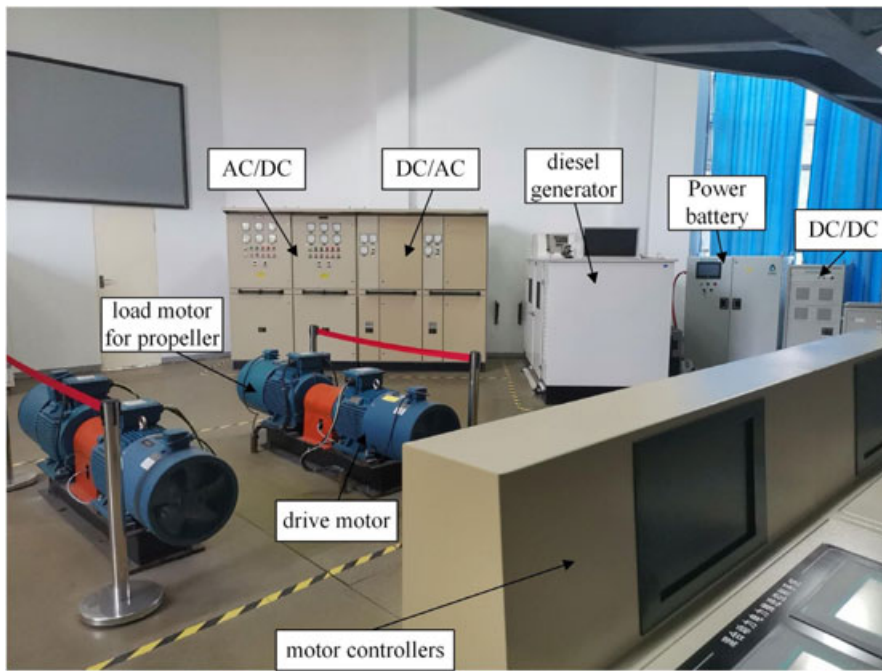


FIGURE 2 Hybrid electric ship experimental platform

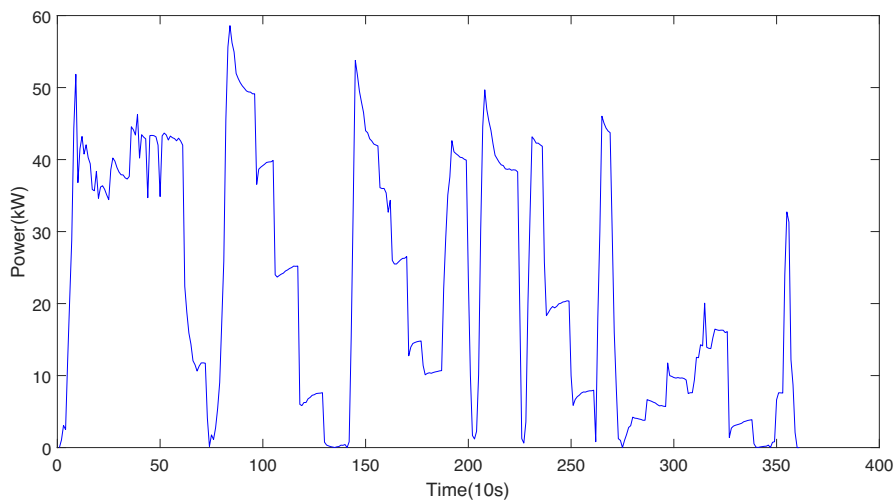


FIGURE 3 Load power profile

TABLE 1 Simulation parameters

Diesel generator			
Rated power	60 kW	Rated speed	1500 rpm
Rated voltage	400 V	efficiency	96%
Power battery			
Energy	9.84 kWh	Capacity	27.6 Ah
Rated voltage	356 V	Max discharge power	40 kW
Max charge power	15 kW	Max SOC	70%
Min SOC	30%	Kind	Lithium iron phosphate battery

