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Review

A Comprehensive Review of Shipboard Power Systems with New Energy Sources

He Yin [1], Hai Lan [2,*], Ying-Yi Hong [3], Zhuangwei Wang [1], Peng Cheng [2], Dan Li [1] and Dong Guo [1]

[1] Yantai Research Institute of Harbin Engineering University, Yantai 264000, China
[2] College of Intelligent Systems Science and Engineering, Harbin Engineering University, Harbin 150001, China
[3] Department of Electrical Engineering, Chung Yuan Christian University, Taoyuan 32023, Taiwan
* Correspondence: lanhai@hrbeu.edu.cn

Abstract: A new energy ship is being developed to address energy shortages and greenhouse gas emissions. New energy ships feature low operational costs and zero emissions. This study discusses the characteristics and development of solar-powered ships, wind-powered ships, fuel cell-powered ships, and new energy hybrid ships. Three important technologies are used for the power system of the new energy ship: new-energy spatio-temporal prediction, ship power scheduling, and Digital Twin (DT). Research shows that new energy spatio-temporal prediction reduces the uncertainty for a ship power system. Ship power scheduling technology guarantees safety and low-carbon operation for the ship. DT simulates the navigational environment for the new energy ship to characterize the boundary of the shipboard's new energy power generation. The future technical direction for new energy ship power systems is also being discussed.

Keywords: ship power system; new energy; spatio-temporal prediction; ship power scheduling; digital twin

PACS: J0101

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Citation: Yin, H.; Lan, H.; Hong, Y.-Y.; Wang, Z.; Cheng, P.; Li, D.; Guo, D. A Comprehensive Review of Shipboard Power Systems with New Energy Sources. *Energies* **2023**, *16*, 2307. https://doi.org/10.3390/en16052307

Academic Editor: Maria Carmela Di Piazza

Received: 31 December 2022
Revised: 21 February 2023
Accepted: 24 February 2023
Published: 27 February 2023

1. Introduction

Energy shortages and environmental pollution are becoming increasingly severe. Ships emit pollutants such as greenhouse gases (GHG), sulfur oxides (SO_x), nitrogen oxides (NO_x), and particulate matter (PM) in operation, which causes global warming [1]. The most recent estimates from the Fourth IMO (International Maritime Organization) GHG Study 2020 show that GHG emissions due to shipping have increased from 977 million tons in 2012 to 1076 million tons in 2018 due to a continuous increase in global maritime trade. The proportion of shipping emissions in the global anthropogenic GHG emissions has increased from 2.76% in 2012 to 2.89% in 2018.

The Paris Agreement states that the increase in global average temperature must be less than 2 °C more than pre-industrial levels [2]. In 2018, the Initial IMO Strategy on reducing GHG emissions from ships required that the total annual maritime GHG emissions be reduced by at least 50% by 2050, compared to 2008. The resolution states that carbon emissions from the shipping industry must be measured using the Energy Efficiency Design Index (EEDI) [3]. This index is used to calculate the energy efficiency of ships throughout the voyage [4]. The shipping industry is undergoing a transition to a low-carbon industry.

Four technologies (Table 1) are currently used to reduce maritime emissions and fossil fuel consumption:

(1) Marine diesel engine transformation technology features three categories. In terms of increased fuel injection technology, In 2019, Liu [5] proposed a high-pressure common rail injection system to increase the operating efficiency of diesel engines and reduce fuel consumption. Alaattin Osman Emiroğlu [6] determined the effect of fuel injection pressure

on the combustion process and emissions from single-cylinder diesel engines. The results illustrate that the droplet diameter decreases, and the fuel burns more efficiently as the injection pressure increases, in terms of alternative fuels. Maja Pečić [7] determined the technical, environmental, and economic characteristics of cleaner fuels (electricity, methanol, liquefied natural gas, hydrogen, ammonia, and biodiesel) as a substitute for fossil fuels in 2021. The study shows that all-electric ships that use clean fuels will reduce carbon emissions by up to 51%. In 2022, Wang [8] determined the environmental benefits of using multiple low-emission alternative fuels (marine gas oil, liquefied natural gas, methanol, biodiesel, and hydrogen with various energy production pathways), particularly for super yachts. The study shows that the most environmentally friendly alternative fuel for ships is hydrogen, which is produced using wind power. Hydrogen reduces GHG emissions by 93.95% and potential acid emissions by 91.95%, compared with fossil fuels.

In terms of exhaust gas treatment technology, in 2018, Manuel Kleinhenz [9] designed an exhaust gas treatment system to reduce PM and NO_X emissions using a diesel oxidation catalyst (DOC) and selective catalytic reduction coated diesel particulate filter (SDPF). The system enables marine generators to comply with new emission legislation and does not limit fuel quality. In 2019, Flagiello [10] proposed two units that use seawater to achieve flue gas desulfurization: a spray column that is equipped with full hydraulic spray nozzles and a packed-bed column with structured packing. These units were increased for use in marine diesel engines. Tian [11] proposed a dual-pressure organic Rankine cycle system to recover heat from marine engine exhaust gases to reduce cost. A combined thermodynamic-economic-environmental evaluation method was used to determine the optimal operating conditions for the system in 2021.

(2) A new marine propulsion system reduces energy consumption and GHG emissions and increases propulsion efficiency. In 2019, Yang [12] reduced the fuel consumption of a propulsion engine by improving the thermodynamic efficiency of the engine. In 2022, Fayas Malik Kanchiralla [13] conducted a life cycle study of the environmental and cost impacts on three propulsion systems (engines, fuel cells, and carbon capture technologies) using different energy sources (electrolytic hydrogen, electro-ammonia, electro-methanol, and electricity). This study shows that using different energy sources will achieve the 2050 GHG emission reduction targets. In 2022, Cheng [14] determined the feasibility of using a hybrid propulsion system for a large intercontinental vessel. The results showed that the experimental vessel emitted 3.4 tons fewer emissions, and its fuel consumption decreased by nearly 1 ton per kW h over a 12-day voyage.

(3) Selecting an appropriate navigational speed reduces fossil fuel consumption and GHG emissions. In 2018, Yan [15] established an energy efficiency optimization model for a ship that uses multiple environmental factors by analyzing the energy transfer between the hull, the propeller, and the main engine. The model determines the optimal navigational speed for different routes. The experimental results showed that traveling at the optimal speed reduces fuel consumption by 3% and CO_2 emissions by 2.38% over a voyage. In 2018, Kwang-Il Kim [16] used a dynamic programming method to determine the optimal sailing speed for different external forces, such as tides, waves, and wind. The simulation results show that the method reduces energy consumption in a complex environment by 20%.

In 2022, Wang [17] determined the relationship between uncertain factors (flow velocity, wet surface area of a ship, and cargo loading rate) and the energy efficiency operation index (EEOI). A double-layer nested interval optimization method was used to increase the value of the EEOI of a ship.

(4) In terms of hull optimization technology, reducing the resistance of a ship (hull modification, hull cleaning, and increased hull coating) saves energy and reduces emissions for a ship. In 2018, Elizabeth Lindstad [18] determined the relationship between hull design, the power plant, and fuel. The results demonstrate that slender hulls with conventional engines can comply with the 2020 EEDI regulations, and a hybrid powerplant with a slender hull can comply with the 2025 EEDI requirements.

Table 1. Maritime energy conservation and emission reduction technologies.

Technology Classification	Object of Study	Technology	Effect	References
Marine diesel engine transformation technology	High-pressure common rail injection system	Fuel injection improved technology	Enhanced the operating efficiency of diesel engines and reduced fuel consumption	[5]
Marine diesel engine transformation technology	Fuel injection pressure controlling system	Fuel injection improved technology	Droplet diameter decreased as the injection pressure increased	[6]
Marine diesel engine transformation technology	Prime motor	Clean fuels generation technology	Carbon emissions were reduced by up to 51%	[7]
Marine diesel engine transformation technology	Prime motor	Multiple clean fuels generation technology	Hydrogen fuel ship (wind-hydrogen generation system)	[8]
Marine diesel engine transformation technology	Exhaust gas treatment system	Exhaust gas treatment technology	Marine generators met new emission legislations	[9]
Marine diesel engine transformation technology	Marine diesel engine	A spray column that is equipped with full hydraulic spray nozzles and a packed-bed column with structured packing	Achieved flue gas desulfurization	[10]
Marine diesel engine transformation technology	Dual-pressure organic Rankine cycle system	Operating conditions optimization technology	Recovered heat from marine engine exhaust gases	[11]
New marine propulsion system	Marine engine	Improve the thermodynamic efficiency of the engine	Improved the thermodynamic efficiency of the engine and reduced the fuel consumption	[12]
New marine propulsion system	Three marine propulsion systems	Economy and environmental benefit analysis technology	Achieved the 2050 GHG emission reduction targets	[13]
New marine propulsion system	Large intercontinental vessels	Hybrid propulsion technology	Fuel consumption was decreased by nearly 1 ton per kW h over a 12-day voyage	[14]
Navigational speed optimization	The hull, propellers and marine engines	Energy efficiency optimization technology	Fuel consumption was reduced by 3% and CO_2 emissions were reduced by 2.38%	[15]
Navigational speed optimization	Marine propulsion system	Dynamic programming method and to determine the optimal sailing speed optimization technology	Energy consumption was reduced by 20%	[16]
Navigational speed optimization	Marine propulsion system	EEOI optimization technology	EEOI was improved	[17]
Hull optimization	Hull	Hull design technology	Slender hulls with conventional engines met the 2020 EEDI regulations and a hybrid powerplant with a slender hull met the 2025 EEDI requirements	[18]

These technologies reduce the consumption of fossil fuels or use clean fuels while sailing. However, new energy ships could eliminate the emission of GHG and pollutants. New energy ships use renewable or clean energy, such as wind and solar energy, instead of fossil fuels. They have long-term economic and environmental benefits, so new energy ships are developing rapidly.

Nowadays, a new energy ship is one of the most critical types of transportation. The Amsterdam Port and H2Ships project, funded by the European Union, aims to develop a zero-emission shipping infrastructure with a hydrogen fuel propulsion system. The Dutch shipbuilding company, Next Generation Shipyards, won this project and intended to achieve the goal of zero-emission shipping in Dutch ports by 2050. The UK marine technology company, Smart Green Shipping, spent £5 million to improve the full-automatic wind propulsion technology which would be applied in commercial vessels. The project also developed a weather-routing software, TradeWind, to analysis the wind condition and plan the navigation route. A high-capacity shore power charging station that uses tidal energy will be constructed by the Port of London Authority in 2023 for the Thames River. This charging station will supply power for electric vessels and other equipment. It will reduce the fossil fuel consumption and greenhouse gas emissions of the river fleet. The suction wing sail propulsion system SW270 which is designed by CRAIN Technologies, a French research and development office, uses wind power and the main engine to propel a ship. SW270 effectively reduced greenhouse gas emissions of cargo ships. In Japanese, a shipping giant, Mitsui O.S.K. Lines (MOL) and National Institute for Environmental Studies (NIES), are investigating the quality analysis of ship fuels. This work aims to study the impact of different fuel qualities and characteristics on environmental factors. The Carnival Corporation, one of the largest cruise companies, is developing alternative ship fuels, LNG ships, and methanol-hydrogen-driven fuel cells to achieve the 2023 sustainable development goal.

There are three categories of new energy ships: solar-powered ships, wind-powered ships, fuel cell-powered ships, and new energy hybrid ships. Solar-powered ships harvest solar energy to supply electricity for ship-lighting and ship-appliances. Solar-powered ships use energy storage systems to store surplus solar energy and eliminate power fluctuations. Solar energy is green energy and reduces the pollution that are generated by ships. The propulsion load for a small and medium-sized ship could be supplied by solar energy.

In May 2007, the "Sun 21" (Figure 1a) became the first vessel to sail across the Atlantic using solar energy exclusively. The "Sun 21" weighs 12 tons and is 14 m long and 6 m wide. The ship is powered by 65 m^2 of photovoltaic panels on the hull. Even on cloudy and foggy days, the ship can sail for about 18 h. In 2012, the largest solar-powered ship, the "Tûranor PlanetSolar" (Figure 1b), completed a circumnavigation of the globe without using fossil fuels. The ship has 537 m^2 of photovoltaic panels and is 31 m long and weighs 85 tons. The rated power of the ship is 93 kilowatts when sailing at a maximum speed of 19 km/h. However, the output power from the solar power system is unstable and fluctuates randomly. Solar energy is usually used as an auxiliary energy source on a large solar ship for lighting loads or appliance loads. The "Auriga Leader" (Figure 1c) is a car carrier with 328 photovoltaic panels on the deck and rated at 40 kilowatts. The shipboard photovoltaic power generation system supplies 6.9% of the power demand for the lighting load or 0.2% to 0.3% power demand for the propulsion load.

Wind energy applied is used for wind-assisted ship propulsion (WASP) and wind power generation. WASP uses sails to harness the wind power and propel a ship forward. In 1986, a 2000 m^2 sail was erected on the "Wind-star" (Figure 2a). The ship has a top speed of 12 to 13 knots. The sail generates propulsive power for 90% of the navigation time, and the energy efficiency is about 25% greater. The first "SkySails" wind-assisted propulsion ship was completed in 2007 and is called the "Beluga Skysail" (Figure 2b). The "SkySails," whose surface area is 160 m^2, resembles a massive paraglider and produces up to 20% of the engine power. Wind energy is also used to drive wind turbines to generate electricity. However, wind-powered ships are unstable, feature-poor power quality, and are stochastically volatile, so they are few in number.

(**a**)

(**b**)

(**c**)

Figure 1. Solar-powered ships: (**a**) "SUN 21", (**b**) "Tûranor PlanetSolar," and (**c**) "Auriga Leader".

(**a**)

(**b**)

Figure 2. Wind-powered ships: (**a**) "Wind-Star" and (**b**) "Beluga Skysail".

Fuel cells are used in ships to provide power through an electrochemical reaction tank. They allow greater electrical efficiency, create a dependable system, and have lower maintenance costs. A fuel cell ship also has a more comfortable cabin environment because fuel cells are quiet. German engineers created the "Alsterwasser" (Figure 3a), which is the first commercial fuel cell ship, as a part of the "Zemships" (Zero Emission Ships) plan in 2010. Two integrated fuel cell systems are mounted in this ship, and the fuel cell generates 48 kW of electrical power. The first full-scale pure electric ship is "Jun LV" (Figure 3b), which was completed in China in 2019. The ship is 53.2 m long and 14.3 m wide. It is powered entirely by lithium batteries, so 100 tons of fuel is saved annually, compared to traditional, similar ships. The average noise of the "Jun LV" is 54 decibels when sailing. However, the construction cost of fuel cell ships is very high, and the operational security is worse than that for fossil fuel ships.

(**a**) (**b**)

Figure 3. Fuel cell ships: (**a**) "Alsterwasser" and (**b**) "Jun LV".

