Coordinated Optimal Energy Management and Voyage Scheduling for All-Electric Ships Based on Predicted Shore-Side Electricity Price

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***Abstract*—Unlike a land-based standalone microgrid, a shipboard microgrid of an all-electric ship (AES) needs to shut down generators during berthing at the port for exanimation and maintenance. Therefore, the cost of onshore power plays an important role in an economic operation for AESs. In order to fully exploit its potential, a two-stage joint scheduling model is proposed to optimally coordinate the power generation and voyage scheduling of an AES. Different from previous studies that only consider the operation cost of the ship itself, a novel coordinated framework is developed in this article to address the shore-side electricity price variations on the ship navigation route. A deep learning-based forecasting method is utilized to predict the electricity price in various harbors for ship operators. Then, a hybrid optimization algorithm is designed to solve the proposed multiobjective joint scheduling problem. A navigation route in Australia is adopted for case studies and simulation results demonstrate the high energy utilization efficiency of the proposed algorithm and the necessity of on-shore power influence on the AES voyage.**

***Index Terms*—All-electric ship, deep learning, energy storage system, joint energy management and voyage scheduling, real-time electricity price prediction.**

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NOMENCLATURE

A. Acronyms

AES	All-electric ship.
BPNN	Back-propagation neural network.
DG	Diesel generator.
EEOI	Energy efficiency operational indicator.
ESS	Energy storage system.
Elman NN	Elman neural network.
FC	Fuel consumption.
GHG	Greenhouse gas.
MAPE	Mean absolute percentage error.
MODE	Multiobjective differential evolution.
MILP	Mixed integer linear programming.
LSTM	Long short-term memory.
RBFNN	Radial basis function neural network.
RMSE	Root mean square error
RNN	Recurrent neural network.
SOC	State of charge.

B. Sets and Indices

t, T	Index and set of time periods.
i, j, N	Index and set of ports.
$T_{anc,i}$	Set of anchoring periods at the ith port.
$T_{dep,i}$	Set of leaving periods from the ith port.
$T_{app,i}$	Set of approaching periods to the ith port.

C. Parameters

$T_{cru,i}$	Set of cruising periods from the ith port to the jth port.
a_0, a_1, a_2	FC coefficients of the ith DG.
b_0, b_1, b_2	GE coefficients of the ith DG.
C_0, C_1, C_2	Maintenance cost parameter.
h_{p1}, h_{p2}	Proportional and exponential coefficients of the propulsion-speed relation.
E_{ESS}, SOC_0	Rated capacity and initial SOC of the ESS.
m_{AES}	Mass of the on-board cargo.
$P_{ESS}^{\min}, P_{ESS}^{\max}$	Minimal and maximal power of ESS.
$P_{DG,k}^{\min}, P_{DG,k}^{\max}$	Minimal and maximal output power of the kth DG.
$R_u^{\max}$	Maximal ramp-up rates.
η_{ch}, η_{dc}	ESS charging and discharging efficiency.
SOC_{min}, SOC_{max}	Minimal and maximal SOC of ESS.

Δt	Voyage time of each time-interval.
η_{ch}, η_{dc}	ESS charging and discharging efficiency.
$V_{\min}, V_{\max}$	Minimal and maximal ship speed.
δ_{OR}	Operating reserve requirement.

D. Variables

$Dist(t)$	Voyage distance at *t*th time interval.
$E_{ESS}(t)$	Energy stored in ESS at *t*th time interval.
$FC_{DG,k}(t)$	FC of *k*th DG at *t*th time interval.
$OMC_{DG,k}(t)$	Operation and maintenance cost of *k*th DG at *t*th time interval.
$GE_{DG,k}(t)$	GHG emissions of *k*th DG at *t*th time interval.
$P_{DG,k}(t), P_{ESS}(t)$	Active power output of *k*th DG and ESS at *t*th time interval.
$R_{DG,k}(t)$	Spinning reserve capacity of *k*th DG at *t*th time interval.
$R_{ESS}(t)$	Spinning reserve of ESS at *t*th time interval.
$P_{UG}(t)$	Active power of onshore power at *t*th time interval.
$Price(t)$	Electricity price of onshore power at *t*th time interval.
SOC(t)	SOC of ESS at *t*th time interval.
$V(t)$	Ship speed at *t*th time interval.
u	ON/OFF state vector.

I. Introduction

DUE to the global concern on the increasing fossil energy consumption and environmental pollutions produced by the traditional ships, strict restrictions have been imposed by the international maritime organization (IMO) to limit the CO_2 emissions from ships [1]. Recently, the AES equipped with electric propulsion system and energy storage systems (ESSs) has become a helpful solution to minimize the operation cost and emissions [2]–[5].

Unlike traditional ships with fixed mechanical drive, the electric propulsion technology makes a voyage more flexible and controllable but increases complexity of the AES operation. In [6] and [7], an efficient operation of a shipboard power system consisting of full electric propulsion and ESS has been achieved. In order to further reduce the GHG emissions, an optimal demand-side management method was proposed in [8] and [9]. In [10], a hybrid power system was modeled for the system-level analysis of AESs and different operational modes were considered. In [11], an integrated ship power system comprising on-board battery, PV modules and DGs were modeled and a power management of an AES was designed based on a decentralized model predictive strategy to control DGs for longer voyage. A two-step multiobjective optimization method was developed in [12] for a hybrid ESS management to reduce the fuel cost of AES microgrids. An optimal management algorithm based on Benders decomposition was explored in [13] to reduce both fuel consumption and emissions of an AES. Some other methods are explored to improve ship energy efficiency, such as optimal planning [14], power system reconfiguration [15], and power factor correction [16]. Even though these methods have proved their priorities in ship operation, rare research takes into account the influence of the onshore power. Moreover, the spinning reserve is fully ignored in previous studies.

