Chapter 9

The Ways Ahead

9.1 Future Maritime Grids

To illustrate the future maritime grids, we re-draw Fig. 4.1 here and give a more detailed illustration for future maritime grids. The following Fig. 9.1 is renamed as “future maritime grids”.

In Fig. 9.1, the main types of maritime grids including harbor city grid (2), seaport microgrids (4), offshore platforms (10), shipboard microgrids (12), offshore wind farms (14), island microgrid (15).

In the first place, harbor city grid (2) is the core and acts as the main grid for the rest of maritime grids. The main functions include receiving the land-based renewable generation (1), supplying the industrial facilities (9), providing power to seaport microgrids (4), and operating two-way ferries (12) to island microgrid (15). The former four are energy connections and the fifth is a transportation connection.

Then seaport microgrid (4) is the network within a seaport, and this microgrid receives electricity from the harbor city grid (2) and providing raw materials to the industrial facilities (9). The seaport microgrid also receives energy from the seaport renewable (6). Seaport provides berth positions to the cargo ships (16), and handling the cargos by the port cranes (13). The cargos are then lifting by the transferring vehicles (5) to the stackyard (8), and the cold-chain containers are stored in the reefer area (7). Besides, seaport microgrid provides cold-ironing power to the shipboard microgrid (12).

The offshore platforms (10) include oil drilling platforms or other construction ships. They produce raw materials and transmit them to the industrial facilities (9) or island (15) by the oil pipes or other networks. The raw materials can be also transported by cargo ships (16).

The shipboard microgrid (12) is the network installed in cargo ships (16), offshore support vessels (3), and other ships. It receives the cold-ironing power from the seaport microgrid (4), and it periodically sails between seaport and islands (15) or other places to transfer cargos.

- (3) The coordination between the shipboard microgrids and the island microgrids. This scenario is similar to the case between seaport and ships when an island has a very strong power network. When the power grid of the island is weak, the ships may in reverse support the islands, which is referred to as “mobile power plant” [7].
- (4) The coordination between the offshore platforms. There are generally many offshore platforms in an ocean area, and they should coordinate with each other to complete the same task, i.e., oil drilling, construction, and so on.

9.2 Data-Driven Technologies

9.2.1 Navigation Uncertainty Forecasting

Navigation uncertainty generally comes from uncertain weather, and Chap. 4 has emphasized the influences of navigation uncertainty on the operation of maritime grids. Until now, there are many data-driven maritime weather forecasting methods for ships and seaport [8–10], in different timescales, or by different algorithms, using different attributes, and also have different advantages and disadvantages. Our focus is on how to use those forecasting datasets to generate the distributions and uncertainty sets of energy management models. With the obtained distributions or uncertainty sets, stochastic and robust programming models can be formulated for different operating scenarios.

In recent research [11], a novel data-driven heuristic framework for vessel weather routing is formulated as Fig. 9.2. Based on the weather forecasting results, the ship chooses a better sailing route to save fuel consumption. The main key performance indicators (KPIs) of ships can also be predicted.

Fang et al. [12] also studies the robust energy management of all-electric ships when considering navigation uncertainties, but the weather conditions are simply classified as four sub-scenarios and only the worst case is considered. In the future, more accurate uncertainty sets should be forecasted to facilitate the operation of maritime grids.

9.2.2 States of Battery Energy Storage

Chapters 5–8 have emphasized the critical roles of battery energy storage in the maritime grids for load leveling and power quality issues. Generally, there are six states for battery energy storage, i.e., state of charge (SOC), state of power (SOP), state of energy (SOE), state of safety (SOS), State of temperature (SOT), and state of health (SOH). The above states are all essential indicators for the battery management system and many methods have been proposed to estimate them, and various data-driven techniques have been utilized.

Fig. 9.2 Flowchart of the data-driven weather routing method

Generally, SOC is defined as the ratio of available capacity to the nominal capacity. Here the nominal capacity stands for the maximum amount of charge. Using the tank of a fuel vehicle as an analogy, SOC is similar to the fuel gauge. The definition of SOC is shown in (9.1) [13].

$$SOC(t) = SOC(t_0) + \int_{t_0}^t I(t) \cdot \eta / Q_n dt \quad (9.1)$$

where $I(t)$ is the current of battery energy storage; Q_n is the nominal capacity; η is the coulombic efficiency.

Another indicator, SOP is generally defined as the available power that a battery can supply to or absorb over a time horizon [14]. The definition of SOP is shown as (9.2).

$$\begin{cases} SOP^{charge}(t) = \max(P_{min}, V(t + \Delta t) \cdot I_{min}^{charge}) \\ SOP^{discharge}(t) = \min(P_{max}, V(t + \Delta t) \cdot I_{max}^{discharge}) \end{cases} \quad (9.2)$$

where P_{min} and P_{max} are the lower and upper limits of power; I_{min}^{charge} and $I_{max}^{discharge}$ are the lower and upper limits of current.

