Artificial Intelligence Techniques for Efficient Control of Shipboard Power Systems: A Review

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Artificial Intelligence Techniques for Efficient Control of Shipboard Power Systems: A Review

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Abstract

Maritime transport contributes approximately 2.5% to global greenhouse gas (GHG) emissions and faces rising operational costs due to increasing fuel prices. Optimizing shipboard energy systems has become essential to enhancing sustainability and efficiency. This paper presents a comprehensive review of artificial intelligence (AI), machine learning (ML), and deep learning (DL) methods applied to the optimization and control of ship microgrids. It highlights the architectures, challenges, and benefits of integrating AI into marine energy systems. A comparative analysis of AI-driven schemes for energy efficiency, fault diagnosis, and emission reduction is presented. The findings underline the transformative potential of AI-based control systems in enabling intelligent, adaptive, and environmentally compliant marine operations.

Keywords: Ship Microgrid, Artificial Intelligence, Machine Learning, Deep Learning, Renewable Energy, Energy Storage Systems

Introduction

Although Earth is around 4.54 billion years old, humans, who make up just 0.01% of its life forms have drastically reshaped it in a very short time. Particularly over the last 50 years, human activity has led to the loss of 83% of wild mammals and nearly half of plant species, while consuming 30% of known natural resources, putting future ecological stability at risk. Driven by rapid population growth and environmental degradation, this impact has intensified. Atmospheric CO_2 levels, a major driver of climate change, have climbed from 323 ppm in the 1970s to over 411 ppm today. Since the 1970s, freshwater animal populations have fallen by 75% [1]. According to the UN Climate Report 2021, greenhouse gas levels hit record highs in 2020 and continued rising in 2021, with CO_2 reaching 413.2 ppm 149% above preindustrial levels [2].

The maritime sector is under increasing pressure to minimize its environmental footprint and improve energy efficiency. According to the International Maritime Organization (IMO), global shipping emitted over 940 million tons of CO_2 annually, a

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figure that could rise significantly by 2050 if unaddressed [10][11]. With fuel prices soaring and stricter emissions regulations being introduced, ship operators are compelled to seek advanced energy management strategies [3][12].

Recent advancements in electrification have introduced hybrid and all-electric ship designs. These rely heavily on microgrid technologies that integrate distributed energy resources (DERs), storage systems, and high-demand variable loads such as propulsion units [12][13]. However, managing these complex power systems requires intelligent, real-time control strategies. Traditional rule-based or PID control approaches lack the flexibility to adapt to non-linear and dynamic marine environments [14][15][16].

Artificial intelligence, including machine learning and deep learning methods, has emerged as a promising solution. These techniques offer predictive maintenance, dynamic power demand estimation, real-time decision-making, and improved load balancing, ultimately reducing fuel consumption and GHG emissions [17]. This paper surveys the current state-of-the-art in AI applications to ship microgrids, identifies key challenges, and outlines future research directions.

Background and Related Work

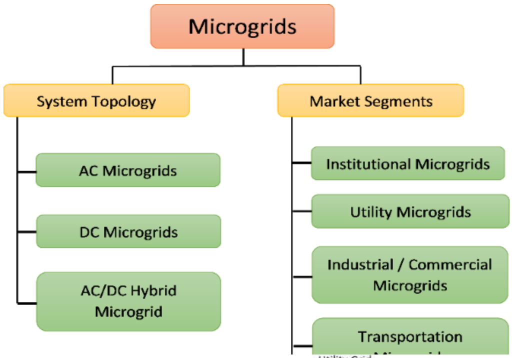
Microgrids are localized electrical power subsystems that integrate distributed energy resources (DERs), including both renewable and traditional sources such as photovoltaic (PV) systems, hydroelectric plants, wind turbines, gas turbines, internal combustion engines, and microturbines, along with a collection of loads [18], [19]. The U.S. Department of Energy defines a microgrid as "a group of interconnected loads and DERs with clearly defined electrical boundaries that operates as a single controllable entity with respect to the grid and can function in either grid-connected or islanded mode" [20], [21]. Other researchers describe microgrids as "a miniature power system comprising distributed energy resources, loads, and controllers" [22] or "a system of movable DERs and multiple loads within the existing power network, including solar PV, microturbines, wind turbines, and storage devices capable of operating in grid-connected or stand-alone mode" [23]. The following sections provide an overview of the different classifications of microgrids.