New energy hybrid ships use many new-energy power generation systems. A hybrid power generation system allows increased use of renewable energy and increases the reliability of a new energy ship. The "SOLAR SAILOR" (Figure 4a) was launched for sea trials in Australian waters in November 2000. The ship is powered by two new-energy systems, a wind power system and a solar energy system, which can operate separately or together. The "Hornblower Hybrid" (Figure 4b)is the first wind-solar passenger ship in the United States. Two Savonius wind turbines and solar photovoltaic panels provide electrical power simultaneously.

(**a**) (**b**)

Figure 4. New energy hybrid ships: (**a**) "SOLAR SAILOR" and (**b**) "Hornblower Hybrid".

New energy ships have obvious advantages, but new energy ship power systems present severe challenges in terms of technology. With the development of artificial intelligence and high-speed communication technologies, new energy ship power systems are tied to smart ships. This review focuses on smart ship technologies, which have been widely concerned in the past five years. Thus, the three most noticeable ones are summarized in this comprehensive review:

(1) Electricity power that is generated by renewable energy, such as solar energy or wind power, features uncertainty and stochastic volatility [19]. These characteristics significantly reduce the operational stability of new energy ships. In order to determine the power fluctuation for new-energy and to predict the output of an integrated power system, accurate power forecasting is required. The forecasting results for new-energy are used to determine ship scheduling and voyage planning. New energy ships can operate safely and stably using new-energy forecasting technology.

(2) New energy ships have variable operational modes and complex energy sources. The variation in the characteristics of power units, such as new-energy generation systems and energy storage systems, is not applicable to new energy ships [20]. The power flow for

a new energy ship features spatio-temporal fluctuation and is composed of many types of energy. Traditional ship power system scheduling schemes are not applicable to new energy ships. Ship scheduling maintains a high-quality power supply and ensures reliable ship operation for new energy ships.

(3) A new energy ship power system is complicated and uses many electronic components, so traditional ship modeling methods cannot accurately simulate the operating conditions for new energy ships. In order to allow smart operation and maintenance of new energy ships, modeling methods are combined with artificial intelligence to simulate ship operating conditions and failure modes.

The remainder of this paper is organized as follows. Section 2 outlines the background and research for spatio-temporal new-energy prediction. Section 3 details new energy ship scheduling technology and the advantages and disadvantages of the technology. Section 4 describes various modeling technologies for a new energy ship power system. Section 5 describes the engineering challenges for new energy ships and the direction of technology development. The overall organization of topics in the review paper is shown in Figure 5. This study uses the latest research and application of key technologies for a new energy ship power system.

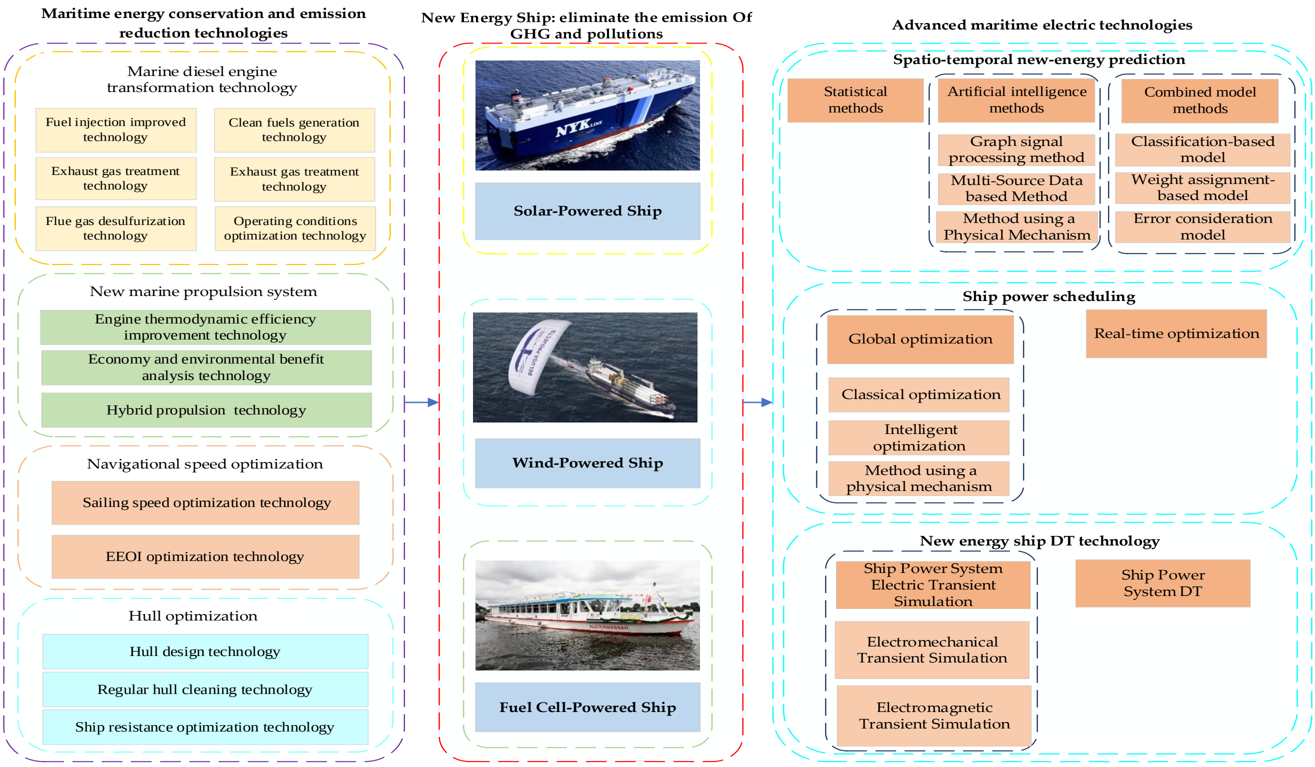

Figure 5. The organization chart.

2. Spatio-Temporal New-Energy Prediction

New-energy power generation features significant intermittency and volatility due to the chaotic nature of weather systems. The uncertainty in the new-energy generation is a factor in the development of new energy ships. Spatio-temporal prediction predicts the output power from multiple or mobile new-energy power stations to allow reliable power system scheduling. A new energy ship power system is a mobile microgrid that uses spatio-temporal prediction technology to predict the output fluctuations in output power.

Recent studies on new-energy spatio-temporal prediction concern power grids. Prediction technology uses point forecasts, interval forecasts, and probabilistic forecasts. It is used for wind power generation forecasting and Photovoltaic (PV) power generation forecasting for forecasting different objects. There are two types of prediction models: a mechanistic model and a data-driven model. The maritime spatio-temporal prediction problem is the same as that for land, but maritime spatio-temporal prediction involves interference to ship motion, currents, and waves. This paper classifies new-energy spatio-temporal forecasting methods as either traditional statistical, artificial intelligence (AI), or combined model methods.

2.1. Statistical METHODS

Statistical methods use historical data to construct the mapping relationship between past changes and future changes. Traditional statistical methods feature a simple structure, low training complexity, and high interpretability. Statistical methods include the Auto-Regressive Moving Average (ARMA) model [21], the Auto-Regressive Integrated Moving Average model [22], the Markov Chains [23], Vector Auto-Regressive [24] (VAR), and the Least Absolute Shrinkage and Selection Operator (LASSO).

In 2015, R.J. Bessa [25] counted surrounding distributed PV sites and exogenous variables(measured values for microgeneration units using smart meters) in the VAR to increase spatio-temporal prediction accuracy. The outcomes for the Evora city dataset show an 8–12% increment compared to the univariate model. Maïna Andre [26] constructed a multivariate spatio-temporal VAR model for three sites in 2016. The proposed algorithm differs from the classical linear model in that it uses the lag for each prediction site. The study redefined the spatial structure of all sites and removed low-correlation sites from the input space during the iterative process.

In 2018, Zhao [27] proposed a spatio-temporal Markov chain model that transitions the state of neighboring wind farms to the predicted wind farm state. The method optimizes the output weights for different spatio-temporal Markov chain models in the neighborhood to predict the output from wind farms. Agoua [28]. Modified the model by using a LASSO to address the problem of variable selection. The modified model uses external data from other PV sites in the regression model and the least squares method with the residual sum of squares. The normalized root mean square error (NRMSE) that is calculated using method is 20% more accurate than that for the univariate statistical model R. Amaro e Silva [29] proposed an Auto-Regressive with Exogenous (ARX) model that correlates other PV site information to the linear Auto-Regressive model and determines the effect of spatial information on the forecast. The accuracy of the prediction results is increased by testing datasets with different resolutions and determining the normalized weighted average distance.

In 2019, Agoua [30] used a QR-LASSO model to increase the accuracy of predictions for multiple data sources. Data from adjacent PV sites were used to reduce the 3-h prediction error by 10%. Using satellite images reduces the 6-h prediction error by 13%. Jun [31] proposed a calibrated regime-switching (CRS) method that uses the reactive regime-switching model. The model extrapolates the non-sample properties using the inherent bias of different states. The CRS method reduces the bias for state calibration technology to accurately predict wind speed variations for other monitoring points.

In 2020, Rafael E. Carrillo [32]. Proposed a spatio-temporal autoregressive model that uses the LASSO estimator to assign weights to the most informative nodes. A graphical model captures spatial correlation and reconstructs missing data. Tests on 303 real PV systems in Switzerland and 1000 simulated PV systems showed that the 6-h NRMSE metric is 13.8% and 9%, respectively.

Statistical methods require high-quality and smooth data, so they are not widely used for new-energy plants or for scenarios that involve large amounts of missing historical data. Statistical models cannot address multidimensional nonlinear complex forecasting problems. Statistical methods in combination with machine learning technologies are becoming more common, and statistical forecasting methods are frequently used to create a baseline for controlled experiments. The Predictive Models, Predictive variables, Prediction Form, Predictive scales, and Predicted Performance for Statistical methods are shown in Table 2.

Table 2. Summary of statistical, artificial intelligence, and combined spatio-temporal prediction methods.

Technology Classification		Predictive Models	Predictive Variables	Prediction Form	Predictive Scales	Data Source	Predicted Performance	Ref.
Statistical Method		VARX	PV Power	Point Forecast; Probability Forecast	6 h	Portugal, Évora City Real Data	5.5~10% increase in RMSE and 1.4~5.9% increase in CRPS	[25]
Statistical Method		VAR	GHI	Point Forecast	5 min~1 h	Guadalupe Real Data	The average RMSE is 19.4~20.91	[26]
Statistical Method		Spatio-temporal Markov chain (STMC)	Wind power	Point Forecast	15 min	Real data of 100 wind farms in China	Average RMSE is 4.8768%	[27]
Statistical Method		Spatio-temporal (ST) model	PV Power	Point Forecast	1~6 h	185 photovoltaic plants in central and western France	10.23% and 6.83% increase in RMSE compared to AR and RF	[28]
Statistical Method		ARX	GHI, PV Power	Point Forecast	10 s~2 h	NREL radiometer grid (USA), Microgen database (UK)	Forecast skill 10~15% on average	[29]
Statistical Method		ARX	GHI, PV Power	Point Forecast	15 min~6 h	136 photovoltaic plants in central and western France	MAE ranges from 2.62% to 12.59%	[30]
Statistical Method		Calibrated regime-switching	Wind Speed	Point Forecast	1~12 h	Onshore wind farm in US	1–12 h MAE ranges from 1.12% to 2.56%	[31]
Statistical Method		ST-AR	PV Power	Point Forecast Probability Forecast	6 h	303 real PV systems and 1000 simulated PV systems in Switzerland	NRMSE of real and simulated dataset is 13.8% and 9%, respectively	[32]
Artificial Intelligence Method	Graph Signal Processing Method	Graph convolutional deep learning architecture (GCDLA)	Wind Speed	Point Forecast	10 min~3 h	Eastern Wind Integration Dataset	RMSE for 10 min~3 h prediction is 0.431~0.807	[33]
Artificial Intelligence Method	Graph Signal Processing Method	CGAE	GHI	Point Forecast Probability Forecast	30 min~6 h	NSRD dataset	MAE is1.45% and GHI probability density is 85~90%GHI_{MAX}	[34]

Table 2. *Cont.*

Technology Classification		Predictive Models	Predictive Variables	Prediction Form	Predictive Scales	Data Source	Predicted Performance	Ref.
Artificial Intelligence Method	Graph Signal Processing Method	Spatio-temporal correlation graph neural network(STGN)	Wind Speed	Point Forecast	6~168 h	CCMP wind data	The average RMSE for 6~168 h prediction are 1.239~2.454	[35]
Artificial Intelligence Method	Graph Signal Processing Method	GCLSTM and GCTrafo	PV Power	Point Forecast	15 min~6 h	303 real PV systems and 1000 simulated PV systems in Switzerland	NRMSE for 15 min~6 h prediction ranges from 3.350 to15.53	[36]
Artificial Intelligence Method	Graph Signal Processing Method	STCM and hierarchical directed graph structure	Wind Power	Point Forecast	1~4 h	32 adjacent wind farms in a northern Chinese province	RMSE and MAE ranges from 2.936~4.682% and 2.391~3.801%, respectively	[37]
Artificial Intelligence Method	Graph Signal Processing Method	short-term solar irradiance forecasting model with surrounding meteorological factors that use optimal graph modeling.	GHI	Point Forecast	24 h, 72 h	A photovoltaic power plant in Inner Mongolia, China and a CTA for the Fengyun 4 satellite	RMSE and MAE is 97.1487 and 44.4796, respectively	[38]
Artificial Intelligence Method	Graph Signal Processing Method	Multi-graph prediction model	PV Power	Point Forecast	24 h	Desert Knowledge Australia Solar Centre	MAPE ranges from 10.14% to 15.45%	[39]
Artificial Intelligence Method	Graph Signal Processing Method	U-Convolutional model	Wind Power	Point Forecast	1 h, 6 h	Climate Forecast System Reanalysis (CFSR) dataset	RMSE for 1 h and 6 h is 0.3081 and 0.7196, respectively	[40]
Artificial Intelligence Method	Graph Signal Processing Method	MST-GNN	GHI	Point Forecast	1~24 h	ASOS station real data set	RMSE for 1~24 h prediction ranges from 0.27 to 0.36	[41]
Artificial Intelligence Method	Graph Signal Processing Method	Graph attention convolutional net-work (GACN) with LSTM (GACN-LSTM)	GHI	Point Forecast	1 h	official website and database of the Japan Meteorological Agency	MAE and MSE is 2.5 and 1.26, respectively	[42]