Another indicator, SOE is defined as the supplying/absorbing discrepant energy amounts in different voltage levels, which is given as (9.3).

$$SOE(t) = SOE(t_0) + \int_{t_0}^t P(t) / E_N dt \quad (9.3)$$

where $P(t)$ is the power; E_N is the nominal energy capacity.

Another indicator, SOS represents the hazard level when battery operating, and the definition is given as (9.4).

$$H_r = H_s \cdot H_l \quad (9.4)$$

where H_r , H_s , H_l represent the hazard risk, hazard severity, and hazard likelihood, respectively. In [15], H_s can vary from 0 to 7 as an integer to represent the hazard level; H_l can take values from 1 to 10 to represent the occurrence percentage of failures; H_r utilizes two states (i.e., H_s and H_l) to find a safe operating region.

The temperature has been recognized as one main factor for battery degradation, and the SOT indicates the operating temperature of battery, including the estimations of external, internal, and temperature distribution. In general, the external temperature is easy to control, and the internal temperature and temperature distribution are much more important to represent the state of battery. The estimation of SOT is based on the thermal dynamic model as (9.5) [16].

$$\begin{cases} C_c \cdot \dot{T}_c = \dot{Q} + (T_s - T_c) / R_x \\ C_s \cdot \dot{T}_s = (T_\infty - T_s) / R_u + (T_s - T_c) / R_c \end{cases} \quad (9.5)$$

where T_s and T_c are the surface and core temperature, respectively; R_u and R_c are the conductive and convective resistances, respectively; T_∞ is the ambient temperature. The last indicator is the SOH to represent the health state of battery, which is given by the following.

$$SOH = C_a / C_r \times 100\% \quad (9.6)$$

where C_a and C_r are the actual and rated capacity, respectively.

There are many estimation methods for the above six states of battery energy storage [13–20], and these methods belong to multiple timescales, which are shown as Fig. 9.3 below.

Besides, there are different timescales for each state. For example, there are offline training and online estimation stages for SOH estimation in Fig. 9.4 [21].

In summary, current state estimation methods can be used in maritime grids when addressing the working conditions of highly humid and saline, and high-temperature. In Fig. 9.4, these characteristics should be considered in the experimental conditions and the uncertainty management of SOH estimation model. However, there is still very little literature on this topic now.

Fig. 9.3 Time-scale of state estimation of battery

Besides, the above state estimation methods are for a single battery cell. As shown in Fig. 9.5, a battery pack is comprised of many battery cells and generally different cells have different degradation speeds. This difference should be considered, named as the inconsistency of state estimation.

9.2.3 Fuel Cell Degradation

The importance of fuel cells in maritime grids has been clarified in Chap. 8, and the technological development will drive the further large-scale integration of fuel cells. Similar to battery, the degradation of fuel cells is important and certain methods should be proposed to estimate the degradation in different scenarios. Generally, the fuel cell degradation methods can be classified as (1) stack voltage degradation model; (2) Electrochemical impedance spectrometry (EIS) impedance estimation; (3) Remaining useful life (RUL) estimation. Their advantage and disadvantages are shown in Table 9.1.

The stack voltage degradation models use the output voltage V_{stack} to demonstrate the degradation phenomenon, and are usually based on two prototypes, shown in (9.7) and (9.8), respectively.

$$\begin{cases} V_{stack} = V_{rate} \cdot D_{fc} \\ D_{fc} = k_p \cdot (P_1 \cdot n_1 + P_2 \cdot n_2 + P_3 \cdot t_1 + P_4 \cdot t_2) \end{cases} \quad (9.7)$$

$$V_{stack} = V_0 - b \cdot \log(i_{fc}) - r \cdot i_{fc} + \alpha \cdot i_{fc}^\sigma (1 - \beta \cdot i_{fc}) \quad (9.8)$$

In (9.7), V_{stack} is the stack voltage; D_{fc} is the degradation rate; k_p is the accelerating coefficient; P_1, P_2, P_3 and P_4 are the degradation rates led by the load change, start-up/shut-down, idling, and high-power demand, respectively; and n_1, n_2, t_1, t_2 denotes the corresponding times/time-periods. In (9.8), V_0 represents the open-circuit voltage; i_{fc} is the current of fuel cell; b, r, α , and σ are parameters deduced from the experiment dataset. When the dataset changes, all the parameters should be adjusted.