TABLE 2 Initial SOC = 40%

λ	Effective Ah (Ah)	Fuel consumption (L)	Total cost (CNY)
0	35.49	6.67	44.56
0.1	31.80	6.68	44.42
0.2	26.49	6.69	44.21
0.3	24.19	6.70	44.18
0.4	23.03	6.71	44.15
0.5	17.94	6.77	44.27
0.6	8.71	6.93	44.81
0.7	6.97	6.97	44.98
1	6.58	7.03	45.35

TABLE 3 Initial SOC = 50%

λ	Effective Ah (Ah)	Fuel consumption (L)	Total cost (CNY)
0	33.82	6.41	42.81
0.1	31.14	6.41	42.66
0.2	25.63	6.42	42.46
0.3	21.71	6.44	42.39
0.4	19.90	6.45	42.35
0.5	14.58	6.52	42.49
0.6	6.01	6.67	43.00
0.7	3.29	6.74	43.28
1	2.96	6.76	43.39

TABLE 4 Initial SOC = 60%

λ	Effective Ah (Ah)	Fuel consumption (L)	Total cost (CNY)
0	35.46	6.15	41.22
0.1	31.35	6.15	41.01
0.2	24.90	6.16	40.76
0.3	21.21	6.18	40.72
0.4	17.69	6.21	40.68
0.5	12.10	6.28	40.82
0.6	5.26	6.40	41.24
0.7	2.75	6.47	41.55
1	2.05	6.52	41.82

The equivalent fuel consumption of battery can be expressed as:

$$C_B(t) = s \times \frac{P_B(t)}{Q} \quad (27)$$

where s is the equivalent factor (EF), Q is the low calorific value of fuel.

The battery life loss can be expressed as:

$$C_{lif}(t) = \frac{\sigma(I_c, \theta, SOC) \times |I(t)|}{\Gamma} \times C_a \quad (28)$$

4.2 | Extraction of the global optimal EF

The equivalent factor (EF) is the decisive factor to determine the performance of ECMS. For a given demand power and SOC, there is a one-to-one relationship between EF and the optimal DG power.¹⁸ Figure 6 shows the relationship between the total consumption and DG power when the demand power is 25 kW, SOC is 40% and the equivalent factors are 1, 2.5, and 4, respectively.

It can be seen from Figure 6 that when the EF is small, the fuel consumption of the battery after conversion is also small. The control strategy tends to use the power provided by battery, so the optimal DG power is small. With the increase of the EF, the fuel consumption of the battery after conversion increases, so the control strategy is more inclined to use the power provided by the DG.

According to the initial SOC and final SOC, the optimal control solution under a given voyage condition has been obtained by DP algorithm in Section 3. Therefore, when an EF is selected at a certain time to make the current optimal DG power value the same as the value solved by the DP, it can be considered as the instantaneous optimal EF at that time. In this paper, the instantaneous optimal equivalent factor is extracted by iterative calculation method. The equivalent factor starts from 1 and iterates with a 0.01 step size. The optimal DG power of ECMS at this time is calculated under different EFs. The EF which makes the DG power and SOC trajectory closest to the DP solution is selected as the instantaneous optimal EF, as shown below:

$$s^*(t) = \arg \min (\omega_1 \times (P_{DG}(s) - P_{DG,ref}(t)) + \omega_2 \times (SOC(s) - SOC_{DG,ref}(t))) \quad (29)$$

where ω_1 and ω_2 are the coefficients of the equation, $P_{DG}(s)$ and $SOC(s)$ are the optimal DG power and SOC of ECMS under the corresponding EF, respectively, $P_{DG,ref}(t)$ and $SOC_{DG,ref}(t)$ are, respectively, the optimal DG power and SOC of DP at this time.

Taking the initial SOC = 60% as an example, the EF is extracted from the DP solution. Figures 7 and 8 show the simulation results of the optimized ECMS algorithm and DP algorithm.

As shown in Figures 7 and 8, the SOC trajectories of the optimized ECMS algorithm and DP algorithm are basically the same, and the difference of DG power between the two optimizations is also very small.