Table 2. *Cont.*

Technology Classification		Predictive Models	Predictive Variables	Prediction Form	Predictive Scales	Data Source	Predicted Performance	Ref.
Artificial Intelligence Method	Multi-Source Data based Method	BILST	PV Power	Point Forecast	5 min~15 min	A 3 MW PV plant at the Gatton Solar Research Facility, the University of Queensland (UQ) and actual measurement data for the corresponding area in Australia	nRMSE of 5~15 min prediction ranges from 0.11 to 0.12	[43]
Artificial Intelligence Method	Multi-Source Data based Method	Bi-Directional Extrapolation-Graph-GRU	PV Power	Point Forecast	30~60 min	Desert Knowledge Australia (DKA) Solar Centre	RMSE for 3~6 h prediction is 6.945; Running speed is 0.0478 s, 42.4% lower compared to GNN	[44]
Artificial Intelligence Method	Multi-Source Data based Method	Advanced U-Net–LSTM	PV Power	Point Forecast	15~60 min	50 real-world PV power stations; Numerical weather prediction; Himawari-8	The mean value for RMSE, MAE and MAPE is 1.9806, 1.2753 and 27.19, respectively	[45]
Artificial Intelligence Method	Physical Mechanism based Method	MLClouds physics-guided neural network	GHI, DHI	Point Forecast	15 min	National Solar Radiation Database	The MAE for GHI and DHI are 11.48 and 23.82	[46]
Artificial Intelligence Method	Physical Mechanism based Method	MCSIP Net	Satellite image	Image Prediction	8 min	National Meteorological Satellite Center (NMSC)	PSNR value is 22.04	[47]
Artificial Intelligence Method	Improved neural network structure	CovnGRU-VB	GHI	Interval Forecast, Point Forecast	1~3 h	National Solar Radiation Database	The mean values of RMSE, MEA, and NSE were 69.5, 34.8, and 0.929, respectively	[48]
Artificial Intelligence Method	Improved neural network structure	PSO-LSTM	PV Power	Point Forecast	30 min	Actual data from 8 PV sites in Asia	The mean values of MAE and RMSE are 7.71 and 18.21	[49]

Table 2. *Cont.*

Technology Classification		Predictive Models	Predictive Variables	Prediction Form	Predictive Scales	Data Source	Predicted Performance	Ref.
Artificial Intelligence Method	Improved neural network structure	ATCN	Wind Speed PV Power	Point Forecast, Probability Forecast	Point Forecast: 2 h, 4 h Probability Forecast: 2 h	National Renewable Energy Laboratory (NREL)	The average accuracy of point and probabilistic prediction are increased by 15.08% and 15.85%, respectively	[50]
Combined Model Method	Classification-based Model	EEMD-SOM-BP	GHI	Point Forecast	24 h	SolarGIS data set	The mean values of RMSE and MAE are 73.04 and 117.42	[51]
Combined Model Method	Classification-based Model	CVAR	Wind Speed	Point Forecast	1~6 h	Measured data from 23 weather stations in UK	1~6 h prediction RMSE ranges from 0.93 to1.82	[52]
Combined Model Method	Classification-based Model	Weather classification based wasserstein-GAN(WGAN)-CNN	GHI	Point Forecast	15 min	Surfradstation, NOAA	Overall increase in accuracy compared to the classification model without WGAN	[53]
Combined Model Method	Classification-based Model	VMD-StackGRU	wind speed	Point Forecast	1~3 h	European Re-analysis (ERA5) dataset	The RMSE metrics for the three steps are 0.1436, 0.1733, and 0.1889, respectively.	[54]
Combined Model Method	Classification-based Model	EWT-ARIMA-NARX-Adaboost	GHI	Point Forecast	1~5 h	Weather Stations in Changde, Beijing and Hunan Province, China	MAE for1-step, 3-step, 5 step prediction is 6.8, 7.1 and 13.37, respectively	[55]
Combined Model Method	Classification-based Model	Quantile regression monotone broad learning system(QRMBLS)	PV Power	Interval Forecast	5 min~1 h	dataset of five PV units in Yulara, Australia	Log Scroe and Energy Scroe are 25.71065 and 47.9802	[56]

2.2. Artificial Intelligence Methods

AI methods have evolved as mainstream methods in the field of new-energy spatio-temporal prediction because they generate an excellent fit for complex nonlinear problem mapping. The generalization ability and prediction accuracy of AI methods are also better than that of statistical methods. AI methods are classified as a graph signal processing method, a multi-source data-based method, a physical mechanism-based method, or an optimized network architecture. Details of the Artificial Intelligence Methods are listed in Table 2.

2.2.1. Graph Signal Processing Method

The new-energy spatio-temporal prediction method uses the complex correlations between new-energy sites, such as the coupling between input features, the spatial correlation between new-energy sites, and the temporal correlation for the output power from each site. The graph signal processing method uses graphical plots to illustrate the interdependence of signals that are defined in irregular domains. It is widely used for traffic prediction and weather prediction. In new-energy spatio-temporal prediction models, nodes represent new-energy sites or individual input features, and edges represent the correlation between two adjacent nodes. Spatio-temporal correlation and factorial correlation modeling are two modes of graph signal processing that are used for new-energy spatio-temporal prediction.

Spatio-temporal correlation modeling uses the graphical structure to determine the spatial correlation between new-energy nodes. Khodayar [33] proposed a spatio-temporal deep learning method that uses a time series analysis in 2019. The method uses a graph convolutional deep learning architecture to determine the interval depth features of wind datasets. The architecture uses graph theory, a convolutional neural network, and rough set theory. The proposed method increases the RMSE by 7.4–30%, compared to state-of-the-art Single-Model Methodologies for prediction durations from 10 min to 3 h.

In 2020, Khodayar [34] proposed a spatio-temporal probabilistic prediction method (Figure 6) that uses a convolutional graph autoencoder(CGAE). The method uses a graphical structure to represent the distribution for multiple new-energy sites. Khodayar compared the results for this method with those for spatio-temporal Copula (ST Copula), spatio-temporal QR Lasso (ST QR Lasso), compressed spatio-temporal forecasting (CSTF), and spatio-temporal support vector regression (ST-SVR). The results for the National Solar Radiation Database (NSRDB) show that the MAE of CGAE is 1.45% more accurate than the other methods.

Geng [35] proposed a spatio-temporal correlation graph neural network for multi-mode offshore wind power prediction in 2021. The network uses a channel-wise attention mechanism to assign weights to the input nodes. In 2022, Jelena [36] used graph-convolutional long short-term memory (GCLSTM) and graph-convolutional transformer (GCTrafo) models that use graph signal processing to achieve high-resolution spatio-temporal prediction. Wang [37] proposed a prediction method that uses ultrashort-term clusters to predict wind power with dynamic spatial-temporal correlation and variable causality. The model determines the relationship between each input factor and output by constructing a hierarchical-directed graphical plot. Zhang [38] increased the spatio-temporal prediction accuracy by optimizing the structure and the connectivity of the graph. A satellite image inversion spatio-temporal prediction model was proposed to create the spatio-temporal data around the prediction point. The results show that graph connectivity is positively correlated with prediction accuracy.

Factor correlation modeling determines the coupling relationship between each input feature of the nodes. In 2021, Cheng [39]. Proposed a graphical modeling method for short-term PV power prediction to determine the interrelationships between various meteorological input factors. The method uses a Chebyshev layer and a multi-layer perceptron, and two readout methods to achieve the mean absolute percentage error (MAPE) of 10.14% for the Desert Knowledge Australia Solar Centre dataset.

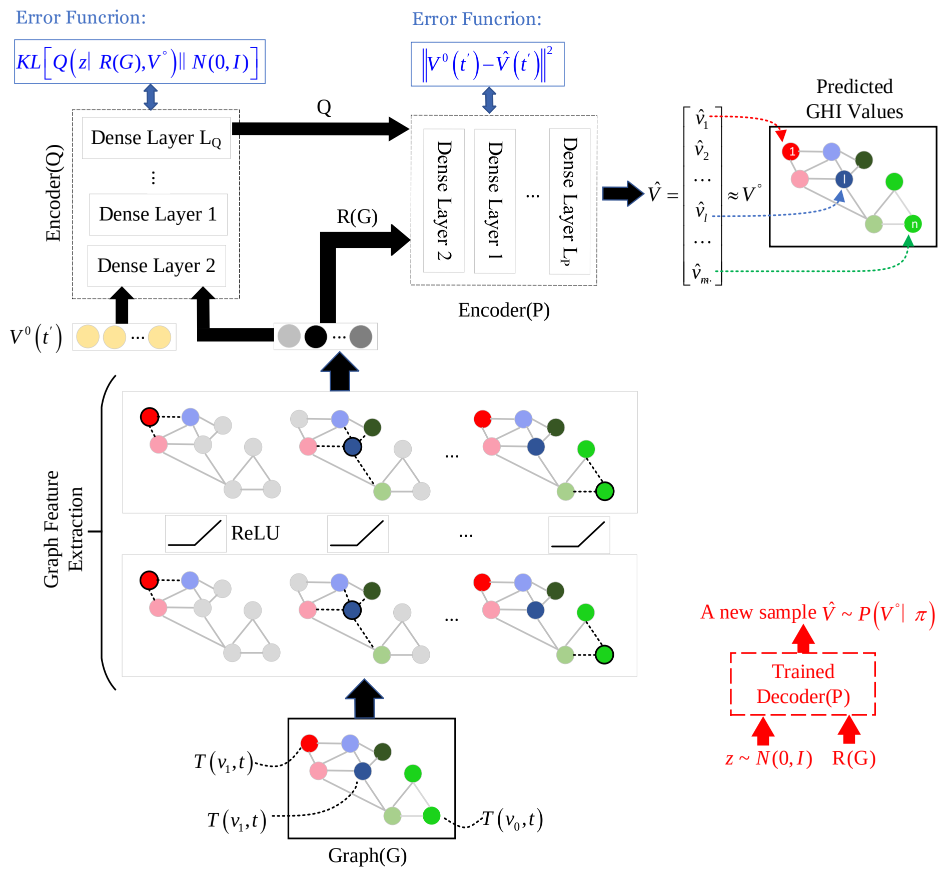

Figure 6. Convolutional graph auto encoder general structure.

Bruno [40] proposed a U-Convolutional model for processing spatiotemporal data with multiple explanatory variables. The U-Net synthesizes the input information to map the synthesized data into a single-site prediction model using convolutional layers. This study did not determine the interrelationship between variables or extract information on the temporal dimension, but multiple input variables are analyzed at the same site.

Jeon [41] proposed a spatio-temporal prediction method for the solar irradiance model that is called a Multi-Attributed Spatio-Temporal Graph Convolutional Network (MST-GCN). Multi-Attribute Fusion fuses three features of meteorological data. The model was used for the automated surface observing systems (ASOS) dataset for 42 solar irradiance measurement sites on the Korean Peninsula. The prediction results for this method are more accurate than those for a Temporal Graph Convolutional Network(T-GCN), a recurrent gated unit (GRU), a Graph Convolutional Network (GCN), or multilayer perceptron (MLP), so the proposed method is eminently suited to multi-attribute spatio-temporal problems.

In 2022, Gao [42] proposed an interpretable data-driven model that uses an attention mechanism and a graph neural network (GNN) to determine the correlation and interpretability of new-energy predictor variables. Gao used the attention mechanism for the time dimension to increase the interpretability of the model. The relationship between predictor variables is graphically expressed using a GNN and a long short-term memory (LSTM) network.

In 2019, Chen [57] proposed a multifactor spatio-temporal correlation (MFSTC) model that uses spatio-temporal correlation and factor correlation. It is a data reconstruction method that uses a three-dimensional matrix. The correlation information for three dimensions is calculated by correlating points between sites, historical time points, and meteorological factors.

2.2.2. Multi-Source Data-Based Method

The performance of spatio-temporal AI prediction models depends on the quality of historical data. However, poor quality or missing data are unavoidable in the practical application of the models. Data from multiple sources increases the robustness of the input space. The amount of information from single-source data is narrow. For PV prediction, local Measurement data (LMD) only provides historical records for PV power generation and other meteorological variables at a single site. Numerical Weather Prediction (NWP) uses 24-h information for multiple sites in advance. Satellite cloud maps feature multi-channel information on a broad spatial scale and reflect intra-hourly changes in cloud masses. However, prediction models that use local satellite imagery alone become significantly less accurate over time.

Prediction models that use data from multiple sources are commonly used for PV prediction. Data sources include LMD, NWP, satellite clouds, and ground-based clouds. In 2019, Zhang [43] pooled the ground-based cloud maps and spatio-temporal information for surrounding stations into a unified Bi-level spatio-temporal (BILST) PV nowcasting model. This model determines the temporal correlation between picture sequences and time series using the residual structure and an attention-based model. The proposed model was validated using a real dataset for the Brisbane area, and the results demonstrate that ground-based cloud maps increase prediction accuracy.

Cheng [44] addressed the non-Euclidean dynamic input problem for satellite images by treating the ROI in satellite images as an entire directed graph. A dual extrapolation method that uses dense Optical Flow was used to preserve the original pixels and to reduce the number of input pixels by simulating cloud motion. The calculation time for the model is reduced by 42.4%, and prediction accuracy is high.

Yao [45] used an advanced U-net model to extract features from satellite cloud maps. The proposed hybrid model uses an LSTM network to extract features from e historical sequences for multiple sites in the same area. The attention mechanism fuses different modal features. In 2021, Zhang [58] proposed a multi-source and temporal attention network model that uses a multi-source variable attention mechanism to dynamically adjust the weights of each NWP input data at every time step.

2.2.3. Method Using a Physical Mechanism

Artificial intelligence methods directly fit the mapping relationship between historical data and predicted values for new-energy sites. A lack of guidance that uses relevant domain knowledge often leads to unreasonable prediction results. Methods that use a physical mechanism modify the original model by using specific area knowledge and rules to increase the prediction accuracy.

In 2022, Buster [46] proposed a physically guided machine learning method for cloud retrieval that uses a physical loss term in the loss function for a neural network. The method was used for several datasets, such as Geostationary Operational Environmental Satellites (GOE), Clouds from AVHRR Extended (CLAVR-x), Modern-Era Retrospective Analysis for Research and Applications Version 2 (MERRA2), and the global horizontal irradiance. The mean absolute percentage error in the global horizontal and direct normal irradiance decreases by 2.16% and 3.95%, respectively. The results for gap-filled cloudy weather are significantly more accurate.

Lee [47]. proposed a Multichannel Satellite Image Prediction (MCSIP) network that uses a Generative Adversarial Net (GAN) to navigate the increase in the accuracy of prediction results by using the meteorological knowledge for the discriminator. The experimental results show that the proposed model uses meteorological knowledge to increase the prediction accuracy.

The prediction accuracy of artificial intelligence methods is affected by the hyperparameters and architecture of neural networks. In 2019, Liu [48] proposed a variational Bayesian convolutional GRU(CovnGRU-VB) model that replaces the matrix multiplication in a GRU with the convolution kernel. The loss function, which is different tom the sum of squares function, is derived using variational inference technology. In 2020, Zheng [49] used Particle Swarm Optimization(PSO) to optimize the LSTM parameters to predict solar power output (SPO). In 2021, Pan [59] proposed a spatio-temporal graph neural network architecture search method that uses a Differentiable Architecture Search (DARTS) framework. This treats each search unit as an acyclic N-node graph and performs the operations according to the architecture scores for the two nodes.