With the large-scale penetration of the ESS in the AES, it becomes important to coordinate voyage scheduling and AES operation while considering the cost of shore-side electricity. Since ships have to shut down diesel generators for checking and maintenance, the onshore power also named cold ironing will supply the electricity for the ship loads and ESS charging. Accordingly, the charging cost depends on the price of cold ironing, which cannot be ignored in an optimal management of an AES. Furthermore, the real-time electricity price of cold ironing forms an essential factor for the AES to select when to arrive at the port. However, due to the time varying nature of the demand and supply, the electricity price of seaport is highly volatile, which increases forecasting difficulty using deterministic prediction methods [17]–[21]. As a consequence, a deep learning-based forecasting technique is utilized in this article to predict the shore-side electricity price. The predicted information is used to assist AES operators to determine the best time to berth at the harbour. The main contributions of this work are summarized as follows.

1) Different from previous research works [6]–[16] that only considered ship itself, the impacts of onshore power on the joint voyage and generation scheduling are first evaluated in the AES operation problem.
2) Unlike previous studies on fuel optimization of AESs, the fuel efficiency and spinning reserve are first considered in the shipboard power system to improve the energy efficiency and reliability.
3) The problem is formulated and solved as a multiobjective optimization problem for simultaneously reducing the cost and air pollutants under consideration of operational and technical constraints, including minimum–maximum generation outputs, ramp rate limits, power balance, ship speed limits, and route length.

Owing to the conflicts among optimization objectives, the problems of energy management and voyage scheduling are coupled and cannot be addressed independently. In this article, a multistage hybrid optimization algorithm is proposed to solve this complex optimization problem in an AES considering uncertainties of the real-time electricity price of onshore power. The proposed approach is employed to a full electrified cruise ferry, and realistic operating conditions are modeled. Numerical simulations reveal that the proposed method is able to achieve an economic operation for AESs under uncertain onshore power costs and provide a more flexible and costless navigation than traditional ships.

The rest of this article is organized as follows: Section II states the problem and Section III formulates the multiobjective problem. Section IV introduces the multistage hybrid optimization algorithm for joint energy management and voyage scheduling. Section V verifies the effectiveness of the proposed method by serval case studies. Section VI concludes this work.

II. Problem Statement

Different from a fixed terrestrial microgrid, a shipboard multienergy microgrid is treated as a mobile microgrid, comprising

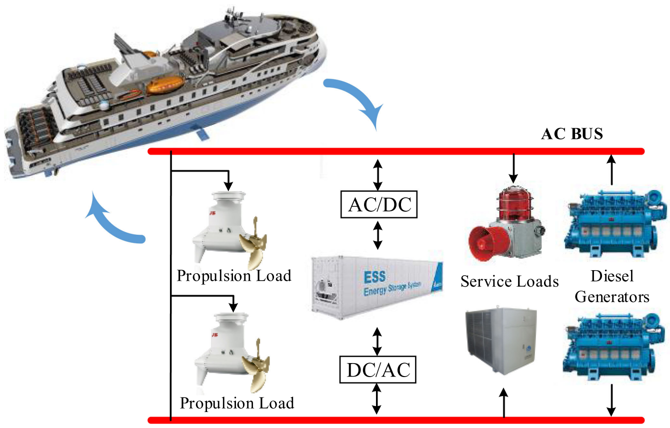

Fig. 1. Configuration of shipboard microgrid.

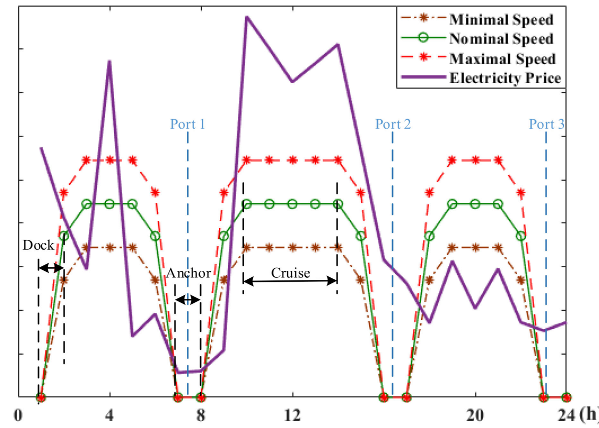

Fig. 2. Voyage scheduling under predicted electricity price.

diesel generators and an ESS to meet the power requirement of both the service and propulsion loads, which is described in Fig. 1.

Note that the cruise ferry needs to stop at different seaports for exchanging passengers and maintenance, the cost of onshore power should be considered to achieve a more efficient and environmentally friendly operation. Therefore, the focus of this work is to optimize the navigation ahead for the AES based on the real-time electricity price of onshore power after that the economic operation is realized by an optimal energy management.

A. Shore-Side Electricity Price Forecasting

Electricity price plays a significant role in the operation of an AES since the power of service loads and ESSs is supplied by onshore power when ships berth at the port. However, influenced by complicated factors, shore-side electricity prices vary with the time periods and various seaports, which increases the difficulty for traditional forecasting methods to obtain a relatively small forecasting error.

In this regard, a deep learning-based forecasting technique is critical to improving the forecasting performance and the adopted prediction method has a great potential to support various operations for AESs, which provides reliable information for ship operators to select the best port and time to berth.