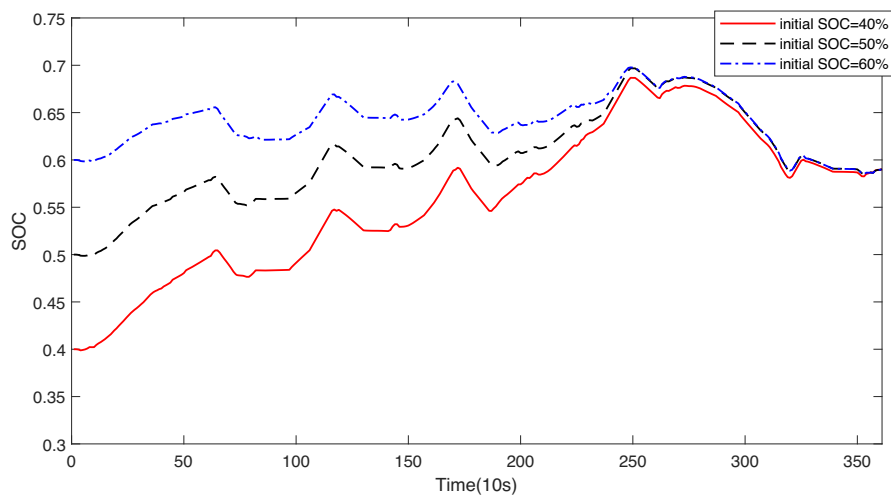


FIGURE 4 Global optimal SOC trajectory of the battery

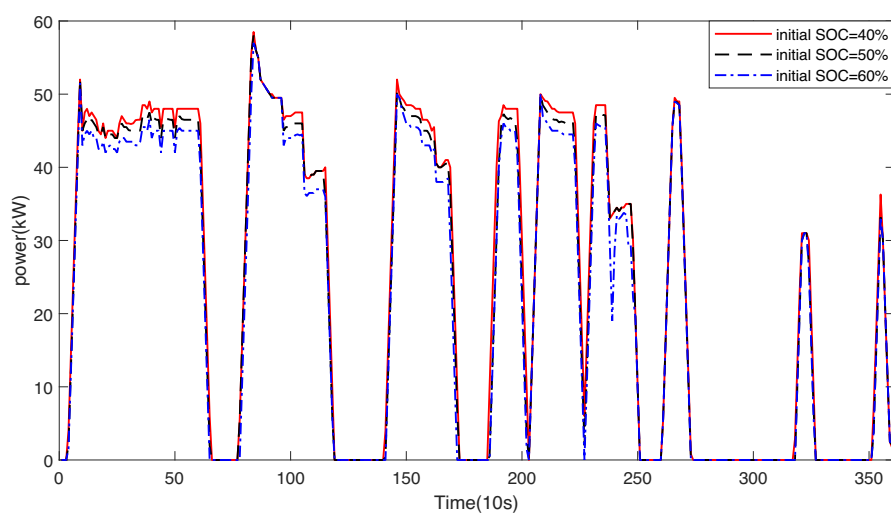


FIGURE 5 Global optimal power of the diesel generator

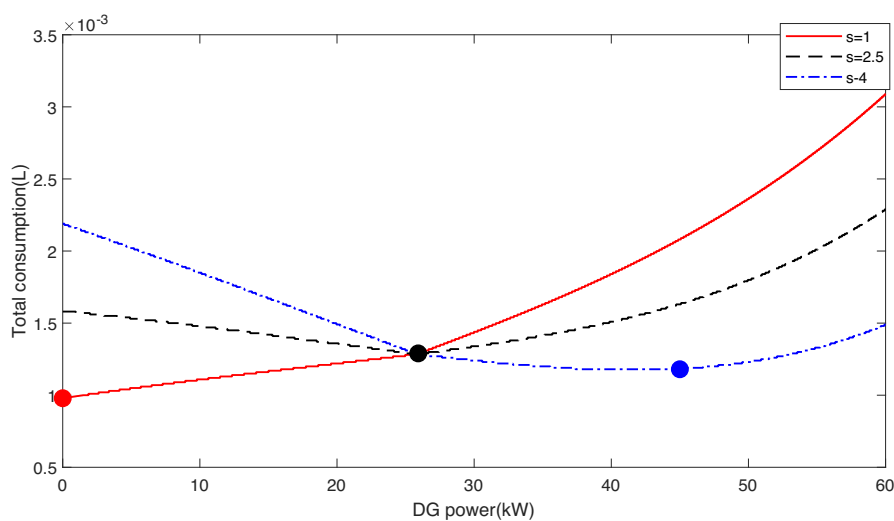


FIGURE 6 Relationship between the total consumption and DG power under different EF