In 2022, Liang [50] proposed an Attention Temporal Convolutional Network(ATCN) model that uses stacked, dilated causal convolutional and attention mechanisms for the ultra-short-term forecasting of renewable energy. This model does not use expert knowledge or feature selection technology. It is widely applicable to many prediction objects. The point prediction and probabilistic prediction accuracy for the proposed method for the National Renewable Energy Laboratory (NREL) dataset increased by 15.08% and 15.85%, respectively.

2.3. Combined Model Methods

Machine learning models feature unstable performance for different datasets. The spatio-temporal prediction accuracy for machine learning models for multiple sites significantly decreased because of the difference in the distribution characteristics of new energy. The combination model combines the advantages of different individual machine learning models and achieves flexible combinations for a specific application scenario to increase the generalization ability of the prediction model. Depending on the form of the combination, combined models are either classification-based models, weight assignment-based models, or error consideration models. Details of the methods for Combined Models are presented in Table 2.

2.3.1. Classification-Based Model

A classification-based model is categorized in terms of data type or the distribution characteristics of new-energy. The prediction results use different time-series classified prediction models. In 2018, Yin [51] proposed a decomposition-based day-ahead spatio-temporal prediction method for a solar ship that considers a ship for which the position varies with time. Ensemble empirical mode decomposition (EEMD) is used to extract data features and to decompose the raw historical data into multiple frequency bands. Yin used the data from the four nearest weather stations and a self-organizing map-back propagation (SOM-BP) hybrid neural network to predict the solar radiation that is incident on shipboard PV panels in the next 24 h. The results show that the method accurately predicts solar radiation along the navigation route.

Browell [52] proposed an improved regime-switching vector autoregressive method that uses a self-organizing map(SOM) network to cluster different regional weather patterns and to optimize prediction performance. In 2019, Wang [53] reclassified 33 meteorological weather types as 10 new weather types. GAN was used to enhance the training data for each weather type. Wang determined the quality of the enhanced data using the Standard deviation (STD), the Euclidean distance (EDD), and the Cumulative distribution function. The enhanced data were used to train the weather classification model. The results show that weather classification is essential for increasing the accuracy of day-ahead PV power prediction. In 2021, Xie [54] proposed a new multi-step prediction model for an offshore new-energy generation system that uses variational mode decomposition (VMD) to prevent the band overlap that affects traditional empirical mode decomposition (EMD). The stacked GRUs increase the capability in terms of nonlinear problem modeling and the training degradation problem. The model was validated using three new-energy power systems in the Atlantic, Pacific, and Indian Oceans (ERA5 dataset). The method does not classify the weather types or new-energy distribution areas, but different modes of the method allow a type of classification.

Huang [55] proposed a hybrid EWT-ARIMA-NARX-Adaboost model for 1–3 h ahead prediction, for which the computational cost is significantly reduced. A one-hour solar irradiance prediction result is calculated within 10 min. In 2022, Zhou [56] proposed a spatio-temporal probabilistic prediction model that uses the monotone broad learning system (MBLS) and Copula theory to address the quantile crossing problem by specifying a quantile ranking that is equal to the input ranking during the model training process. The joint probability distribution for PV power is determined using SOM and Copula functions. SOM is used to cluster PV power, and meteorological data and Copula functions are established for each cluster to model the spatio-temporal correlation between multiple PV units for different time steps and external conditions. The experimental results show that the model addresses the quantile crossing problem and simulates spatio-temporal PV power generation scenarios.

Li [60] increased the resolution of a 3-h numerical weather forecast data to 1 h using bicubic interpolation technology and a bidirectional long-short-term memory (BiLSTM) network. Weekly weather classification is performed using meteorological parameters and weather changes, and weekly PV power scenarios are generated that use the weekly weather classification. The final forecasting result is calculated using a gated recurrent unit-convolutional neural network (GRU-CNN).

2.3.2. Weight Assignment-Based Model

Weight assignment-based models comprise several sub-models for which the output weights are adaptively adjusted according to the scenario or the prediction time scale. In 2019, Cai [61] proposed a combined SVR + SDA + UKF (Support Vector Regression, Stacked De-noising Auto-encoder, Unscented Kalman Filter) forecasting model to address the problem of a fixed prediction time scale. Actual data that were collected from offshore wind farms demonstrated the superiority of the proposed model.

Lin [62] proposed a multi-model combination method that uses sparse Bayesian learning, kernel density estimation, and beta distribution fitting. The method calculates the sub-model output weights using maximum likelihood and expectation maximizing (EM) algorithms. Application to the Global Energy Forecasting Competition 2014 (GEFCom2014) dataset for wind farm data from 10 different regions showed that the method is robust and effective.

In 2021, Wen [63] proposed a solar-integrated interval prediction method that uses a stochastic ship motion model. It consists of a back propagation (BP) neural network, a radial basis function (RBF) neural network, an extreme learning machine (ELM), and an Elman neural network (Figure 7). This model adaptively assigns the output weights using a PSO algorithm. The method was validated using the database for SolarGIS along the route from Dalian, China, to Aden, Yemen. The results show that this model outperforms other combined and individual models.

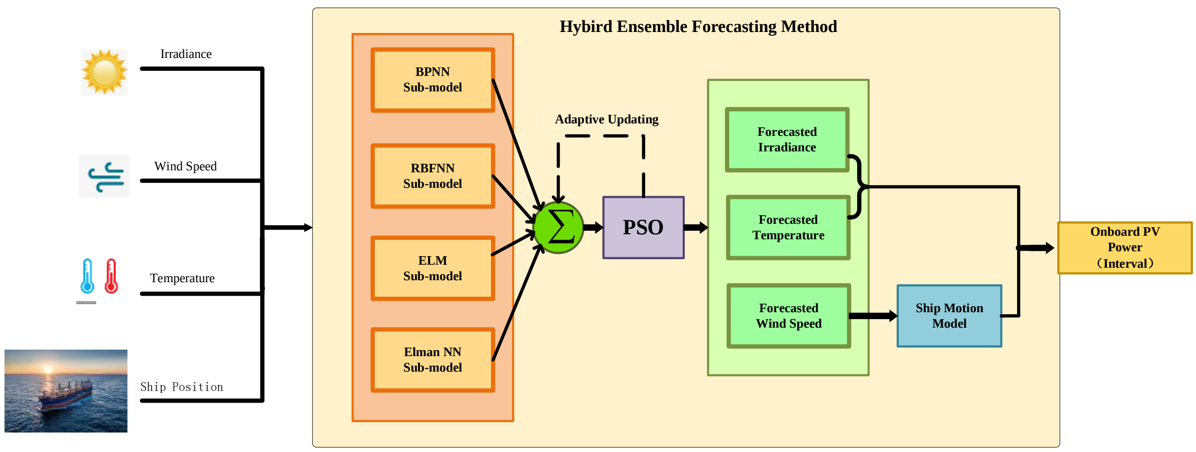

Figure 7. BP + RBF + ELM + Elman model.

In 2022, Nikodinoska [64] used a dynamic elastic net (DELNET) that uses rolling-window estimation to avoid overfitting and to reduce model complexity. DELNET also addresses the multiple-collinearity problem of combinatorial models. A dynamic data pre-processing (DDP) routine is used to mitigate the dataset quality problem.

2.3.3. Error Consideration Model

Objects for new-energy spatio-temporal forecasting normally exhibit non-stationary, heteroskedasticity, and high uncertainty characteristics. The uncertainty is either cognitive or accidental uncertainty, depending on the source of uncertainty. The prediction error is either a cognitive or accidental error. Cognitive error is inevitable because there is incomplete knowledge of the predicted object or the prediction model. Accidental error originates from data measurement or environmental noise.

In 2022, Sun [65] proposed a short-term wind power probabilistic forecasting model that mitigates the effect of accidental forecasting errors by calculating the temporal correlation between errors. The model uses the Random Forest method to weigh the NWP output for multiple locations. Forecasting errors are classified after correlation tests are performed. Sun determined the probability density distribution for wind power for different error distributions.

Su [66] proposed a two-stage solar power generation forecasting model with forecasting correction to mitigate the effect of cognitive errors on forecasting results. The model comprises a primary model that performs the initial prediction and a supplementary model to assign the dynamic error compensation (DEC). The DEC adaptively updates the residuals during the forecasting process using hierarchical residual (HR) learning and Choquet fuzzy integration (CFI) aggregation. The model was applied to an actual solar power dataset for Taiwan, and the results demonstrated that DEC increases prediction accuracy.

Nam [67] integrated the Naive Bayes Classifier and used the Kriging method to determine the temporal and spatial features of predicted data in 2019. Sun proposed an aggregated probabilistic wind power spatio-temporal prediction model that uses a Copula function. The model calculates the correlation between sub-wind and main wind farms. The model uses a Gaussian mixture model (GMM) to model the distribution of sub-wind and main wind farms. The Copula function is used to establish the spatio-temporal correlation between all wind farms. The model uses a reinforcement learning method to increase the accuracy of deterministic forecasting. Test data from nine wind farms in the Wind Integration National Dataset (WIND) was used to verify the model, and the results used a pinball loss metric to demonstrate the effectiveness of the increased model.

2.4. Summary

New-energy spatio-temporal prediction calculates the spatio-temporal correlation information for a new-energy distribution by modeling the relationship between the input and the output in a particular region. The appropriate prediction framework and loss function are constructed for a specific scenario to determine the variations in the new energy power.

Statistical methods use fewer computing resources and are easy to be designed. But statistical methods are implemented under the assumption of fixed distribution probability. The prediction errors are quite large when using these methods. Artificial intelligence methods have the ability to predict the power of shipboard new energy accurately and solve complex prediction problems. However, artificial intelligence methods are 'black box' systems. These methods feature poor interpretability and must input high-quality data. Combined model methods have the advantages of various algorithms. Combined model methods are flexible and designed according to the requirements of different users.

In the future, the new-energy spatio-temporal prediction technology will accurately model the correlation between inputs and post-processing technology and increase the interpretability and generalization ability of models.

3. Ship Power Scheduling

Power scheduling maintains the security and stability of a ship's power system and controls the outputs of power units efficiently. A power scheduling problem is actually a multi-scenario and multi-constraint mathematical optimization problem [68] that is classified as a deterministic or uncertain scheduling problem in terms of uncertain variables [69]. Many power scheduling schemes have been proposed for power grids. Depending on the time scale, they involve either medium-long-term scheduling (year, month), day-ahead scheduling (future 24 h), or intra-day scheduling (minute, hour) in terms of the time scale for dispatching. Ship power scheduling (Figure 8) is much more complicated than that onshore scheduling. Fluctuations due to meteorological factors, such as wind, waves, and currents, complicate the power scheduling for a new energy ship. Ship power scheduling is a power-voyage coupled optimization problem that ensures sufficient power supply and satisfies voyage constraints [70]. New energy ships have significant demands in terms of flexibility and reliability due to the uncertainty of new energy. This section comprehensively summarizes new energy ship power scheduling techniques using optimization methods. The classic literature on ship Scheduling is presented in Table 3.

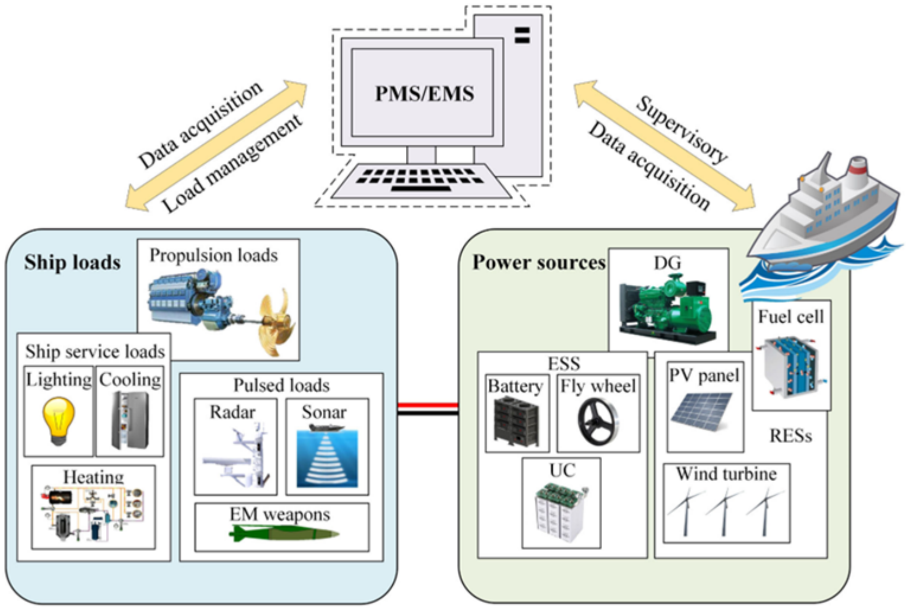

Figure 8. Power scheduling system for a typical new energy ship.

3.1. Global Optimization

Global optimization determines the optimal solution for variables in the feasible domain to achieve a global optimum for the objective function. It involves dividing by either classical optimization or intelligent optimization, depending on the optimization technology [71]. Classical optimization is only used for low-dimensional scenarios. In general, it uses commercial solvers, such as CPLEX and GUROBI.

Classical optimization problems include linear programming, nonlinear programming, mixed integer programming, and dynamic programming [72]; Intelligent optimization is used for complex non-linear scenarios. Heuristic algorithms, such as a Genetic Algorithm (GA) and a PSO algorithm, are used to calculate the optimal solution [73]. Global optimization requires highly linearized technologies and many power system parameters to achieve a global optimum. Global optimization is one of the most widely used optimization techniques for new energy ship scheduling and is used to determine economic, low-carbon, and reliable operation schemes.

3.1.1. Classical Optimization

Classical optimization methods calculate the accurate global optimal solutions for dispatching problems. To address nonlinear scheduling, a ship power scheduling model is usually transformed into a mixed integer linear programming model using linearization technology.

In 2018, Hamadi Bouaicha [74] proposed an adaptive speed control strategy to adjust the propulsion power for a solar-powered cruise ferry. The study modeled a nonlinear programming schedule for propulsion power and used a General Algebraic Modeling System (GAMS) to solve the model. The results demonstrate that the proposed strategy allows flexible power generation and ship power scheduling.

In 2019, Li [75] proposed a combined cooling heat and power (CCHP) unit for a multi-energy ship to enhance the energy utilization in the power system. A multi-objective mixed integer linear programming model used an Augmented ε-Constraint Method that considers operation economy and environmental benefits. The results illustrate that the ship's operational cost is reduced by 7%, and gaseous emissions are decreased by 10.55 tons.

Fang [76] defined PV power generation as a power generation-voyage collaborative optimization problem for a shipboard microgrid. The proposed problem is transformed into a two-level programming problem using loose constraints, and the result is calculated using a column-and-constraint generation method. The results show that the shipboard new-energy utilization rate has significantly increased, and the ship EEOI is reduced by about 3.5%.

In 2020, Kyaw Hein [77] proposed a two-stage multi-objective optimization framework that uses a mixed integer nonlinear programming model to increase the efficiency of shipboard PV power generation. In the first stage, the economic power dispatch scheme is determined using PV power forecasting results. In the second stage, the weights of multiple objectives are determined to increase the flexibility of the ship's power system.