B. Optimal Voyage Scheduling Under Dynamic Electricity Price

Unlike the conventional land-based microgrid, the shipboard power system is subject to not only operation restrictions but also navigation limitations. As illustrated by Fig. 2, the AES always navigates under different ship speeds corresponding to various time-intervals, that are 1) docking mode (the ship approaches or leaves from the port); 2) cruising mode (the ship sails within speed limits), and 3) anchoring mode (the ship berths at the port). To model the traveling characteristic of the AESs, a spatial-temporal model is established, which is defined as follows:

$$\begin{cases} u_{dep,0}(0) = 1 \\ u_{dep,i}(t-1) \geq u_{dep,i}(t), \forall t \in T_{dep,i}, i \in N \\ u_{dep,i}(t-1) \geq u_{cru,i}(t) \geq u_{\mathrm{cru},i}(t+1), \forall t \in T_{cru,i}, i{\in}N \\ u_{cru,i}(t-1) \geq u_{app,i}(t) \geq u_{app,i}(t+1), \forall t \in T_{app,i}, i{\in}N \\ u_{app,i}(t-1) \geq u_{anc,i}(t) \geq u_{anc,i}(t+1), \forall t \in T_{anc,i}, i{\in}N \\ u_{anc,i}(t-1) \geq u_{dep,i}(t), \forall t \in T_{anc,i}, i \in N/\{0\} \end{cases} \tag{1}$$

$$x_{T,i} \cap x_{T,-i} = \emptyset, x_{T,i}$$
$$\in \{T_{dep,i} \cup T_{cru,i} \cup T_{app,i} \cup T_{anc,i}\}, i \in N \tag{2}$$

$$\sum_{i \in N} |x_{T,i}| \leq T. \tag{3}$$

With the help of the predicted electricity prices, the AES is encouraged to adjust the ship speed for onshore power cost reduction. In this way, the voyage scheduling is optimized herein.

It can be observed from Fig. 2 that the AES will arrive at the sea port when the shore-side electricity price is low and the relationship between propulsion load and ship speed is defined as (4)

$$P_{\mathrm{propulsion}}(t) = h_{p1} V(t)^{h_{p2}}. \tag{4}$$

Notice that (4) is crucial to the energy management of shipboard microgrid since the arrival time of the AES is able to select by adjusting the ship speed and, various ship speeds result in various propulsion power demands.

III. Joint Energy Management and Voyage Optimization

A. Joint Scheduling Model

A new coordinated framework is developed in this article not only to jointly optimize the navigation and generation management but also to evaluate the influence of shore-side electricity on the AES operation. In order to reduce environmental negative effect and operational cost, while considering the electricity price variations of onshore power, the joint scheduling model is established as follows

$$\begin{cases} \min Cost = \sum_{t\in T}\sum_{k\in G} u_{DG,k}(t)(FC_{\mathrm{DG},k}(t) \\ \quad + OMC_{\mathrm{DG},k}(t))\Delta t + \sum_{t\in T_{anc}} Cost_{\text{cold ironing}}(t) \\ \min EEOI = \frac{\sum_{t\in T}\sum_{k\in G} u_{DG,k}(t)(GE_{DG,k}(t)\cdot \Delta t)}{m_{AES}\cdot Dist^{NT}} \end{cases}. \tag{5}$$

Compared with previous research works on shipboard microgrids [6]–[16], the operation and maintenance cost of DGs is optimized in this work to enhance the fuel efficiency. Moreover, the cost of onshore power is also considered to allow AES operators to choose the best arrival time for a more efficient operation. The total cost of the AES comprising the fuel cost, the operation and maintenance cost of DGs along with the charging cost is presented in (6), as shown at the bottom of this page.

Additionally, to evaluate the unit GHG emissions of ships during the whole voyage, the $GE_{DG,k}$ is detailed in (7)

$$GE_{DG,i}(t) = b_2\cdot {P_{\mathrm{DG},k}}^2(t) + b_1\cdot P_{\mathrm{DG},k}(t) + b_0. \tag{7}$$

The optimal operation of shipboard microgrid is separated into sailing mode and onshore mode and different constraints should be followed in different operating modes.

Sailing Mode: The sailing mode contains the docking mode and cruising mode, and the AES needs to satisfy not only electrical constraints but also limitations to guarantee the security and stability of the shipboard power system, which are detailed as follows.

1) Service Load Constraint:

$$\begin{cases} P_{service}(t) = u_{ful}(t)P_{L,full} + u_{cru}(t)P_{L,cruise} \\ \quad + u_{dep}(t)P_{L,dock} + u_{app}(t)P_{L,dock} \\ \quad + (1-u_{anc}(t))P_{L,anchor} \\ u_{ful}(t)+u_{cru}(t)+u_{app}(t)+u_{dep}(t) \le u_{anc}(t) \end{cases}. \tag{8}$$

2) Generator Power and Ramp-Rate Constraint:

$$\begin{cases} P_{DG,k}(t) + R_{DG,k}(t) \le \mu_{DG,k}(t)P_{DG,k}^{\max} \\ \mu_{DG,k}(t)P_{DG,k}^{\min} \le P_{DG,k}(t) - R_{DG,k}(t) \\ \mu_{DG,k}(t) \le \sum\limits_{i\in N}[\mu_{app,i}(t)+\mu_{cru,i}(t)+\mu_{dep,i}(t)] \\ |P_{DG,k}(t+\Delta t) - P_{DG,k}(t)| \le R_{u,k}^{\max}\Delta t \end{cases}. \tag{9}$$