FIGURE 7 Optimal SOC trajectory of DP and optimized ECMS

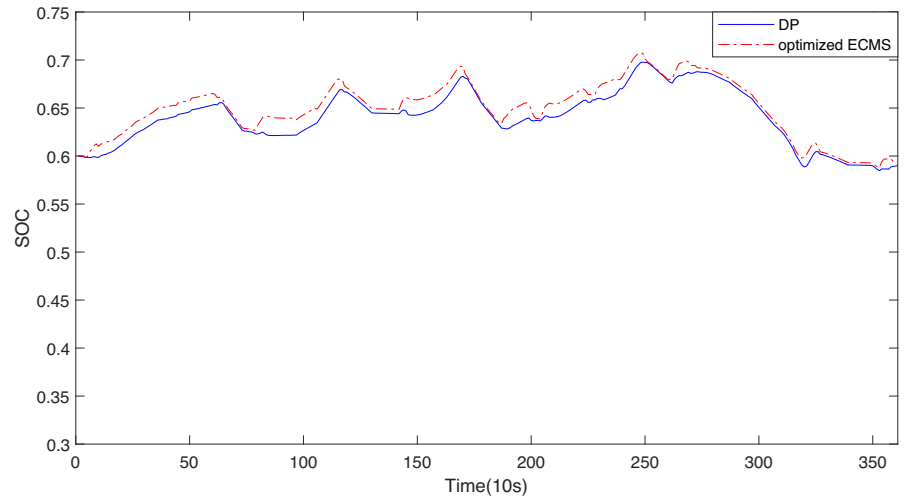
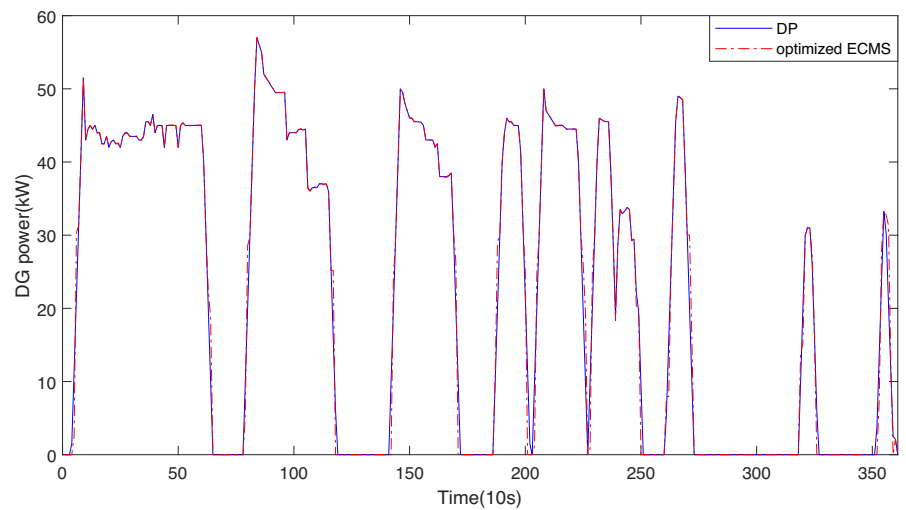


FIGURE 8 Optimal DG power of DP and optimized ECMS



5 | BP-BASED ADAPTIVE ENERGY MANAGEMENT STRATEGY

The EF obtained in Section 4 is based on the DP algorithm when the initial SOC is known. However, in the actual operation, the initial SOC is uncertain, so in this section, BP neural network is used to optimize the EF of A-ECMS algorithm in real time.