Pouya Firouzmakan [78] proposed a new ship power management strategy that uses a Lagrangian relaxation method to dispatch conventional units, co-generators, and heating units in a new energy ship. The proposed strategy reduces the operational cost of the ship by 6.5%, compared with a PSO-based strategy.

Zhang [79] constructed a ship power scheduling model that uses the state of an energy storage system. The integrated energy system for the ship consists of a new-energy generation system, an energy storage system, and a combined heating and power device (CHPD). The results show that fuel consumption and operational cost are significantly reduced.

Li [80] proposed an adaptively stochastic optimization method, which uses a value-at-risk (CvaR) model to dispatch a multi-energy shipboard microgrid. The experimental results demonstrate that the proposed method stabilizes stochastic power fluctuations that are caused by new energy and ship-swinging. The operational risk and cost are reduced by 2.5% and 3.5%, respectively.

In 2021, Sun [81] proposed a three-level control framework that uses voltage control and power scheduling to realize a connection between all-electric ships and seaport microgrids. In the first level, the voltage level of the seaport microgrid is calculated by predicting the new energy and load power to determine the arrival time for the ship. In the second level, Sun uses a mixed integer quadratic programs model to navigate the ship route and schedule ship power generation. The third level controls the ship's voltage in real-time. The results show that the proposed method reduces the power generation cost on a ship by $24.6, and 52.45 kW less propulsion power is required compared with the experienced route.

Neda Vahabzad [82] also studied the hybrid energy ship power scheduling problem. A hybrid energy ship power system consists of diesel generators, a solar generation system, an energy storage system (ESS, and cold-ironing (CI) facilities. The solution is calculated using a mixed integer linear robust optimization to dispatch the shore power system (SPS) and shipboard ESS. The results show that the proposed method reduces the total cost and the CI services operational cost by about $1674 and 7%, respectively.

Uncertain optimization methods are suited to the uncertainty factors in new energy ship scheduling problems [83]. In 2019, Fang [84] used a two-stage data-driven robust optimization algorithm and a PV output prediction model to schedule a new energy ship. The results show that the proposed method reduces fuel consumption by 1.6% and achieves 100% PV power generation utilization.

In 2020, Li [85] used a two-stage robust optimization method for voyage scheduling and power scheduling schemes for a hybrid AC/DC multi-energy ship (MES) microgrid. The proposed method increases the economic efficiency and voyage-load joint scheduling flexibility for the MES. In 2022, Fan [86] proposed a two-stage optimization model for a shipboard microgrid that uses hydrogen fuel cells. The optimization objectives for the model are the operational and pre-sailing costs of hydrogen, fuel, and electricity. The method reduces total operational costs by 4.6%.

3.1.2. Intelligent Optimization

A classical optimization method cannot be used to calculate high-dimensional, multi-objective nonlinear scheduling problems. Heuristic algorithms, such as the PSO algorithm and a GA, are widely used to optimize the power scheduling for new energy ships.

In 2018, Tang [87] presented an optimal energy management model for maritime photovoltaic/battery/diesel/cold-ironing hybrid energy systems that ensures the stable and efficient operation of a large green ship. The scheduling model is transformed into an unconstrained global optimization model using a penalty function and uses an adaptive PSO algorithm. In 2020, Yang [88] proposed a multi-objective power scheduling model for a shipboard solar-diesel hybrid generator system that considers economy and diesel generator efficiency. A PSO algorithm is used to optimize the operational economy and diesel generator efficiency. The proposed model increases the reliability of the ship power system by calculating the useful life of diesel generators in low-load condition. Mehdi Rafiei [89] used a stochastic optimization sine–cosine algorithm (SCA) to determine a power scheduling scheme for a shipboard hybrid energy system with fuel cells, batteries, and cold ironing and discussed the feasibility of a zero-emission hybrid energy system applied in a ferry boat. The study shows that the proposed method significantly reduces the operational cost of hybrid energy ships.

Huang [90] constructed a multi-energy complementary co-optimization model of a multi-energy ship power system and used a shipboard virtual energy storage system to increase the operational economy and environmental benefits of multi-energy ships. A shipboard virtual energy storage system is defined as an energy polymer and comprises an ESS, an electricity load, a thermal energy storage system, and a thermal load. Huang used a PSO algorithm to determine the power scheduling scheme, and the results demonstrate that the total cost and gas emissions for a new energy ship decreased by $13,334 and 11,419 kg, respectively. Feng [91] used a differential evolutionary algorithm to determine a multi-objective economic scheduling scheme for a shipboard microgrid. The study shows the contradictory relationship between fuel efficiency and gas emission for an all-electric wind-solar propulsion ship. In 2021, Yang [92] proposed a coupled ship power scheduling model for a shipboard new-energy generation system and ESS. The study uses a second-order filtering method and a PSO algorithm to control an ESS in real-time to smooth power fluctuations. The results show that the method reduces power loss on a new energy ship. In 2022, Kyaw Hein [93] proposed a multi-objective collaborative data-driven scheduling scheme that considers the nonlinear components of a new energy ship scheduling model. Shipboard PV power is predicted using long and short-time memory networks (LSTM) to optimize power scheduling. The study uses the Pearson correlation coefficient method and non-dominated sorting algorithms (NSGA-II and NSGA-III) to determine a power scheduling scheme for a new energy ship. Simulation experiments demonstrate that the proposed method allows multi-objective ship power scheduling.

Xu [94] proposed a new energy ship power scheduling model that considers economic cost, GHG emissions, and ship failure. The study discusses the non-convexity and computational complexity of the dispatching problem for a hybrid power ship system (HPSS). A multiple-population particle swarm optimization (MPPSO) algorithm is used to calculate the dispatching results. Compared with other heuristic algorithms, the proposed model reduces GHG emissions by 8% and total operational costs by 7.45%. Wang [95] proposed a joint optimization model for the wing attack angle and sailing speed by determining the spatio-temporal characteristic of wind energy along the navigation route. The results show that the fuel consumption and the cost of a wing-diesel engine-powered hybrid ship being reduced by 40 tons and 142,000 RMB, respectively. Wang [96] also proposed an energy consumption optimization model to increase the application value and increase the effectiveness of wind energy for sailing ships. The study considers the coupling effects of the sailing path, speed, angle of attack of the wing sails, and environmental parameters. The optimal (Figure 9) decisions for multiple operating conditions are calculated using a PSO algorithm. The results show that the fuel consumption and gas emissions for a full-range ship are reduced by 8.9%.

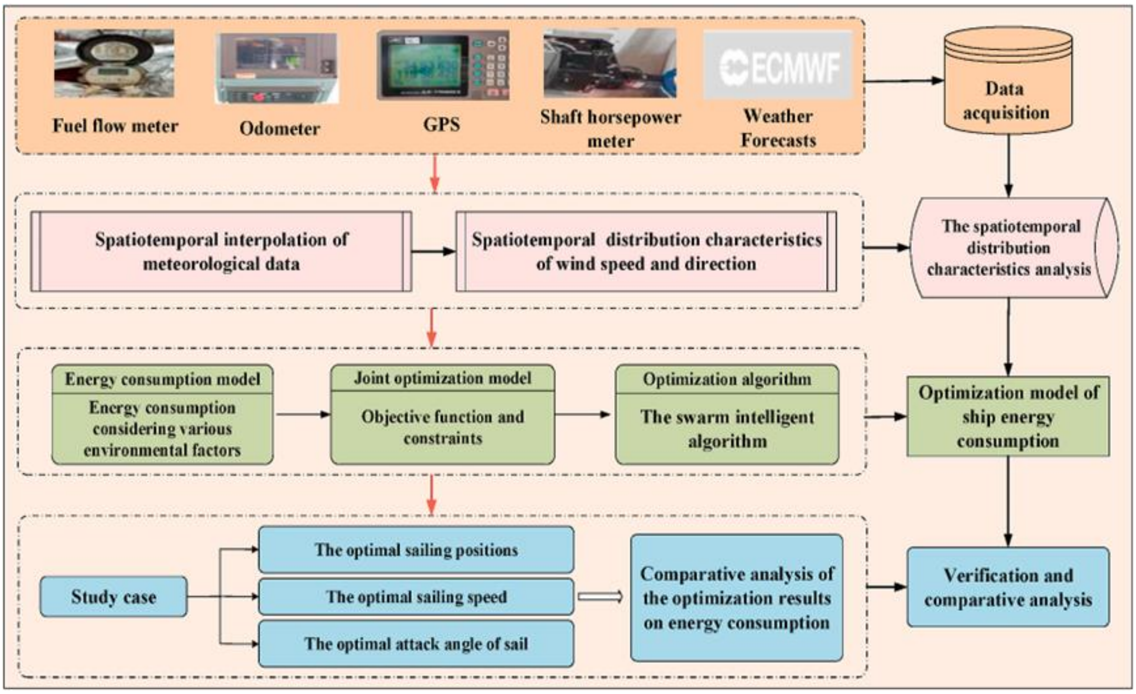

Figure 9. The collaborative optimization process for a typical new energy ship.

In summary, global optimization technology uses global information for new energy ships to realize optimal power allocation for ship power generation units. Global optimization effectively reduces energy consumption and operational cost, increases the utilization rate of new energy, and ensures low-carbon operation. However, it is difficult for global optimization to deal with the vagueness and uncertainty that is inherent in ship power scheduling. Global optimization uses a large number of computational resources because of the complexity of new energy ship power systems. Global optimization requires data-driven technologies to realize new energy ship power scheduling schemes quickly, and this is a major development direction for ship power global scheduling.

3.2. Real-Time Optimization

Real-time optimization technology for power scheduling for new energy ships is in development. Real-time optimization is a process-control method that updates the optimal control sequence online by measuring the system state and the disturbance variables [97].

Real-time optimization uses the latest information to operate the system, which increases system flexibility and prevents disturbance, but real-time optimization requires a highly accurate system model, and the dynamic performance of the system can significantly affect the optimization results. In terms of power scheduling for new energy ships, common real-time optimization techniques include model predictive control (MPC), deep reinforcement learning, and distributed real-time optimization. Real-time optimization generates real-time commands for new energy ships to ensure economical and reliable operation under uncertain conditions.

In 2017, Kuntal Satpathi [98] developed a Platform Supply Vessel (PSV) power system with PV power generation and ES and proposed a power generation scheduling scheme (Figure 10) that uses the optimal power flow (OPF) and real-time transient simulation. Kuntal simulated various operating conditions to increase the reliability of power scheduling. In 2021, a two-stage offline-to-online multi-objective optimization algorithm was proposed to address the economic scheduling problem for a shipboard-integrated energy system. Typical solutions are calculated offline [99]. Using big data processing and a feasible solution is determined online using a multi-objective evolutionary algorithm (MOEA).

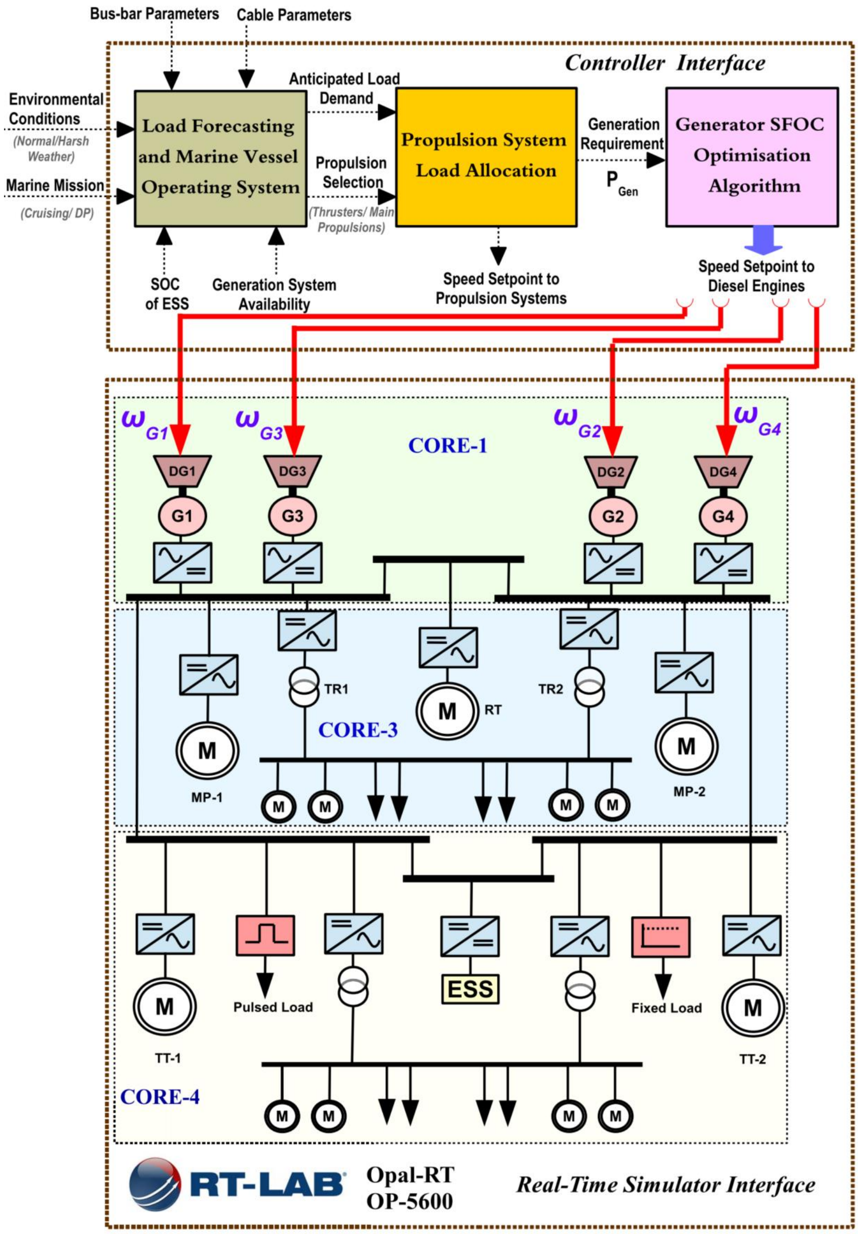

Figure 10. Real-time optimization technology for typical new energy ships.

MPC uses prediction technology to determine the changes in a system state. The rolling optimization strategy of MPC allows real-time scheduling for new energy ships. MPC [100] determines the dynamic time-varying performance for new energy ships to increase the applicability and flexibility of ship power scheduling.

In 2018, Zhou [101] proposed an electricity-price-driven operation cost minimization scheduling scheme that determines the off-grid and on-grid operation modes for new energy ships. The optimization result is calculated using MPC, considering the power fluctuations for new energy and the load. The method gives a $14,300 reduction in operating costs and a 3% reduction in fuel consumption and GHG emissions. Tang [102] proposed an optimal power control scheme that uses different cold-ironing prices and emission regulations for a maritime PV/battery/diesel/ cold-ironing hybrid system. The study used an MPC to minimize the berthing cost. The results show that the proposed scheme reduces the berthing cost for a new energy ship by 2–5% if there is a change in electricity price. In terms of artificial intelligence technology, a data-driven machine learning method is used for real-time optimization that uses environmental factors and multi-dimensional data for the ship. The machine learning method [103] achieves optimized scheduling of a ship power system more precisely and avoids over-dependence on the system, and increases the accuracy in real-time and the reliability of scheduling results.