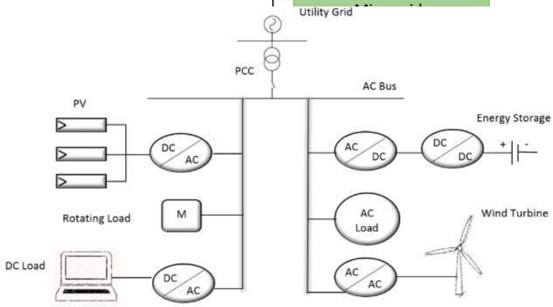
Classification of Microgrids

Microgrids are classified by topology into AC, DC, and hybrid AC/DC systems [24], [25], and by application into institutional, utility, industrial/commercial, transportation, and remote-area categories [26], [27], as shown in figure 1 [28]. AC microgrids dominate conventional power systems, while DC systems offer higher efficiency. Hybrid configurations combine both advantages for improved flexibility. This dual classification framework highlights the technology's diverse implementations across sectors. Microgrid architectures have evolved significantly to accommodate diverse energy resources and operational requirements.

Figure 1: *Microgrid classification by topology and application [28]*.

1. AC Microgrids





AC microgrids remain the most prevalent configuration due to their compatibility with existing power infrastructure, utilizing power electronic converters (PECs) to integrate distributed energy resources (DERs) such as fuel cells, wind turbines, and solar PV systems [29]. These systems enhance power distribution efficiency in medium- and low-voltage networks while reducing transmission losses [28]. However, their operation requires precise synchronization of phase angle, frequency, and voltage with the main grid [30], and the multiple conversion stages inherent in AC systems can compromise reliability compared to DC alternatives as shown in figure 2 [31].

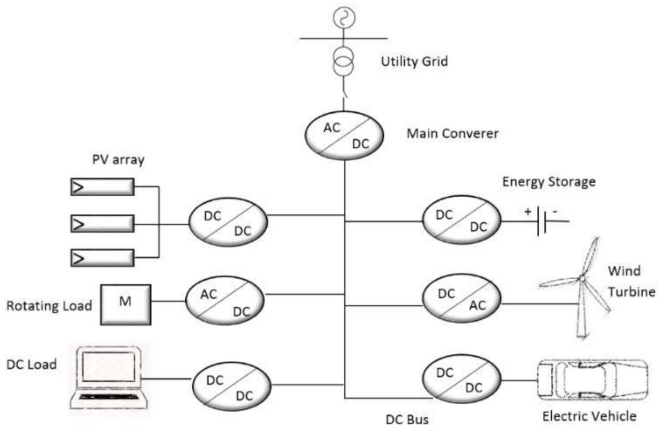
Figure 2: *AC microgrid configuration with interconnected elements [31]*.

2. DC Microgrids

The emergence of DC microgrids has introduced notable advantages, particularly in minimizing energy conversion stages and eliminating reactive power complications

[34,35]. These systems demonstrate particular efficacy in specialized applications including telecommunications, spacecraft, and data centers [38]. Despite their benefits, widespread adoption faces barriers such as substantial network restructuring costs, immature protection schemes, and lack of standardization [36,37]. Recent technological advancements in power electronics have begun addressing these challenges, making DC architectures increasingly viable for broader implementation. Fig. 3 [31] illustrates an example architecture of a DC microgrid.

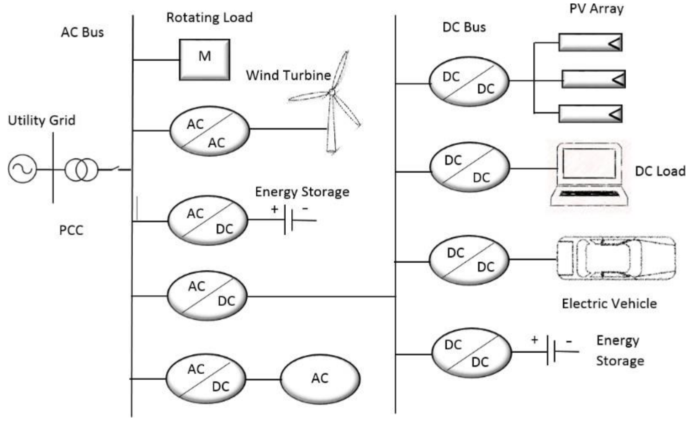
Figure 3: *DC microgrid configuration with interconnected elements [31].*



3. Hybrid AC/DC Microgrids

Hybrid AC/DC microgrids represent an innovative synthesis of both paradigms, offering enhanced efficiency and reliability through optimized integration of AC and DC components [39,40]. These systems facilitate direct connection of diverse DERs and energy storage systems while minimizing power conversion losses [41,42]. The architecture's complexity, however, demands sophisticated control strategies to manage synchronization, reactive power flow, and converter interfacing [28]. Current research focuses on developing intelligent control algorithms to overcome these challenges and fully realize the potential of hybrid configurations.