5.1 | BP neural network

BP neural network was proposed by Rumelhart and McClelland in the 1980s.¹⁹ It is a kind of multilayer feedforward network which is trained according to the error back propagation algorithm.²⁰ The topological structure of a three-layer neural network is shown in Figure 9.

where X_1, X_2, \dots, X_N are the input data of network, Y_1, \dots, Y_J are the predicted output data of network,

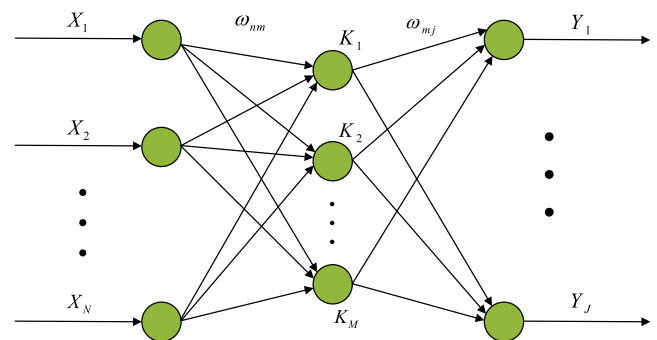


FIGURE 9 Structure of a three-layer BP Network

K_1, K_2, \dots, K_M are the hidden layer neurons. The number of neurons in the input layer, hidden layer and output layer is N, M , and J , respectively. The weight between the n -th neuron in the input layer and the m -th neuron in the hidden layer is ω_{nm} , and the weight between the m -th neuron in the hidden layer and the j -th neuron in the output layer is ω_{mj} .

After determining the number of layers and the number of neurons in each layer, BP neural network calculates the error between the network output and the target output by learning the samples of the known target output, and adjusts the weights and thresholds of each layer according to the error. After repeated iteration, the error no longer decreases, and the training is terminated. Taking the three-layer BP network shown in Figure 9 as an example, the specific process of weight and threshold adjustment is as follows:

The output of the m -th neuron in the hidden layer is calculated as:

$$H_m = f \left(\sum_{n=1}^N \omega_{nm} X_n + a_m \right) \quad (30)$$

where H_m is the output of the m -th neuron in the hidden layer, ω_{nm} is the connection weight between the n -th input layer and m -th hidden layer, X_n is the input of the n -th neuron in the input layer, and a_m is the threshold value of the m -th neuron in the hidden layer. f is the incentive function of the hidden layer.

$$f(x) = (1 + e^{-x})^{-1} \quad (31)$$

The output of the j -th neuron in the output layer is calculated as:

$$Y_j = \sum_{m=1}^M H_m \omega_{mj} - b_j \quad (32)$$

where Y_j is the output of the j -th neuron in the output layer, ω_{mj} is connection weight

between the m -th hidden layer and j -th output layer, b_j is the threshold value of the m -th neuron in the output layer.

The network output error is calculated and the weights are updated as:

$$\begin{cases} e_j = D_j - Y_j \\ \omega_{mj} = \omega_{mj} + \eta H_m e_j \\ \omega_{nm} = \omega_{nm} + \eta H_m (1 - H_m) X_n \sum_{m=1}^M \omega_{mj} e_j \end{cases} \quad (33)$$

where D_j is the expected output, e_j is the network output error, and η is the learning rate.

The threshold is updated as:

$$\begin{cases} b_j = b_j + e_j \\ a_m = a_m + \eta H_m (1 - H_m) X_n \sum_{j=1}^J \omega_{mj} e_j \end{cases} \quad (34)$$

5.2 | A-ECMS

According to the relevant information of ship voyage, the current battery SOC, load demand and ratio of the remaining miles to the total miles are selected as the input parameters of the BP neural network, and the output parameters of neural network are EF. The EF of instantaneous optimization is used in ECMS strategy to calculate the optimal control decision. The principle of A-ECMS algorithm based on BP neural network is shown in Figure 10.

The current battery SOC, load demand and ratio of the remaining miles to the total miles are the input for the neural network model, and the EF optimized by DP algorithm is used as the expected output for training. Through the fitted network, the EF can be modified in real time according to the current information of HES, and then the instantaneous optimal control can be achieved by ECMS.