In 2020, Saeed Hasanvand [104] used a deep reinforcement learning algorithm for zero-emission power scheduling for an all-electric ferry boat power system that uses fuel cells, batteries, and cold ironing. The proposed scheme reduces the daily operating cost by 1% using real-time simulation-based hardware-in-the-loop (HIL) and the loss of load expectation (LOLE) index.

In 2022, Chengya Shang used deep reinforcement learning for the optimal scheduling of a ship power system. The raw measurement data for the ship power system is used to drive the generator and the energy storage system. In 2022, Xia used a complex peer-to-peer system. The experimental results demonstrate that the error is only 9.2% compared to the DQN algorithm and the benchmark method. In 2021, Hoda Ahmadi [105] studied a zero-emission hybrid energy system for ferries that uses Proton Exchange Membrane (PEM) fuel cells, batteries, a Recuperative organic Rankine cycle (RORC) system, and cold-ironing. A Deep Deterministic Policy Gradient (DDPG) algorithm was used for 24-h dispatch for the ship. The proposed method reduces the total cost by about 8%. Various kinds of artificial neural networks are widely used in the power scheduling of smart ships. Due to the limited number of nodes on the ship, many other advanced machine learning techniques have not been well used in ship power systems, such as reinforcement learning, federal learning, hybrid enhanced intelligence, and so on.

Distributed optimization techniques reduce the computational burden of local controllers, prevent a single point of failure and ensure the safety and reliability of new energy ship power scheduling. In 2022, Xia will have a peer-to-peer power dispatching model-joint seaport-AES microgrid (MG) system with practical shore power systems and carbon trade mechanisms. The parameter projection distributed optimization (PPDO) algorithm [106] was used to minimize the operational cost. The results demonstrate that the method increases the convergence rate and increases the fault tolerance.

Real-time optimization increases the flexibility and reliability of power scheduling for a new energy ship. This technology allows optimal control of new energy ships for a system that features dynamic performance and time-varying characteristics, but the optimization results for real-time scheduling are significantly affected by system communication delays, power uncertainty, and computing power. The benefits of real-time optimization decrease as the scale of new energy ship power systems increases. Weighing the relevant factors to make full use of different energy resources is a challenge for new energy ships.

Table 3. Summary of ship power scheduling.

Technology Classification		Optimization Methods	Scheduling Variables	Optimization Objective	Time Scale	Scheduling Effect	Object of Study	Ref.
Global Optimization	Classical Optimization	Nonlinear programming	Photovoltaic, energy storage, diesel unit output, propulsion load	Minimal total cost of ownership	30 min	Increased economy and flexibility	Cruise ferry	[74]
Global Optimization	Classical Optimization	Mixed integer linear programming	Photovoltaic, CCHP, energy storage, diesel units, airspeed, propulsion load	Total cost, minimal gas emissions	30 min	7% reduction in total costs and 10.55% reduction in gas emissions	Multienergy cruise ship	[75]
Global Optimization	Classical Optimization	Mixed integer nonlinear programming	Photovoltaic, energy storage, diesel unit output, propulsion load	Minimal fuel consumption	30 min	New-energy utilization increased; EEOI is reduced by 3.5%	All-electric ship	[76]
Global Optimization	Classical Optimization	the Lagrangian relaxation approach	Photovoltaic, energy storage, CHP, pure thermal unit output	Minimal total cost of ownership	1 h	6.5% reduction in total cost of ownership	Cruise ship	[78]
Global Optimization	Classical Optimization	Dynamic Programming	Photovoltaic, energy storage, CHP output, propulsion load	Minimal total cost of ownership	1 h	Increased economy; EEOI index reduction	Intelligent ship	[79]
Global Optimization	Classical Optimization	Random Programming	Photovoltaic, energy storage, CCHP output, airspeed, propulsion load	Minimal total cost of ownership	1 h~30 min	Total cost and risk reduction 2.5% and 3.5% respectively	Multi-energy cruise ship	[80]
Global Optimization	Classical Optimization	Mixed integer quadratic programming	Land-based photovoltaic wind turbines, nodal voltage, ship energy storage, diesel engine sets, air speed, propulsion load	Minimal total cost of ownership; Saving electricity	1 h~30 min~1 min	Effective saving of electric power; Propulsion power is reduced by 8.4%	Cruise ship	[81]
Global Optimization	Classical Optimization	Mixed integer linear programming	Photovoltaic, energy storage, CI, diesel units out of power	Minimal total cost of ownership	1 h	7% reduction in total cost of ownership	Hybrid electric cruise ship	[82]
Global Optimization	Intelligent Optimization	stochastic optimization SCA algorithm	Hydrogen fuel cell, energy storage, CI out power	Minimal total cost	1 h	Increased economy and applicability	Zero-Emission Ferry Boat	[89]
Global Optimization	Intelligent Optimization	Self-Adaptive Collective Intelligence DE Algorithm	Wind turbines, photovoltaic, diesel units, energy storage out of power	Minimal total cost of ownership and reduced battery life loss	1 h	Increased economy; Convergence increasement	Shipboard microgrid	[91]
Global Optimization	Intelligent Optimization	GA	Photovoltaic, energy storage, diesel unit output, shore power interaction power	Lower fuel consumption, lowest total cost, lower losses in energy storage system	1 h	Increased economy and environmental friendliness	Passenger ferry	[93]

Table 3. *Cont.*

Technology Classification		Optimization Methods	Scheduling Variables	Optimization Objective	Time Scale	Scheduling Effect	Object of Study	Ref.
Global Optimization	Intelligent Optimization	PSO	Photovoltaic, energy storage, diesel units, airspeed, propulsion load	(1) Minimal total cost (2) Minimal gas emissions	1 h	Reduction of gas emissions by approximately 8%; Total cost reduction 7.45%	Hybrid power ship	[94]
Real-Time Optimization	Transient Simulation	Optimal current, transient modeling	Photovoltaic, energy storage, diesel unit output, propulsion load	Lower fuel consumption	Fixed-Time	19% reduction in fuel consumption	Platform supply vessel (PSV)	[98]
Real-Time Optimization	Transient Simulation	NSGA-II	Wind turbine, energy storage, diesel unit output	Minimal total cost and EEOI index minimum	1 h	10% reduction in total costs and 25% reduction in gas emissions	Ship integrated energy system	[99]
Real-Time Optimization	Model predictive control	Quadratic Programming	Photovoltaic, energy storage, diesel units, propulsion load	Minimal total cost	1 h	Total cost reduction of $14,300 and 3% reduction in fuel consumption and gas emissions	Specific hybrid electric green ship	[101]
Real-Time Optimization	Model predictive control	Mixed integer linear programming	Photovoltaic, energy storage, diesel units, CI output	Minimal total cost	1 h	2–5% reduction in total cost	Maritime hybrid energy system	[102]
Real-Time Optimization	Intensive Learning	DQN	Hydrogen fuel cell, energy storage, CI out power	Minimal total cost and optimal loss of load expectation(LOLE) index	1 h	1% reduced in daily operating cost and significantly increased LOLE	All-electric ferry boat	[104]
Real-Time Optimization	Distributed real-time optimization	parameter projection distributed optimization (PPDO) algorithm	Photovoltaic, wind turbines, diesel units, energy storage, interaction with the power grid	Minimal total cost	1 h	Increased economic and fault tolerance	Seaport-AESs interconnection system	[106]

3.3. Summary

Ship power scheduling is an optimization problem. The optimization objectives for power scheduling for a new energy ship are operational cost, gas emissions, and the power supply reliability index. The power allocation scheme for each unit in a new energy ship power system is determined by feasible solutions of the mathematical optimization model. Power scheduling for a new energy ship is essential if ships are to be economical, green, and reliable.

Current power scheduling for new energy ships uses global and real-time optimization. Global optimization is widely used due to its high computation speed and simple optimization model. But global optimization is unable to dispatch the power system in real-time, especially when it is used in a new energy ship. Real-time optimization allows real-time adjustments for new energy ships, but it increases the computational, operational, and communication cost [107]. Optimization technology that is specific to a ship ensures operational stability for new energy ships. Power scheduling for a new energy ship requires optimization, deep learning, and advanced control. Balancing power stability and economy will allow transformation and upgrading of the new energy ship industry.

4. New Energy Ship Digital Twin Technology

The shipping industry will undergo a transformation to low-carbon, intelligent and integrated operation and maintenance (O&M). Ship DT [108–113] technology twins the shipping entity in the real world and the virtual twin in the digital world. A virtual ship twin can reproduce various operational conditions and complicated event processes. Ship DT is a new technology that offers three distinct advantages for new energy ships: It uses multi-dimensional multi-source data to create the navigational environment twin for new energy ships. The navigational environment twin accurately simulates the condition for the shipboard's new energy. DT [114] also combines the ship and the meteorological environment together in a virtual space to predict the power output for a new energy ship; DT allows intelligent O&M for new energy ships and provides smart real-time strategies for ship power scheduling, fault detection, and predictive maintenance. DT determines the whole life cycle performance for new energy ships to increase their long-term and overall economy. DT technology significantly increases the efficiency of ship power studies and reduces the experimental risk. DT for a new energy ship power system allows the transient simulation of a power system. A transient simulation of a ship power system is the basis for ship DT. This section introduces ship power system transient simulation technology.

4.1. Ship Power System Electric Transient Simulation

Shipping navigation conditions are complex, the environment is harsh and changeable, and a new energy ship power system is vulnerable to uncertain power fluctuation, which reduces the ship's power transient stability. Transient simulation technology that uses the transient characteristics of electrical equipment to construct a time-domain high-order differential model is a low-cost, flexible, and convenient operation and is essential for ship power design, stability analysis, and protection. Transient simulation technology is also the basis of DT for ship performance in the ship power system. Current ship power system simulation software is not exclusive. This study determines the transient simulation technology for a land power grid that can be applied to a ship power grid using a different model-solving method. An electromechanical transient simulation and electromagnetic transient simulation are used [115–117]. The applications for transient simulation technology on ships are shown in Table 4.

4.1.1. Electromechanical Transient Simulation

The electromechanical transient simulation calculates the time domain solution for the transient process quantities of power systems by solving a system of differential equations and algebraic equations. Electromechanical transient simulation software is widely used for land grids or equipment-level power simulations, so there are few applications for ship power system simulation. Power system electromechanical transient simulation programs, such as the Power System Simulator/Engineering (PSS/E) software from PTI (USA), the power system synthesis programs Power System Analysis Software Package (PSASP), and Bonneville Power Administration (BPA) power system analysis programs from China, the ABB (Sweden) SIMPOW program, the NETOMAC platform from Siemens, Germany and the DIG-SILENT software from POWERFACTORY [118,119] are used.

PSS/E is widely used for the steady-state and dynamic process analysis of transmission and distribution networks or large generating units. It simulates thousands of power lines or generators simultaneously. PSS/E has calculation capability and is compatible with subroutines. Decurrent

By using PSS/E. In 2021, Michael Abdelmalak [120] converted the New York State Large Grid PSS/E model to an RSCAD model for a semi-physical real-time simulation in the RTDS simulator. The results demonstrate that the average simulation error for the bus voltage magnitude between PSS/E and RTDS simulations is 0.271%, the standard deviation is 0.621%, and the maximum deviation is 4%. These results demonstrate the simulation accuracy and robustness of PSS/E.

PSASP software has a primary grid database, a fixed model base, and a user-defined model base to simulate various power systems. PSASP allows users to build self-defined models without complex program codes and simulates various new electrical components and automatic control devices. In 2020, Wang [121] used PSASP to simulate the black start process for a thermal generator in Vida Bay Industrial Park, Indonesia. The parameters for a diesel governor and an automatic regulator were debugged to determine the effect of the parameters on the power system's transient stability. The results of the experiments show that the PSASP simulation approaches actual operating conditions.

Power System Department-Bonneville Power Administration (PSD-BPA) is a power system analysis software that was developed by the BPA in the 1960s [122]. BPA terminated the development and maintenance of the PSD-BPA transient stability program in 1996, and now PSD-BPA is only serviced by the China Electric Power Research Institute.

4.1.2. Electromagnetic Transient Simulation

The electromagnetic transient simulation uses numerical calculation methods to simulate electromagnetic transient processes for power systems from a few microseconds to several seconds. Electromagnetic transient simulation software is widely used for ship power systems. Electromagnetic transient programs (EMTP) have been developed by many countries. The China Electric Power Research Institute proposed an EMTPE that uses EMTP [123]. Similarly, EMTDC/PSCAD (Electromagnetic Transients including DC/Power Systems Computer Aided Design) was developed by the Manitoba DC Research Centre in Canada [124]. Microtran was developed by Columbia University in Canada, and NETOMAC was developed by Siemens [125,126].

PSCAD/EMTDC/PSCAD was completed in Canada in 1976 and is used worldwide with PSCAD as the user interface. The successful development of PSCAD allows EMTDC to be used for power system analysis. EMTDC simulates any size of AC/DC systems and over-voltage faults, short circuits, and open circuits [127].

In 2020, Wu [128] constructed a ship cyber-physical co-simulation platform that uses a High-Level Architecture (HLA) framework. The co-simulation of shipboard power systems and information networks is accomplished using OPNET HLA using custom modules for simulation. The transmission delay when a fault occurs is 200–1000 µs. In 2020, Lin developed a mathematical model of a ship DC bus and propulsion motor load using a PSCAD hybrid simulation and hardware-in-the-loop testing. The study defined flexible energy scheduling and the virtual inertia of IPS [129]. A flexible energy scheduling algorithm was used to control the propulsion motor load and the pulse load to mitigate the effect of the pulse load on the IPS system. In the simulation experiment, the PSCAD simulation step was 20 µs. The maximum fluctuation in the propulsion motor power is

1.5 MW and the effective value for the bus voltage is 4950 V~5050 V. PSCAD simulation models simulate the operating conditions of a ship power system.

In 2018, Feng [130] proposed a Multi-intelligent Agent System (MAS) that uses decentralized collaborative controllers. The PSCAD simulation results for a dual-zone all-electric ship power system demonstrate that the system frequency decreases to 59.4 Hz when a 10% load (0.4 MW) is disconnected. A UFLS algorithm was developed to adjust the load to restore the frequency of the ship power system. In 2015, Sun [131] developed a simulation model for a PV ship power system (PSPS) that uses a PSCAD/EMTDC platform.

The transient characteristic of PSPS, such as the fault transient process, when a shipboard PV system is connected to the primary grid was studied. A PQ control strategy (Figure 11) was used for the PSCAD model to control a shipboard PV generation system and synchronous generators. The transient simulation results show that the PV generation system has little effect on a single-phase fault.