3) ESS Output Constraint:

$$\begin{cases} P_{ESS}(t) + R_{ESS}(t) \le P_{ESS}^{\max} \\ P_{ESS}^{\min} \le P_{ESS}(t) - R_{ESS}(t) \end{cases}. \tag{10}$$

4) SOC Constraint:

$$\begin{cases} E_{\mathrm{ESS}}(t) = \begin{cases} E_{\mathrm{ESS}}(t-1) + \frac{P_{\mathrm{ESS}}(t)}{\eta_{\mathrm{dc}}}\Delta t\ , & P_{ESS}(t) < 0 \\ E_{\mathrm{ESS}}(t-1) + P_{\mathrm{ESS}}(t)\eta_{\mathrm{ch}}\Delta t\ , & P_{ESS}(t)\ge 0 \end{cases} \\ SOC_{\min} \le SOC(t) = \frac{E_{\mathrm{ESS}}(t)}{E_{ESS}} \le SOC_{\max} \end{cases}. \tag{11}$$

5) AES Speed Constraint:

$$\begin{cases} 0 < V_{dep}(t), V_{app}(t) \le 10\ (kn) \\ 10 < V_{cru}(t) \le 18\ (kn) \\ 18 < V_{ful}(t) \le 30\ (kn) \end{cases}. \tag{12}$$

6) Voyage Constraint:

$$\begin{cases} Dis(t) = Dis(t-1) + V(t)\Delta t \\ \sum_{t\in T_{dep}\cup T_{cruise}\cup T_{app}} V(t)\Delta t \ge Dis_{i\to j} \end{cases}. \tag{13}$$

7) Reserve Constraints:

$$\sum_{k=1}^{G} R_{DG,k}(t) + R_{ESS}(t) \ge \delta_{\mathrm{OR}}\max_{k\in G}(P_{DG,k}(t) + R_{DG,k}(t)). \tag{14}$$

In (15), the operating reserve comes from the spinning reserves of generators and ESSs, and is to be called when any generated fails [22].

Onshore Mode: To prevent the carbon footprint, the seaport will supply the onshore power to ship service loads and on-board ESS, when AESs berth at the harbor. Unlike previous studies, the influence of onshore power is considered in this AES optimal operation to make the research more realistic. The total power balance constraint is given by (15)

$$u_{\text{anchor}}(t)\cdot P_{UG}(t) + \sum_{k=1}^{G} P_{DG,k}(t) + P_{ESS}(t) = P_{\text{propulsion}}(t) + P_{\text{service}}(t). \tag{15}$$

B. Two-Stage Multiobjective Management

The optimal operation of the AES can be separated into the following two stages.

1) First Stage: Navigation Optimization in Advance: The coordinated scheduling subproblem solved in this stage is formulated as follows.

$$\underset{x}{Minimize}\ \ T$$

Subject to (1)–(3)

$$\begin{cases} FC_{\mathrm{DG},i}(t) = a_2\cdot {P_{\mathrm{DG},k}}^2(t) + a_1\cdot P_{\mathrm{DG},k}(t) + a_0 \\ OMC_{DG,i}(t) = \begin{cases} C_0 + \frac{C_0 - C_1}{P_{DG}^{\min} - 0.5}\cdot P_{DG,k}(t) & P_{DG}^{\min} \le P_{DG,k}(t) \le 0.5p.u. \\ \quad 0.5p.u. \le P_{DG}(t) \le 0.9p.u. \\ \frac{C_2}{P_{DG}^{\max} - 0.9}\cdot (P_{DG,k}(t) - 0.9) & 0.9p.u. \le P_{DG,k}(t) \le 0.9P_{DG}^{\max} \end{cases} \\ Cost_{\text{cold ironing}}(t) = Price(t)P_{\mathrm{UG}}(t)\Delta t \end{cases} \tag{6}$$

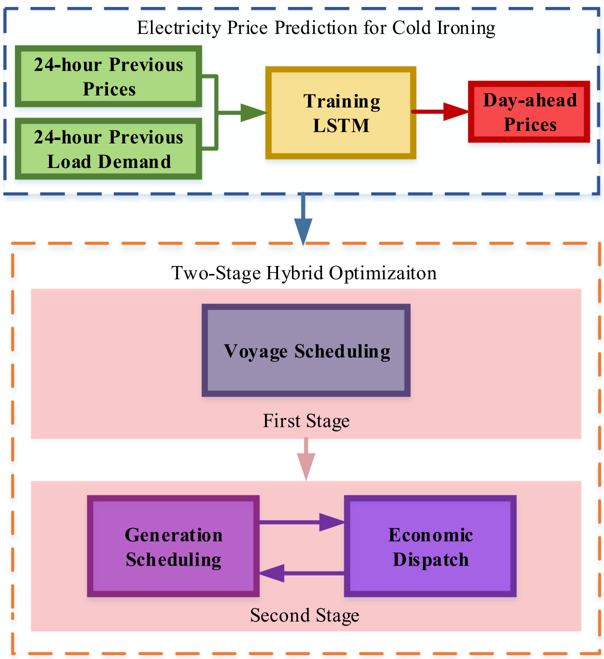

Fig. 3. Electricity price prediction based joint scheduling optimization.