Fig. 9.4 Time-scale of state estimation of battery

Fig. 9.5 Battery cells and Battery pack

Table 9.1 Summary of different fuel cell degradation methods

Model	References	Methods	Advantages	Disadvantages
Stack voltage degradation model	[22–24]	data-driven parameter recognition	1. Easily implement 2. Less requirement on theoretical analysis	1. Highly rely on experiment 2. Hard to adjust the parameters
EIS impedance estimation	[25, 26]	Model-based methods	1. Easily implement 2. Suitable for diagnostics field	Cannot directly forecast SOH
RUL estimation	[27–29]	Hybrid methods	Robustness to uncertainties	Computational stress

EIS is carried out by adding a small sinusoidal perturbation on the nominal current and then the EIS impedance can be calculated as the ratio between the response and the perturbation. This method can characterize the phenomenon inside the fuel cell and evaluate the fuel cell degradation [25], which are widely used in the diagnostics field, but it cannot give the information of SOH. RUL methods are a series of hybrid methods, which can be based on the semi-empirical model [28], or various machine-learning methods [30]. Since the recent development of data-mining techniques, RUL methods also have many new applications [30].

In summary, the fuel cell degradation estimation is similar to the battery and a similar estimation process can be utilized. The gaps before implementing in maritime grids are addressing the working conditions with high humidity, and high-temperature. However, there is still very little literature working on this topic.

9.2.4 Renewable Energy Forecasting

Chapter 5 has emphasized the importance of renewable energy forecasting of maritime grids. Figures 5.10 and 5.11 show that the forecasting of renewables onboard should consider more features. To recall this part, Figs. 5.10 and 5.11 are re-drawn as Fig. 9.6a, b as follows.

Fig. 9.6 Two extra features in onboard renewable energy forecasting [31]

An adaptive clustering method for onboard photovoltaic energy is proposed in [32]. The sketch process is shown in Fig. 9.7.

With the proposed method, the scenarios of photovoltaic energy can be adaptively obtained, and the administrator can give an optimal energy scheme for each scenario. Later in [33], the ship motion, temperature, irradiance, and temperature are all considered and a hybrid ensemble forecasting method is formulated as Fig. 9.8.

With the proposed method in Fig. 9.8, the onboard photovoltaic energy can be predicted with more accuracy. Two representatives above show the keys for the renewable energy forecasting in maritime grids: (1) properly clustering the original dataset, and the main reason is the weather conditions may change more frequent in maritime grids than other land-based applications; (2) putting more practical features into the forecasting model, such as the ship motion and rolling. With the development of renewable energy technology, the penetration of large-scale renewable energy into maritime grids will become reality, and the renewable energy forecasting in maritime grids will find a promising scenario for application.

9.3 Siting and Sizing Problems

9.3.1 Energy Storage Integration

Chapter 6 has clarified the functions of energy storage in the long-term operation of maritime grids: (1) improving economic and environmental characteristics of maritime grids [5, 12, 34]; (2) benefiting the operation of onboard equipment [31, 32, 35]; (3) improving the resilience of maritime grids [36], which are illustrated in Fig. 9.9.

In Fig. 9.9a, the main engines and energy storage are sharing the highly fluctuated power demand via maritime grids. The energy storage shares the highly fluctuated part and the main engines can work in a constant and economic working condition. In Fig. 9.9b, new equipment is integrated into the maritime grid, and the energy storage

Fig. 9.7 Adaptive clustering methods for onboard photovoltaic energy

Fig. 9.8 Hybrid ensemble forecasting method

Fig. 9.9 Main functions of energy storage in maritime grids

can share the power demand of new equipment to improve its behavior. In Fig. 9.9c, energy storage is installed distributionally in different zones of maritime grid, and energy storages in different zones share the power demand, and make the system be resilient to various failures.

Since the important functions above, energy storage gradually becomes essential equipment in maritime grids to improve system characteristics. However, energy

storage, generally battery for long-term operation, is still expensive and the installment area is also another limit for energy storage. The balance between the economic benefits and the system characteristics motivates the siting and sizing problems of energy storage.

Reference [32, 37, 38] propose optimal energy storage sizing methods after comprehensively studying the influences of energy storage on the penetration of photovoltaic energy into maritime grids, which considers effects of the ship motion, deck rolling, and solar irradiation density. In seaport, [2] proposes six indexes to indicate the green operation, and a two-stage energy storage sizing problem is formulated to improve the indexes. Since the battery is limited in power density, [34, 39] propose optimal sizing methods for hybrid energy storage, i.e., high power density energy storage for the high-frequency load demand, and battery for the low-frequency load demand. For the system resilience, a distributed energy storage siting and sizing model is formulated, and the simulation results show that the distributionally installed energy storages benefit the resilience.

In summary, future research should consider more specialties of maritime grids, which are shown as follows.