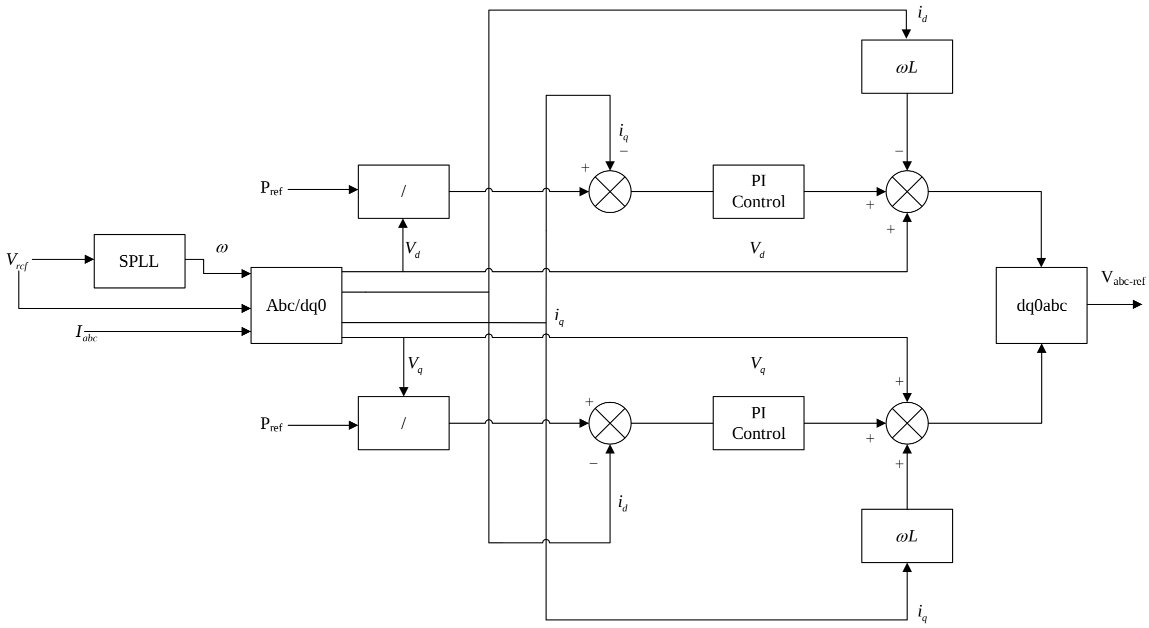

Figure 11. PQ control strategy model.

An Electro-Magnetic Transient Program/The Alternative Transients Program (EMTP/ATP) was developed by Prof. H.W. Dommel in Canada, and featured multiple analysis functions, complete component models, and accurate calculation results. ATP is a free, stand-alone version of EMTP and is one of the most widely used EM transient analysis programs to simulate complex networks and control systems.

In 2021, J.J. Deroualle [132] presented a dual-circuit modeling of an EMTP-ATP time-domain simulation to determine the ability to protect a marine power system with a DC bus. The advantages and limitations of two DC fault methods, fuel cells and battery power for DC structures, are discussed. Their use for feeder protection with high-speed fuses in DC was also studied. The EMTP-ATP time-domain fault comparison results were used to derive time-current curves for 400 A-rated fuses. Two EMTP-ATP circuit models eliminated the fault in less than 10 ms, which demonstrates the effectiveness of the protection components.

Simulink is a visual simulation tool that was developed by Mathworks y. It is a multi-domain model-based simulation software that supports the functions of system design, simulation, automatic code generation, and continuous testing and verification of embedded systems. Simulink has graphical editors, customizable module libraries, and model solvers. Simulink is used in the automotive, aerospace, and industrial automation industries and for large-scale modeling, complex logic, physical logic, and signal processing.

In 2020, Yan [133] developed a ship energy efficiency model for a 53,000 GT Chinese coastal bulk carrier that uses Monte Carlo simulation methods and Simulink software. The designed model has sufficiently high accuracy (Figure 12) to simulate ship energy efficiency considering the consideration of stochastic effects of cargo loading, ship speed, and various natural environments. The energy efficiency operating index for a ship has increased by about 6.44%.

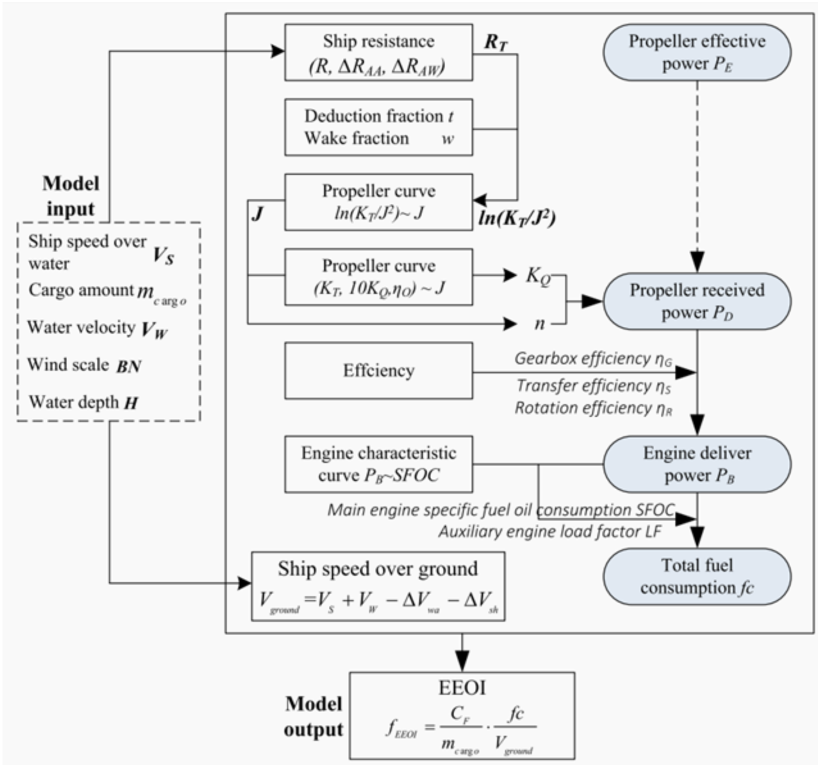

Figure 12. Flow chart for a simulated calculation of EEOI.

In 2019, Samy Faddel [134] simulated an intelligent power coordination algorithm using Simulink that mitigates the effect of pulse loading and ensures power sharing between different storage units. The proposed decentralized coordination strategy for the shipboard hybrid energy storage system does not require a link with other system components, unlike a conventional strategy. To ensure power sharing in the ship power system, the initial SOCs for the batteries are 70% and 25%, and the supercapacitor is 50%.

In 2022, Hyun-Keun Ku [135]. presented a medium voltage DC power system Simulink model for the analysis of an all-electric ship (AES). The proposed model has mechanical and power systems. The effectiveness of the developed individual AES model and the integrated AES model was verified for different ship operating conditions. In 2019, Tien Anh Tran [136] used the Energy Efficiency Operational Indicator as a monitoring tool to establish an improved numerical model of the energy-efficient operation condition of a large ship's main engine using different navigational environments in Simulink. The simulation value for wave resistance varies from 180 kN to 0 for different ship speeds, and the theoretical calculation value varies from 250 kN to 30 kN. In 2017, Kyunghwa Kim [137] simulated a hybrid power system for a medium-sized container ship using Simulink software to determine the optimal allocation of shipboard ESS. The CO_2 emissions for the proposed planning scheme are reduced by 8.6% to 20.7% compared to a traditional ship power system.

This section describes the common simulation tools for ship power system transient modeling. In the future, transient modeling simulation technology will include multi-disciplinary knowledge and multi-intelligence algorithms to increase the automation and intelligence of ship power systems.

4.2. Ship Power System DT

DT technology [138] involves multi-disciplinary knowledge, coupled simulation of multiple physical fields, and multi-time scale data interchange. DT uses historical data, and real-time data that are measured by sensors to map physical entities to virtual entities [139]. It allows real-time operation and is very accurate. Simulation technology and deep learning algorithms are used for DT. Ship DT technology uses operational data and environmental data to mine hidden information from data and to determine an optimum O&M strategy. DT also allows better fault detection and increases the operating efficiency of new energy ships. Ship DT must allow real-time simulation of different physical fields to establish a powerful twin and reduce the simulation time while maintaining computational accuracy and high resolution. The applications for DT on ships are shown in Table 4.

Table 4. Marine power system transient simulation and dt technologies.

Transient Classification		Simulation Object	Applications	Ref.
Electromechanical Transient Simulation	PSS/E	Simulation accuracy	The PSS/E model of the New York State grid was converted to a RSCAD model for real-time simulation on the RTDS simulator. The average error value for the difference between the obtained bus voltage magnitudes is 0.271%, with a standard deviation of 0.621% and a maximum value of 4%	[120]
Electromechanical Transient Simulation	PSASP	Simulation accuracy	Modeling simulation of the black start process for thermal power in Vida Bay Industrial Park, Indonesia and commissioning of diesel governor and automatic regulator parameters. The advantages of PSASP in calculating and analyzing electromagnetic transient processes were used to validate the full black start process simulation	[121]
Electromagnetic Transient Simulation	PSCAD/ EMTDC	Fault scenario simulation	The PSCAD simulation step was 50 μs, and a co-simulation interface used the OPNET HLA node and the PSCAD custom module to simulate a shipboard power system and information network. The rated capacity of the inverter is 562 kVA, the rated output voltage of the inverter is 400 V and the rated output current of the inverter is 811.9 A. Tthe corresponding transmission delay range when a fault occurs is typically 200–1000 μs.	[128]
Electromagnetic Transient Simulation	EMTP/ ATP	Simulation time	J.J. Deroualle analyzed the protection design for a marine power system (SPS) with a DC standard bus distribution and analyzes two DC fault methods, such as fuel cells and battery power for DC structures. Both EMTP-ATP circuit models demonstrated the effectiveness of the protection components, with a fault clearance time of less than ten milliseconds.	[132]
Electromagnetic Transient Simulation	Simulink	CO_2 emissions	Kyunghwa Kim simulated a hybrid power system for a medium-sized container ship using Simulink software. The power system reduces CO_2 emissions by 8.6% to 20.7% > this is better than a conventional power system, which uses only a generator.	[137]
DT of Marine environment and power systems		Two Handymax chemical/product tankers	The effect of marine pollution on ship speed was analyzed by twinning ship speed and the marine environment. The validity of the model was verified using real data from two Handymax chemical/product tankers	[140]
DT of manufacturing systems		Digital twin-driven ship intelligent manufacturing system	Five-layer DT framework for ship smart manufacturing. Validation of the five-layer DT-based application framework using a pipeline processing line	[141]
DT of ship power systems		Naval shipboard power and energy systems	Exploring the optimal DT model simulation method. Modeling the DT for the boost converter as part of the shipboard power system and validating the effectiveness of the hybrid approach for modeling	[142]
DT of ship engine systems		Ship engine system and shipping cargo container	Use DT models to predict ship-specific parameters and specify optimal ship operation strategies. Best mean percentage deviation (MPD) of 5.22% between predicted and experimental values using DT drive	[143]

Table 4. *Cont.*

Transient Classification	Simulation Object	Applications	Ref.
DT of ships	A small group product of ships	Lagging and poor prediction of welding quality control in ship assembly. DT-based prediction model can accurately evaluate product weld angle deformation	[144]
Improving the predictive maintenance capability of new energy ships	Container ship	Monitoring and predicting fatigue damage to ships. A case study of a 7-year old container ship confirmed the effectiveness of DT technology	[145]
Full life cycle assessment of new energy ships	Maritime Digital Twin Architecture (MDTA)	Further digitalization, intelligence and decarbonization of ships. Proposed an offshore DT architecture that can be applied to the full life cycle of a ship	[146]
Full life cycle assessment of new energy ships	Ship whole life cycle digital twin (SWLC-DT)	The DT model uses historical data to build and evolve at each stage of the next generation ship lifecycle. The analysis of historical data from multiple generations of ships for the whole life cycle of new-generation ships proves the effectiveness of SWLC-DT	[147]
Full life cycle assessment of new energy ships	Research vessel Gunnerus	Analyzed various states and behaviors at each stage of the life cycle of the ship to provide reliability strategies for ship control and optimization. Full-scale ship docking experiment using the Gunnerus at Norway's Åle-sund harbor to verify the effectiveness of the ships DT system. Fault analysis, dynamic simulation, network equivalence, and safe operation are ensured.	[148]

A new energy ship power system DT requires electrical parameters for equipment, operating data for the power system, ship attitude data, and meteorological data for the route. Ship DT considers the effect of the navigation environment on the power system of new energy ships. In 2019, Andrea Coraddu [140] proposed a ship DT model that uses sensor data to determine the effect of ship speed on polluting emissions. Tests on two Handymax tankers showed the effectiveness of the proposed model. Ícaro Aragão [145] Fonseca used ship DT to simulate a scale model ship with a dynamic positioning system in an artificial pool in 2022. An advanced version of ship DT software uses experimental results to increase the capacity for motion responses for a ship.

New energy ships have a more complicated power system than traditional ships and additional electrical equipment, so ship power system faults are more complex and difficult to solve. DT analyzes complex faults to decrease the failure rate for new energy ships. In 2021, Wu [141] determined the effect of DT on the intelligent manufacturing of ships. The study assumes that a ship DT framework consists of a physical layer, a modeling layer, a data layer, a system layer, and an application layer. In 2021, Andrew Wunderlich [142] verified that DT must be used for power and energy management in all-electric warships. The study demonstrates various simulation technologies for DT modeling and proposes a DT model of a boost converter that uses a mixed modeling method (Figure 13) for a shipboard microgrid. Wang [143] studied the drive process for ship DT for marine engine systems and marine containers in 2022. The study constructed a ship DT model using Maya modeling technology and Unity 3D scene rendering. A Bayesian neural network was used to fuse multi-source heterogeneous data in a virtual simulation layer and a data layer. The Ship DT model was used to forecast cabin temperature with only a 5.22% MPD error. Li [144] proposed a DT-based quality prediction and control method to eliminate the lag in ship assembly welding and increase the prediction accuracy in 2022. The proposed method predicts and controls the performance of Ship Group Products (SGP). The method uses physical assembly and welding equipment, virtual assembly and a welding model, a prediction and control system, and digital data. In 2022, Eric VanDerHorn [145] used global vessel position data and metocean hindcast data instead of missing fatigue measurement data and used ship DT to simulate the 7-year operation of a container ship to calculate ship fatigue time.