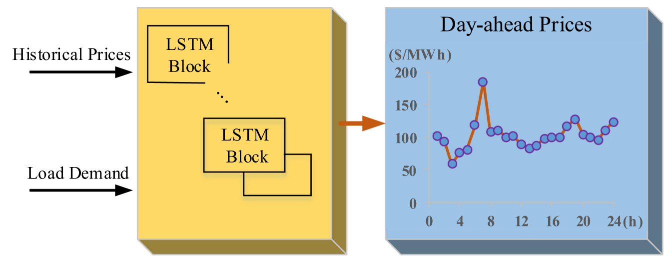

Fig. 4. LSTM based electricity price prediction.

The essence of the first stage optimization is to optimize the navigation for reduction of the sailing time and charging cost, based on the predicted shore-side electricity prices. In this stage, the decision variables (also named as the "here-and-now" variables) including navigation modes in various time-intervals, the total sailing time, and time periods corresponding to the different cruising modes.

2) Second Stage: Generation Scheduling and Economic Dispatch: The first stage operation decisions are obtained by solving the spatial scheduling problem. To further decrease the fuel cost and emissions, the day-ahead economic dispatch problem is formulated as follows.

$$\underset{y}{\text{Minimize}}\ \{\text{Cost}, \text{EEOI}\}$$

Subject to (4)–(15)

In this stage, the "wait-and-see" variables are finally determined, which includes ship speeds, on/off variables of DGs and ESS, outputs of DGs and ESSs.

According to the above decomposition, the subproblem in the first stage turns into a voyage scheduling problem with changing propulsion loads, and the subproblem in the second stage is to realize an economic dispatch for the AES during the voyage deviations by regulating the generations. The whole procedure is shown in Fig. 3.

IV. Solution Method

A. Deep Learning Based Electricity Price Prediction

Electricity prices are a nonstationary stochastic time-series, which are influenced by many factors, such as the policy, load demand, temperature, and fuel prices. To better reflect the characteristics of the electricity prices, the LSTM network [23] is used in this article to predict the short-term electricity price of onshore power because of the strong capability of capturing the complex relationship between inputs and outputs. To train parameters of the LSTM, the previous 24-h data of electricity prices and load demands serve as prior knowledge for LSTM training inputs. The day-ahead hourly electricity prices are the target and the forecasting process can be found in Fig. 4.

B. Two-Stage Hybrid Optimization Method

Different from the previous studies with a fixed time-window optimization, one of the essential goals of this article is to optimize the navigation time for an AES, indicating the time-window is a variable rather than a constant. Furthermore, the entire cost and GHG emissions are minimized by the optimal energy management. Based on the above description, the two-stage multiobjective is redefined as follows

$$\begin{cases} \min\limits_{x\in X} f(x) + \{Q_1(x), Q_2(x)\} \\ Q(x) = \max\limits_{w\in W} Q(x,w) = \max\limits_{w\in W} \{\min\limits_{y\in Y} q(y)\} \end{cases} \tag{16}$$

where x denotes the vector of the first stage decisions, and the function $Q(x)$ is the worst-case recourse cost over all realisations in an uncertainty set W. In this article, $Q_1(x)$ and $Q_2(x)$ represent the total cost and EEOI function, respectively. Suppose that $Q(x, w)$ is the recourse problem under a realization w, and w is the uncertainties of the electricity price. Y represents a feasible set within constraints (5)–(8) and y denotes the energy management decisions which are optimized after the voyage scheduling.

Note that the constraint in (4) is cubic in mathematical and the solution contains a large number of binary variables, including generator state vectors, cruising mode in each time interval, and ESS energy level, which increases the difficulty of traditional optimization approaches in searching the best decision. In order to solve the proposed problem, a hybrid optimization algorithm combined the MODE [24] with the MILP [25] is developed to find the optimal decisions for the coordinated navigation and generation optimization. The whole solving procedure is presented in Fig. 5.

V. Simulation Results

A. Electricity Price Forecasting Result

1) Training Dataset: The training data is important to achieve an accurate performance for artificial neural networks.

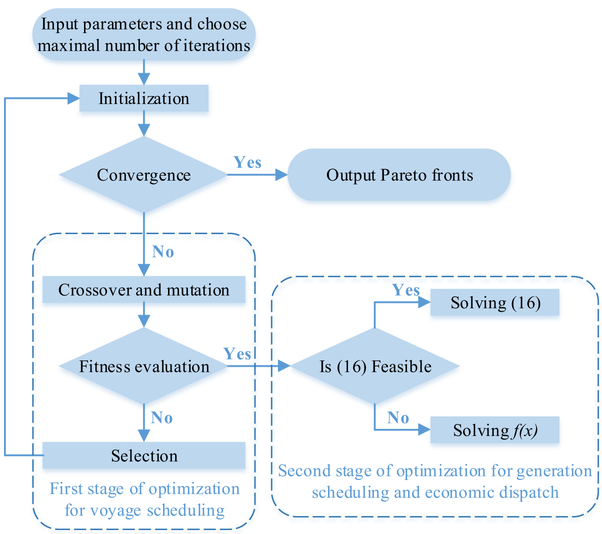

Fig. 5. Flowchart of the hybrid optimization algorithm.

TABLE I
BASIC PARAMETERS FOR MACHINE LEARNING

Method	Layers	Neurons	Epochs
BPNN	3	55	300
RBFNN	3	varied	500
Elman NN	3	50	200
LSTM	3	50	200

Accordingly, the hourly data of electricity prices and load demands in the Australian power system are sampled for prediction [26]. Since different areas have different electricity price variations, the data of various provinces in Australia are utilized to tune the parameters of the LSTM network. More specifically, a 12-month period hourly data in the provinces of Queensland (QLD), New South More specifically, a 12-month period hourly data in the provinces of Queensland (QLD), New South Wales (NSW), and Victoria (VIC) from January 01, 2017 to December 31, 2017 are selected for electricity price prediction, indicating that different factors including various seasons, working days and holidays are considered [27]. The period spans over 360 days (8640 h), which is divided in two subsets for training (from January 01, 2017 to July 31, 2017, and September 01, 2017 to November 30, 2017) and testing (from August 01, 2017 to August 31, 2017 and December 01, 2017 to December 31, 2017).