- (1) Special network structures. Maritime grids have a different network structure compared with conventional land-based microgrids. This feature in ships has been illustrated in Chap. 5 as Fig. 5.11. We re-draw this figure to Fig. 9.10 below, and we can find the network structure of ships is zonal and parallelly designed.
- (2) The distributional installment of energy storage. Different from the land-based applications, the energy storages in maritime grids are mostly distributionally installed. For example, the energy storage system in ships is usually separated into several parts and installed in different watertight compartments for system

Fig. 9.10 The graph topology of an all-electric ship

resilience. In seaport, energy storages have different functions, i.e., for cold-ironing, for port cranes, for electric truck charging, and so on. So the energy storages also need to be distributionally installed.

- (3) The redundant capacity of energy storage. Different from conventional land-based microgrids, maritime grids generally receive less support from the main grid. In this sense, energy storage is viewed as one of the main power sources to improve system resilience, and therefore needs to have a redundant capacity.

9.3.2 Fuel Cell Integration

Chapter 8 has revealed the fuel cell is a promising power source for the future maritime grids, and its integration is an irreversible trend. Currently, there are many practical cases and studies on the siting and sizing of fuel cells in maritime grids. With these cases, fuel cell shows similar effects as the integration of energy storage, i.e., highly flexible, energy-efficient, no combustion process, and easily maintained. The functions are also similar: (1) improving economic and environmental characteristics of maritime grids; (2) benefiting the operation of onboard equipment; (3) improving the resilience of maritime grids. Although these similarities, fuel cell is a power source and has no need to charge, and therefore the fuel cell is able to sustain the long-term power demand.

As above, future research should consider the following aspects as Fig. 9.11 before it can integrate into maritime grids.

- (1) Fuel cell is a power source and has similar functions with the main engines. In this sense, the maritime grids should be expanded for its integration, i.e., structure modification.
- (2) Generally, fuel cell and main engines serve different load demands, i.e., main engines for the large-scale load demand such as propulsion, and fuel cell for the small-scale but critical load demand such as control center. The division of responsibilities should be considered.

Fig. 9.11 Fuel cell integration and maritime grid expansion

9.4 Energy Management

With the above illustrations, the main target for maritime grids is to achieve the cost-efficient and green development of the maritime industry, and the energy management methods/strategies are fundamental for this target. In the future, the energy management of maritime grids should have two main abilities: (1) Ambient environment perception, i.e., the real-time perception of working conditions and the quick responding abilities for the changes of working conditions. (2) Optimal energy scheduling ability, i.e., real-time perception of system conditions and the ability for the optimal energy scheduling among different sources and equipment. These two abilities are shown in Fig. 9.12 below.

From Fig. 9.12, the first ability, ambient environment perception, relies on real-time data measurement and the corresponding data-driven techniques. This ability can provide adequate inputs to indicate the energy scheduling of maritime grids. It should be noted that the ambient environment includes the working conditions and the coordination from other maritime grids, such as the coordination between berthed-in ships and seaport.

Then the second ability, optimal energy scheduling ability, should integrate all the current management methods, i.e., the methods mentioned in Chaps. 5–8, namely, uncertainty management, energy storage management, multi-energy management, and multi-source energy management, and determines an optimal energy scheme to respond to the ambient working conditions.

Fig. 9.12 Energy management of maritime grids

9.5 Summary

Generally, maritime grids are born under the trend of maritime transportation electrification, and this trend is irreversible in the future. From the views of electrical engineering, maritime grids are a series of microgrid-scale networks which undertake different maritime tasks. The electrical network serves as the backbone and connects with other networks with different functionalities. This characteristic determines the operation of maritime grids should have plenty of similarities with conventional microgrids, but the maritime tasks involved further make the maritime grids with many distinguishing features. In this sense, it is essential and also very necessary to study this type of special microgrids before they can be implemented in real-world.

In this book, maritime grids are defined as those networks installed in harbors, ports, ships, ferries, or vessels. A typical maritime grid consists of generation, storage, and critical loads, and can operate either in grid-connected or in islanded modes, and operate under both the constraints of the energy system and maritime transportation system, and formulates as a “maritime multi-energy system”, and the energy management of this special system will shape the energy efficiency improvement of the future maritime transportation system.

In this book, optimization-based energy management methods are comprehensively reviewed and overviewed with plentiful case studies. In Chaps. 1–4, i.e., (1) the introduction for maritime grids, (2) the mathematical basics of optimization; (3) mathematical formulation of management targets and (4) formulation and solution of maritime grid optimization, give illustrative descriptions on the research focus. Then in Chaps. 5–8, four aspects, i.e., (1) energy management under uncertainties, (2) energy storage management, (3) multi-energy management, and (4) multi-source energy management, are discussed. At last, this chapter overviews the future roadmap in four parts, i.e., (1) future maritime grids, (2) data-driven technologies, (3) siting and sizing problems, and (4) energy management. With the above arrangement, the initial research framework of maritime grids has been launched and specific efforts are expected in this field for future development.

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