The neural network controller is built on the MATLAB/Simulink platform, and the global optimal EFs extracted from seven different initial SOC conditions are used to train the neural network. Taking the EFs under three different SOC initial conditions as verification samples to verify the trained neural network. As shown in Figure 11, the EF output by the neural network is basically consistent with the actual optimal EF and their correlation coefficient is 0.84. Therefore, the trained neural network can be applied to the proposed A-ECMS strategy.

5.3 | Simulation

In order to verify the proposed strategy, the ECMS algorithm and DP algorithm are used for optimization under a given voyage condition. The weight coefficient $\lambda = 0.4$ and the initial SOC are 0.45, 0.55, and 0.65, respectively. The battery SOC trajectory is shown in Figure 12. The DG power is shown in Figure 13. Table 5 shows the simulation results of the two energy control strategies and a base-case scenario (ie, diesel engine only, with non-optimal strategy) under different initial SOC.

As shown in Figures 12 and 13, the DG power difference between A-ECMS strategy based on BP neural network and DP strategy is small, the SOC trajectory is basically the same, and the final SOC of A-ECMS strategy fluctuates near the target value. In order to facilitate quantitative improvement, the final SOC of all strategies is set at about 60% in this paper. From Table 5, it can be seen that the total cost of A-ECMS strategy is close to that of DP strategy. Compared with the base-case scenario, the

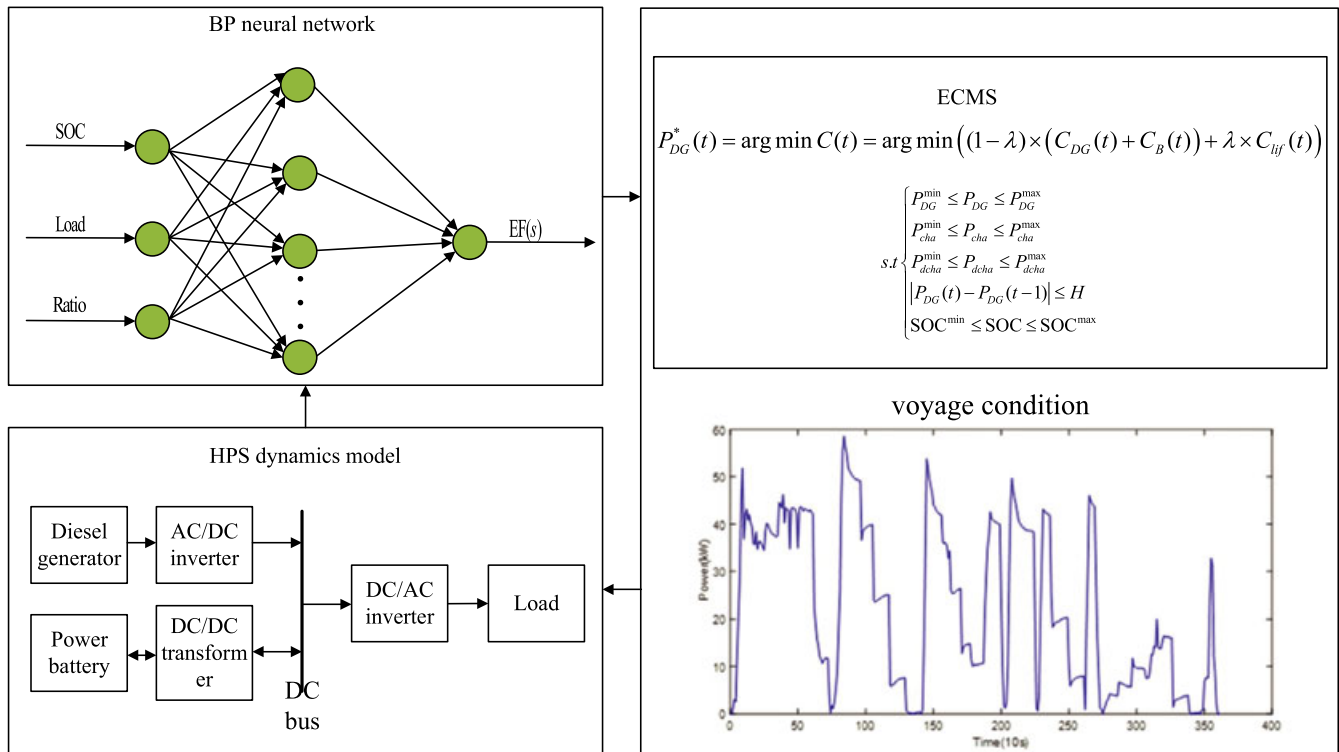
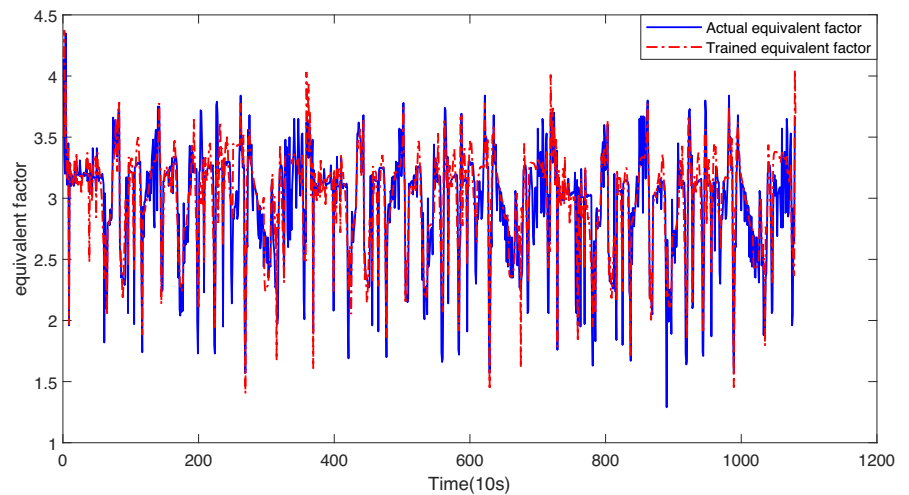