2) Forecasting Performance: In this article, various machine learning methods including the BPNN, the RBFNN and the Elman NN, are applied to predict the electricity prices of cold ironing to verify the high accuracy of the LSTM unit.

The related parameters and conditions of neural networks are listed in Table I.

The BPNN is regarded as a classical approach for short-term electricity price forecasting [28] and its performance is presented in Table II and Fig. 6.

As can be observed from above that the electricity prices in various places show strong diversity and nonlinearity but the BPNN can only capture few features of price variations in

TABLE II
PREDICTION ERROR AMONG DIFFERENT METHODS

	QLD		NSW		VIC	
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
BPNN	15.89%	12.59	18.56%	20.76	21.07%	34.04
RBFNN	14.71%	12.32	16.74%	26.67	15.70%	33.01
Elman NN	8.24%	6.59	11.44%	21.15	8.39%	14.29
LSTM	2.03%	2.38	4.85%	5.03	3.15%	3.82

TABLE III
PARAMETERS FOR CASE STUDY

	Rated Power (MW)	$a_{2,1,0}$ (m.u./p.u)	$b_{2,1,0}$ (uCO_2/p.u)
DG1	8.6	300,2185,30	386,-2070,386
DG2	6.8	210,623,10	362,-613,956
DG3	6.8	204,604,10	362,-613,956
ESS	η_{ch}=95% , η_{dc}=100% , 3.5 MW, 7.5 MWh		
Ship Speed	$h_{p1}=0.003$, $h_{p2}=3$, $V_{max}=33.336$ km/h		

general. When the shore-side electricity price changes dramatically, the BPNN can hardly follow the pattern and even sometimes the predicted values will drop below zero, which is obviously unrealistic in real-world.

To improve the predicting performance, the RBFNN [29] and the Elman NN [30] are used for the electricity price forecasting under consideration of the load demands. Compared to the BPNN, the MAPE is reduced, for instance, in NSW, the MAPE is decreased from 18.56% to 16.74% and 11.44%, respectively. The RMSE, however, is increased to 26.67 and 21.15, respectively, indicating that the day-ahead electricity price forecasting is a comprehensive task and a more accurate method is needed to achieve a greater performance.

To further improve the forecasting performance, the LSTM network is used in this article to predict electricity prices in advance for optimal operation of the AES. Generally, the LSTM achieves the best forecasting performance among all cases, with the RMSE of 2.38 in QLD, 5.03 in NSW, and 3.82 in VIC, respectively. It can be illustrated from forecasting results that the BPNN and the RBFNN have to sacrifice more input parameters and time steps for a relatively accurate performance, while the LSTM can better capture the pattern using less neurons and epochs.

B. Optimization Result of AES

1) Parameter Description: The proposed algorithm is applied to an all-electric shipboard power system on a cruise ferry with three DGs and a lithium-ion battery. The related parameters of this AES [31] are detailed in Table III.

In addition, the cruise sets sails from Sunshine Coast in QLD, and stops at Gold Coast (QLD), Port Macquarie (NSW), and Gabo Island (VIC) for exchanging passengers and maintenance. Fig. 7 depicts the navigation route of this ship.