Figure 4: *An architecture illustrating the structure of a hybrid AC/DC microgrid [31]..*

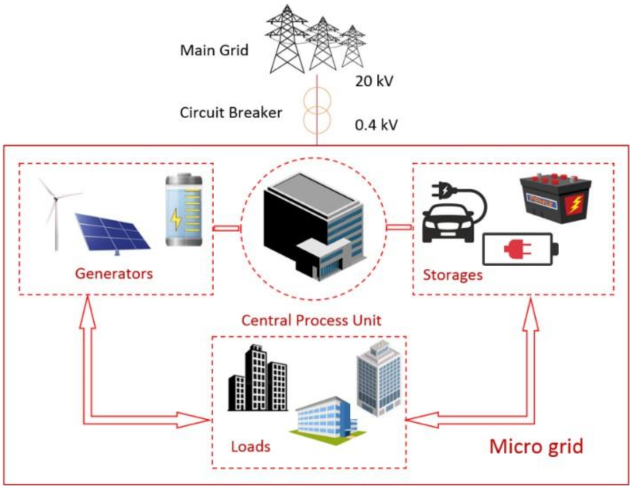


The evolution of microgrid technologies reflects an ongoing effort to balance operational efficiency, reliability, and integration complexity. While AC systems maintain dominance in conventional applications, DC and hybrid architectures are gaining traction in specialized domains and future-looking energy systems. This progression underscores the importance of continued research in power electronics, control systems, and standardization to address existing limitations and unlock new applications for microgrid technologies.

Basic Microgrids Architecture

Microgrid architectures typically consist of distributed generation (DG) sources, distribution systems, PV storage schemes, and communication/control systems [43]. A generic microgrid architecture is shown in figure 5. DG technologies encompass both emerging solutions (wind turbines, micro hydropower, solar PV) and mature technologies (induction/synchronous generators) [44]. Combined heat and power (CHP) systems demonstrate particularly high efficiency (>80%) by utilizing waste heat [45].

Figure 5: *A generic microgrid architecture [43]*



PV systems, while environmentally favorable, face challenges including high installation costs and weather dependency [46], [47]. Distribution networks may employ DC, AC (50/60Hz), or high-frequency AC (HFAC) configurations, with DC systems gaining attention for their power quality advantages [48]. Reliable communication systems, including power-line carrier, fiber optics, and wireless protocols, are essential for microgrid operation [44]. Microgrids require robust control systems to ensure smooth transitions between grid-connected and islanded modes, especially due to the variability of renewable energy sources [49].

Control Methods of Microgrids

Power flow must be ensured between the microgrid and main grid for seamless transitions, while the □G must remain operational post-islanding. Due to the stochastic nature of renewable sources, suitable AC and DC control strategies are essential [49].

1. AC Microgrid Control Methods:

Various control techniques for AC microgrids are summarized below.

a) □Control technique for Grid-connected mode: In grid-connected mode, distributed generation (DG) units are categorized into grid-feeding, grid-forming, and grid-supporting types [50]. Grid-forming units maintain voltage and frequency in islanded conditions and synchronize with the main grid when connected [51]. Grid-feeding units operate under central controllers to manage active and reactive power flow [52][51], while grid-supporting units utilize droop control to stabilize voltage and frequency [53].

b) □Control technique in Islanded mode: In islanded mode, several control approaches are used. i) The Master-Slave method designates one DG unit as the master to provide voltage and frequency references, with others following and central control intervening during abnormalities [54]. ii) The Peer-to-Peer method allows all DGs to share control responsibilities equally using droop characteristics, ensuring system balance during load changes [31][55]. iii) Hierarchical control is structured in three layers: primary control uses droop techniques for power sharing; secondary control restores voltage and frequency deviations and handles grid synchronization; tertiary control optimizes economic dispatch and manages grid interactions [56]. iv) Additionally, the Multi-Agent System (MAS) enables each DG to function autonomously, making local decisions while coordinating with peers to achieve overall system objectives [57].

2. DC microgrid control methods

DC microgrid control methods, generally simpler due to the absence of reactive power and frequency concerns, include several strategies. i) Droop control facilitates load sharing based on voltage-current characteristics and adapts according to the energy storage state [56][58][59]. ii) Hierarchical control mirrors the AC structure with inner voltage/current loops and outer virtual impedance loops for coordinated power regulation. iii) Hysteresis control provides fast response, commonly used in inverters and PLCs, although it features variable switching frequencies [60]. iv) Voltage Mode Control uses a single-loop feedback system to regulate converter output and manage charging/discharging of energy storage systems. v) MPPT (Maximum Power Point Tracking) control is vital for optimizing power output from variable renewable sources like solar PV and wind, typically implemented at the local converter level [49].