FIGURE 10 Schematic diagram of A-ECMS

FIGURE 11 EF output by neural network and the actual EF



proposed A-ECMS strategy can save 5% fuel consumption and reduce the total cost by about 3%. It is worth noting that the optimization performance is not only related to the control strategy, but also related to the specific fuel oil consumption of the diesel generator. In addition, when the initial SOC = 45%, the total cost of the A-ECMS strategy is less than the total cost of the DP strategy because the final SOC of the A-ECMS strategy does not fully reach the target value. Combined with Figure 12, Figure 13, and Table 5, it can be seen that the performance of the proposed A-ECMS strategy can be very close to the DP strategy.

6 | CONCLUSIONS

This paper presents a real-time energy control strategy A-ECMS taking into account the fuel consumption and battery aging. The multi-objective optimization problem is transformed into a single-objective optimization problem by introducing a weight coefficient. In order to obtain the optimal weight coefficient, this paper uses DP algorithm to obtain the global optimal solution of multi-objective optimization problem under different weight coefficients in offline mode and obtains the optimal weight coefficient through comparison. For making the performance of the

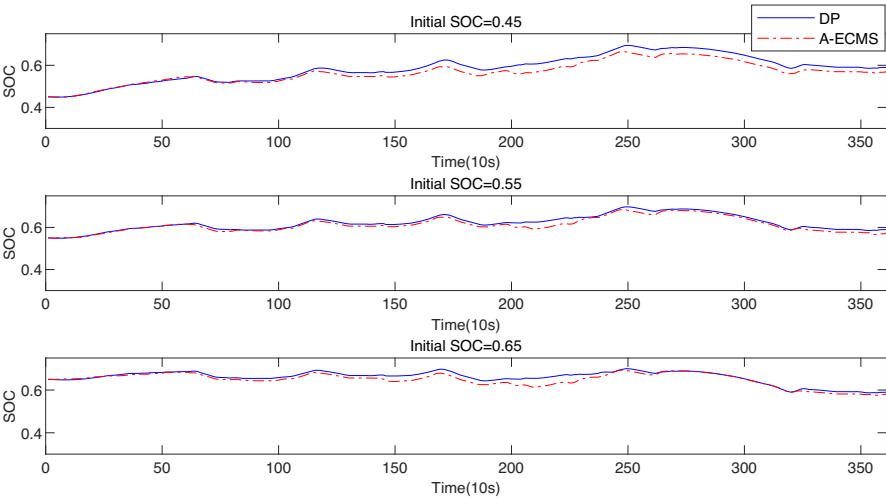


FIGURE 12 Battery SOC trajectory of A-ECMS algorithm and DP algorithm

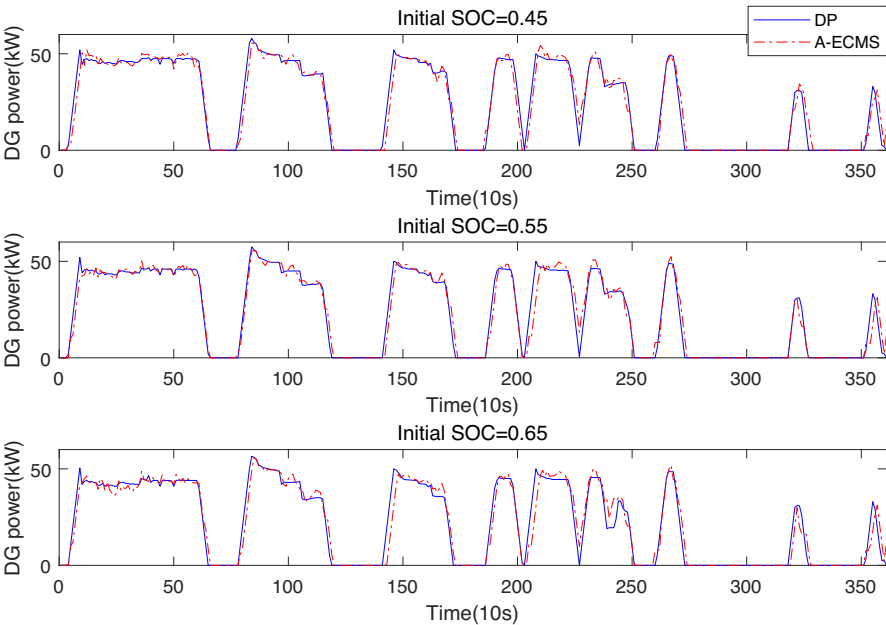


FIGURE 13 DG power of A-ECMS algorithm and DP algorithm