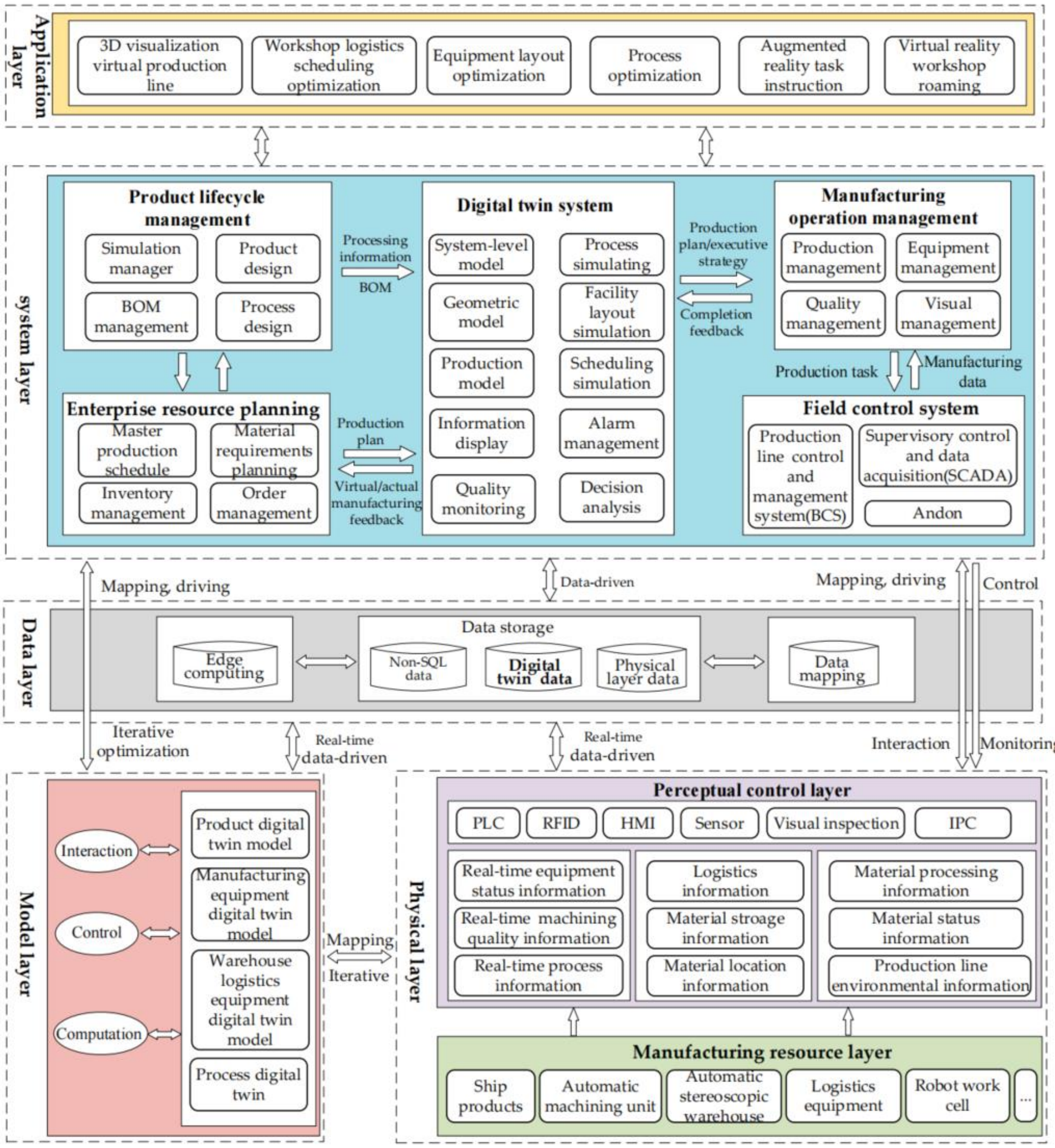

Figure 13. Application framework of DT-driven ship intelligent manufacturing system.

The capital cost of new energy ships is greater than that of traditional ships, but the operating cost is less. New energy ships with DT technology have long-term economic benefits. Ship DT reduces the cost of ship design, manufacture, and O&M. DT also processes the ship and environment information in real-time for the entire life cycle of new energy ships to self-tune the model. In 2021, Jan-Erik Giering [146] studied ship DT from the perspective of the ship life cycle and defined Maritime DT Architecture (MDTA). In 2022, Xiao [147] defined the whole life cycle of a ship to include design, manufacture, operation, maintenance, and scrapping. Information islands are caused by the "One Stage Analysis" of a ship. Xiao proposed a ship design framework that uses DT with historical experience and real-time data. A ship DT model can evolve and be used to predict each stage of the ship's life cycle. In 2021, Lan developed DT software for a ship power system. The software allowed online monitoring and transmission, ship power system health management, and intelligent dispatching functions and was applied to a 25-m all-electric propulsion research vessel (Figure 14). In 2022, Zhang [148] discussed the development of the shipping industry. Ship DT simulates various operating conditions and generates twin data to generate optimum strategies for ship controlling and scheduling. The study performed full-scale ship docking experiments using 'Gunnerus,' which is a Norwegian research vessel, to verify the effectiveness of the ship DT system.

Figure 14. DT software platform of an all-electric smart vessel power system.

DT technology has been widely applied in new energy ships. Ship DT is an important component in the technology system of new energy ships, but it is still in the exploratory stage. Ship DT urgently requires an efficient open-source software platform to quickly unite different simulation systems. A reasonable technical framework for ship DT is also necessary to be proposed to achieve reliable, low-carbon, and intelligent operation and maintenance.

4.3. Summary

Ship electric transient simulation technology needs a lot of manpower and material resources to establish models and tune parameters. Ship electric transient simulation technology is always realized on commercial closed-loop software, which means that it is difficult to establish a real-time data interaction channel among multiple electric transient models. The development from ship electric transient simulation technology to ship DT technology has increased the efficiency of marine electrical research. DT allows the monitoring and detection of ship electric systems to optimize control and prediction. DT is used for all phases of the entire life cycle of new energy ships to increase the accuracy of the model and reduce the experimental cost and the length of the research cycle. A ship DT model contains multi-physical field and multi-source data and prediction technology and accurately predicts the new-energy power output on a ship and generates the optimal strategy for ship power scheduling. Ship DT technology allows better and faster transformation and development of new energy ships. DT technology has developed from real-time to predictive operation. Increased real-time data interaction, fast prediction, and high simulation accuracy are development goals.

5. Conclusion and Future Study

A new energy ship power system is a comprehensive new-born system that involves multi-disciplinary fields. The topology of a new energy ship power system is much more complicated than that of a traditional ship. Many widely-used marine electric technologies are no longer applicable for new energy ships. In recent years, marine electric technologies that are applied in new energy ships are always improved through data processing, artificial intelligence, and high-speed communication technologies. A ship power system is also regarded as an isolated microgrid. Some advanced marine electric technologies often originate from the fields of smart microgrids and electric vehicles.

An AC shipboard microgrid gradually transforms into an AC-DC hybrid shipboard microgrid. A solar-wind complimentary shipboard generation system will supersede traditional solar or wind shipboard generation systems. New-energy generation technology is widely applied in a variety of ship types. In the future, there will be more types of ship electrical power loads. The utilization rate for shipboard new energy will be increased. The commercial value and technological potential of new energy ships will be vigorously exploited.

Maritime spatio-temporal prediction of new energy uses multi-source data to predict power or meteorological change. The time scale for multi-source data is diverse. Multi-source data are informative and increase the generalization ability of prediction models and the performance over different forecasting time scales. Previous studies focused on spatial-temporal correlation calculation and the optimization of the prediction model architecture. Spatial-temporal forecasting models generate unknown errors, so forecasting model post-processing technology could reduce the error in prediction results compared to actual values. New energy ship power systems will comprise different offshore new-energy generation systems, so it is necessary to develop multi-energy spatio-temporal prediction technologies to collaboratively forecast the coupling fluctuations for shipboard new-energy output.

New energy ship power scheduling technology has developed rapidly. Power uncertainty for new energy ships will increase significantly and complicate operating conditions in a variable navigation environment. The fluctuation in shipboard new energy must be determined. The power scheduling technology for new energy ships should analyze the coupling effect between multiple uncertainty factors and establish a comprehensive uncertainty assessment system. New energy ship power systems will be more complex, and different power units have different generation or load characteristics, so power scheduling technology for new energy ships must have a reasonable scheduling time scale to allow a flexible, reliable, and low-carbon operation of new energy ship power systems. Existing power scheduling technology relies on a linear optimization model of a power system. A linear optimization model cannot simulate a complicated ship power system. Data-driven modeling technology mines multiple characteristics of historical data to model complicated power systems. Existing technology that uses centralized optimization cannot be used for the distributed topology of future ship power systems and will be replaced by distributed scheduling technology, which describes the distributed characteristics of the system. An efficient distributed algorithm will increase the reliability and security of new energy ships.

DT, which is an intelligent simulation technology, will be applied to new energy ships. The twin model of a new energy ship allows subprograms and new user-defined models to be embedded. A software platform that uses DT must be compatible with other simulation software, deep learning frameworks, and data communication platforms. The simulation speed for the ship power system will be increased significantly by DT, and real-time simulation will give way to ‘forecast’ simulation. Data that are used by a ship DT software platform will change from single-source to multi-source because multi-source data increases the reliability and accuracy of the ship twin model. A DT model of a shipboard microgrid must be self-renewing and must simulate different operating conditions during the whole life-cycle of a new energy ship to generate optimal operation and maintenance strategies.

New energy ships will transform the shipping industry into a low-carbon venture. With the development of deep learning and cloud-edge cooperative communication, new energy ship power systems will feature energy prediction, power scheduling, and DT to satisfy multiple engineering requirements.

Author Contributions: Conceptualization, H.L.; validation, Y.-Y.H.; investigation, D.L. and D.G.; resources, P.C.; writing—original draft preparation, H.Y. and Z.W.; writing—review and editing, H.Y. and Z.W.; funding acquisition, H.Y. and H.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Nature Scientific Foundation of Heilongjiang Province LH2020E069.

Acknowledgments: This work was financially supported by the project of Nature Scientific Foundation of Heilongjiang Province under LH2020E069, "Research on MAS-based Integrated Energy Management System of an Ocean Liner Power System".

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

T	Digital twin
GHG	Greenhouse gases
SOx	Sulfur oxides
NOx	Nitrogen oxides
PM	Particulate matter
EEDI	Energy efficiency design index
DOC	Diesel oxidation catalyst
SDPF	Selective catalytic reduction coated diesel particulate filter
EEOI	Energy efficiency operation index
PV	Photovoltaic
AI	Artificial intelligence
ARMA	Auto-regressive moving average
VAR	Vector auto-regressive
LASSO	Least absolute shrinkage and selection operator
NRMSE	Normalized root means square error
ARX	Auto-regressive with exogenous
CRS	Calibrated regime-switching
CGAE	Convolutional graph autoencoder
ST Copula	Spatio-temporal copula
ST QR Lasso	Spatio-temporal qr lasso
CSTF	Compressed spatio-temporal forecasting
ST-SVR	Spatio-temporal support vector regression
NSRDB	National solar radiation database
GCLSTM	Graph-convolutional long short-term memory
GCTrafo	Graph-convolutional transformer
MAPE	Mean absolute percentage error
MST-GCN	Multi-attributed spatio-temporal graph convolutional network
ASOS	Automated surface observing systems
T-GCN	Temporal graph convolutional network
GRU	Gated recurrent unit
GCN	Graph convolutional network
MLP	Multilayer perceptron
GNN	Graph neural network
LSTM	Long short term memory
MFSTC	Multifactor spatio-temporal correlation
LMD	Local measurement data
NWP	Numerical weather prediction
BILST	Bi-level spatio-temporal
GOE	Geostationary operational environmental satellites
CLAVR-x	Clouds from avhrr extended

MERRA2	Modern-era retrospective analysis for research and applications version 2
MCSIP	Multichannel satellite Image prediction
GAN	Generative adversarial net
CovnGRU-VB	Convolutional gru
PSO	Particle swarm optimization
SPO	Solar power output
DARTS	Differentiable architecture search
ATCN	Attention temporal convolutional network
NREL	National renewable energy laboratory
VARX	Var with exogenous variables
STMC	Spatio-temporal markov chain
ST	Spatio-temporal
GCDLA	Graph convolutional deep learning architecture
STGN	Spatio-temporal correlation graph neural network
CFSR	Climate forecast system reanalysis
GACN	Graph attention convolutional net-work
GACN-LSTM	Graph attention convolutional net-work (GACN) with LSTM
UQ	University of queensland
DKA	Desert knowledge australia
NMSC	National meteorological satellite center
NREL	National renewable energy laboratory
EEMD	Ensemble empirical mode decomposition
SOM	Self-organizing map
SOM-BP	Self-organizing map-back propagation
STD	Standard deviation
EDD	Euclidean distance
VMD	Variational mode decomposition
MBLS	Monotone broad learning system
BiLSTM	Bidirectional long-short term memory
GRU-CNN	Gated recurrent unit-convolutional neural network
SVR	Support vector regression
SDA	Stacked de-noising auto-encoder
UKF	Unscented kalman filter
EM	Expectation maximizing
GEFCom2014	Global energy forecasting competition 2014
BP	Back propagation
RBF	Radial basis function
ELM	Extreme learning machine
DELNET	Nikodinoska used a dynamic elastic net
DDP	Dynamic data pre-processing
DEC	Dynamic error compensation
HR	Hierarchical residual
CFI	Choquet fuzzy integration
GMM	Gaussian mixture model
WIND	Wind integration national dataset
WGAN	Wasserstein-gan
ERA5	European re-analysis
QRMBLS	Quantile regression monotone broad learning system
ERA5	European reanalysis(dataset)
MMC	Multi-model combination
TSO	Transmission system operator
DBN	Deep belief network
IGRU	Improved gated recurrent unit

GA	Genetic algorithm
CCHP	Combined cooling heat and power
CvaR	Value-at-risk
ESS	Multi-energy ship
CI	Cold-ironing
SPS	Shore power system
MES	Multi-energy ship
SCA	Sine–cosine algorithm
NSGA	Non-dominated sorting algorithm
HPSS	Hybrid power ship system
MPPSO	Multi-populations particle swarm optimization
MPC	Model predictive control
PSV	Platform supply vessel
OPF	Optimal power flow
MOEA	Multi-objective evolutionary algorithm
LOLE	Loss of load expectation
HIL	Hardware-in-the-loop
PEM	Proton exchange membrane
RORC	Recuperative organic rankine cycle
DDPG	Deep deterministic policy gradient
MG	Microgrid
PPDO	Parameter projection distributed optimization
PSV	Platform supply vessel
LOLE	Loss of load expectation
PPDO	Parameter projection distributed optimization
O&M	Operation and maintenance
PSS/E	Power system simulator/engineering
PSASP	Power system analysis software package
BPA	Bonneville power administration
PSD-BPA	Power system department-bonneville power administration
EMTP	Electromagnetic transients program
HLA	High-level architecture
MAS	Multi-intelligent agent system
PSPS	PV ship power system
EMTP/ATP	Electro-magnetic transient program/The alternative transients program
AES	all-electric ship
SGP	Ship group products
MDTA	Maritime digital twin architecture
SPS	Shipboard power system
MPD	Mean percentage deviation
SWLC-DT	Ship whole life cycle digital twin

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