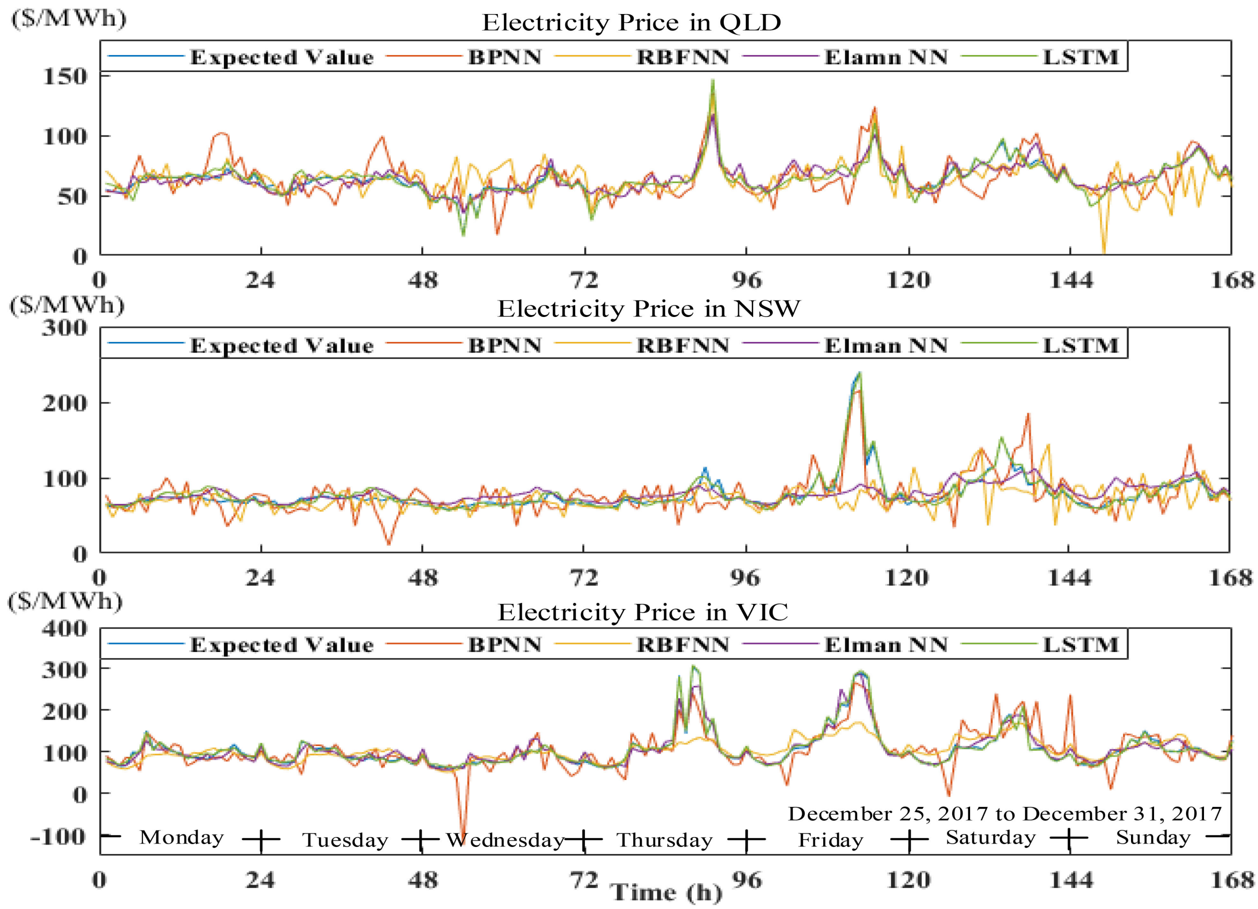

Fig. 6. Forecasting results for comparison.

Fig. 7. Navigation route.

2) Case Study: The impacts of the integration of optimal energy management and voyage scheduling in three cases are studied and compared to verify the efficiency of the developed two-stage hybrid optimization method.

Case 1: A regular cost analysis for the AES without optimal energy management and voyage scheduling.

TABLE IV
OPTIMIZATION RESULT SUMMARY

	Case 1	Case 2	Case 3	Case 4
Fuel cost（m. u.）	126302	122900	113118	120952
O&M（m. u.）	20811	8130	618	6346
Cold ironing cost（m. u.）	3643	3643	2018	2056
Total cost（m. u.）	150756	134559	115754	129354
EEOI (g·CO_2/ton·nm)	19.18	19.04	18.81	18.98
Total sailing time (hour)	46	46	43	45

Case 2: An optimal cost analysis for the AES under optimal energy management but without voyage scheduling.

Case 3: An optimal cost analysis by the proposed framework and method but without spinning reserve.

Case 4: An optimal cost analysis by the proposed method considering spinning reserve.

The resultant operation cost, and GHG emissions of different cases are listed in Table IV.

Case 1:

It can be seen from Table IV that the shipboard power system of the cruise ferry has to suffer from a high cost of 150756 (m.u.)

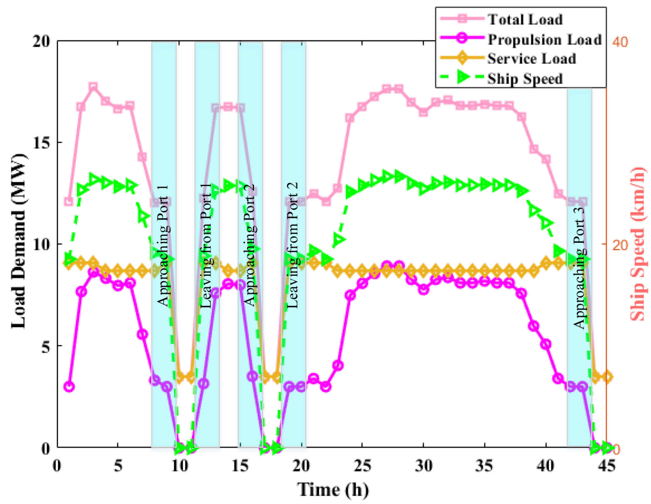

Fig. 8. Ship load profile and sailing speed.

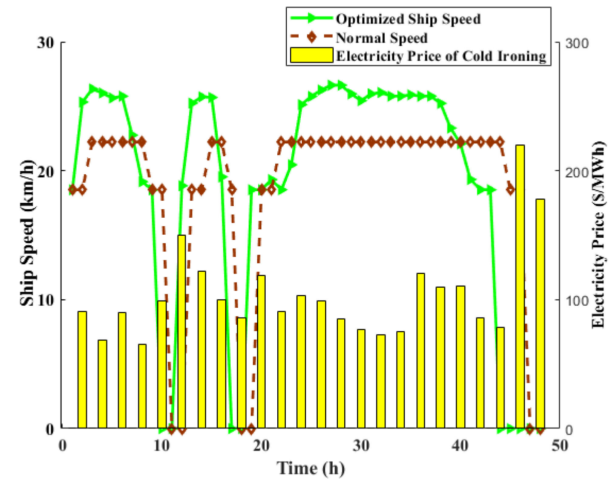

Fig. 9. Optimized ship speed based on predicted electricity price.