Initial SOC	Strategy	Effective Ah (Ah)	Fuel consumption (L)	Final SOC	Total cost (CNY)
45%	DP	20.87	6.58	60%	43.21
	A-ECMS	23.43	6.55	56%	43.15
	Non-optimal	4.18	6.90	60%	44.36
55%	DP	18.83	6.33	60%	41.51
	A-ECMS	21.91	6.31	58%	41.52
	Non-optimal	2.21	6.63	60%	42.54
65%	DP	16.21	6.09	60%	39.85
	A-ECMS	20.93	6.08	59%	40.00
	Non-optimal	2.24	6.41	60%	41.14

TABLE 5 Simulation results

ECMS strategy, which can be used in real time, close to the global optimal solution, the global optimal EF is extracted from DP solution by iterative method. In order to maintain the performance of SOC when the initial SOC is uncertain, BP neural network is used to adjust the EF in real time according to the relevant information of ship voyage. The proposed strategy is simulated in MATLAB, and the results show that the performance of the proposed strategy is close to the global optimal solution in presence of initial SOC uncertainty, which not only reduces the fuel consumption but also extends the battery life. Future work will focus on improving the adaptability of the equivalent factor to different voyage conditions.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTIONS

D.G. and H.J. contributed to Methodology; W.S. and T.W. contributed to validation; H.J. contributed to writing—original draft; D.G., T.W., and Y.W. contributed to writing—review; All authors have read and agreed to the published version of the manuscript.

ORCID

Diju Gao  <https://orcid.org/0000-0001-7564-8061>

Haoyang Jiang  <https://orcid.org/0000-0002-4793-2775>

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