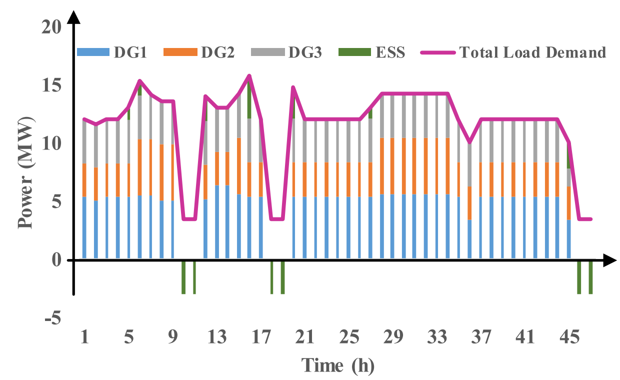

Fig. 10. Energy management of shipboard power system.

and serious emissions of 19.18 (g·CO_2/ton·nm) due to the low efficiency of the DGs. As a consequence, the efficient energy management is necessary to the AES.

Case 2:

An optimal energy management method is explored in this case to optimize the generation outputs on the shipboard. Compared to Case 1, the fuel cost and total cost is reduced from 126302 (m.u.) to 122900 (m.u.), and from 150756 (m.u.) to 134559 (m.u.), respectively. Furthermore, the GHG emissions are decreased by 0.14 (g·CO_2/ton·nm). However, the charging cost from the shore-side electricity is still high with 3643 (m.u.), as the ship stops at the port.

It should be noted that the sailing speed and navigation time play a significant role in both fuel cost and onshore power cost since different sailing speeds correspond to various propulsion load conditions and the related arrival time leads to different expense from cold ironing, which indicates that the voyage scheduling cannot be ignored.

Case 3:

The proposed two-stage hybrid optimization algorithm is utilized in this case for cost and emission reduction. Notice that the service load of the AES varies with operating conditions (full-speed sailing, regular cruising, docking and anchoring), which is different from the continuously changing loads in the standalone power system on land. Moreover, unlike the previous studies whose service load condition is a prior certain value, in the first stage of this optimization framework, the service and propulsion load profile is determined and optimized corresponding to the sailing speed, which is shown in Fig. 8.

According to the above information, the total navigation time is reduced to 43 h, which is 3 h shorter than that in Case 1 and Case 2.

As observed from Fig. 9, after the optimization of the ship speed, the cruise ferry can arrive at the destination in advance, especially when the shore-side electricity price is low. Consequently, the cost from the shore-side electricity drops from 3643 (m.u.) to 2018 (m.u.).

Based on the grid status obtained by the first-stage optimization, an optimal generation scheduling of the shipboard microgrid is realized in the second-stage optimization. Under the proposed method, not only the total operation cost but also the EEOI are the lowest among three cases, implying the efficiency of the proposed algorithm.

Case 4:

In order to ensure the reliability of shipboard power system during contingency, a spinning reserve capacity is considered in this article to withstand the sudden outage of diesel generators or an unforeseen increase in total load. The energy management of this cruise under spinning reserve effect during the whole sailing is presented in Fig. 10.

As illustrated by Fig. 10 that with the support of spinning reserve, the total load demand can be satisfied even when one of DGs shuts down. However, compared with Case 3, the fuel cost and navigation time is increased to $120,952 and 45 h, respectively, since the diesel generators cannot always work at the best operating point due to the capacity of spinning reserve.

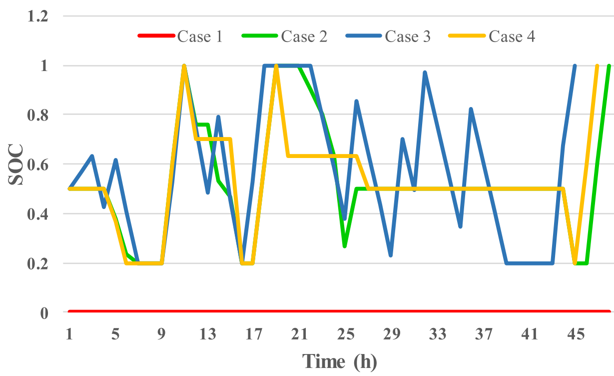

Fig. 11. SOC profile in various cases.

In order to further verify the proposed method, the SOC profile in four cases are shown in Fig. 11.

As shown in Fig. 11, the on-board ESS can help DGs to compensate the imbalance power, when the load demand is high. On the other hand, when the total demand decreases or the ship anchors at the harbor, the ESS will be charged by the onshore power. Furthermore, the proposed generation optimization method helps to improve the ESS charging and discharging performance. The energy efficiency is enhanced by an optimal energy management herein.

VI. Conclusion

With the increasing electrification of on-board power systems, the influence of onshore power becomes significant in navigation optimization and AES energy management. In this study, a coordinated framework is modeled as a joint optimal generation and voyage scheduling problem, taking into account the cost of cold ironing. In order to obtain the accurate information of the electricity prices at different ports, a deep learning-based forecasting technique is adopted to predict day-ahead electricity prices for the AES operators. Then a two-stage hybrid optimization algorithm is developed to improve the energy efficiency and reduce GHG emissions of the AES based on the predicted shore-side electricity prices. Several case studies are analysed and compared to demonstrate the efficiency of the proposed method. Simulation results reveal that with the help of the proposed method, the AES can punctually arrive at the destination with a minimum cost and emission, especially when the electricity price relatively low. Furthermore, the proposed method can be extended to study other mobile microgrids such as container ship and bus fleet. In addition, the regulatory constraints of the onshore power including the maximum power supply and transmission limit will be investigated in the future work to further improve the optimization algorithm.

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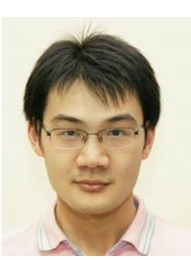

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