Shipboard Micro Grids

Shipboard microgrids share similarities with terrestrial systems but face unique challenges due to pulsed loads and strict power quality requirements [61]. Energy storage systems include batteries (notably Li-ion), supercapacitors, SMES, flywheels, and hybrid configurations, each offering distinct power/energy density tradeoffs [61]-[69]. Basic power system of a hybrid vessel is shown in figure 6 [62]. Table 1 shows the advantages and problems of each technology of energy storage. Hydrogen fuel cells present emission-free potential but require cost reductions [70], [71]. Power quality issues - including voltage sags, frequency variations, and harmonics - stem from high-power loads like propulsion systems and electronic weapons [61], [92]-[95]. Classification societies mandate strict voltage (±10%) and frequency (±5%) tolerances [91], necessitating advanced control solutions for naval applications [74]-[79].

Figure 6: *Power system of a hybrid ship [62]*

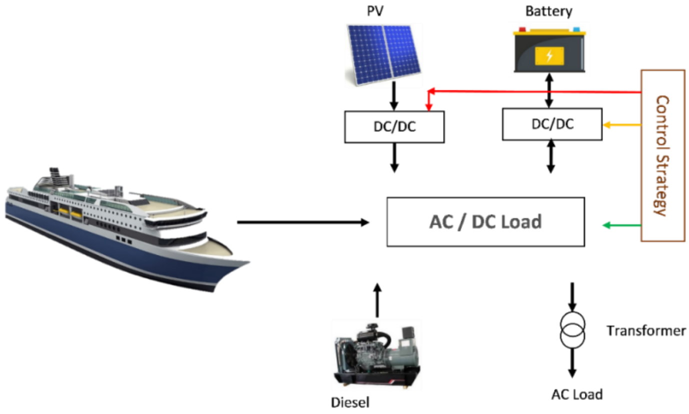


Table 1: *Advantages and problems of multiple energy storage techniques [61]*

Storage Category	Advantages	Problems
Battery	Lesser upkeep, more energy density (for Li-ion)	Quite less power density and life span
Supercapacitors	More life, rapid charging / discharging ability	More per watt cost, less energy density
Superconducting magnetic energy storage (SMES)	High Storage Efficiency, fast response	Expensive, cooling problems
Flywheels	Humid-opposing quality, More power density	Less density of energy, mechanical problems
Hybrid ESS	Can utilize the conveniences of two or more categories	Costly, need complicated control algorithms
Hydrogen fuel cells	No greenhouse gas emissions (GHG)	High cost, drains quickly

Recent research highlights need for: standardized power quality metrics, improved ESS control algorithms, and real-time monitoring integration [97]. The transition toward all-electric ships further emphasizes requirements for robust hierarchical control architectures capable of managing diverse load time constants (1ms-500s) [76]-[78]. Continued development of hybrid AC/DC architectures and adaptive control strategies remains critical for advancing marine microgrid reliability and performance [24], [25], [96].

Marine vessels encompass diverse electrical loads such as propulsion systems, pulsed defense loads, hotel and bridge services, and HVAC equipment, all of which must be considered in the initial power system design to ensure operational reliability and power quality. Load profiles and total capacity requirements determine key specifications like cables and switchgear, with dynamic modeling approaches often used to assess performance under varying conditions [72]. For example, a typical ship may use two propulsion lines with engines, gearboxes, and propellers, while auxiliary systems powered by dedicated engines support lighting, ventilation, and passenger amenities. Heat demands are met through heat recovery systems and auxiliary boilers when necessary, especially in port or cold conditions [73]. High-power loads, particularly propulsion motors and pulsed military equipment like electromagnetic weapons, can significantly affect power quality [74], [75]. Time constants of these components, ranging from milliseconds to several seconds (as shown in Table 2), inform control strategies that adapt to each load's dynamic response [76], [77], [78]. In all-electric vessels, the propulsion system's dynamics heavily influence the microgrid's stability, necessitating control schemes that prioritize critical loads and coordinate power delivery efficiently across variable time constants, especially in vessels equipped with advanced detection and pulsed power systems [61], [79].

Table 2: *TIME CONSTANTS FOR VARIOUS ELEMENTS IN A SHIP ELECTRICAL SYSTEM [76] [77]*

Component	Time Constant

Vessel warmup time	20 - 500 s
Power generator with Gas turbine	5 - 10 s
Propulsion motor stator leakage	1 -10 ms
Propulsion motor	1 - 5 s
Pulse duration modulation	0.5 -2 ms
DC to DC converters	100 - 500 ms
Motor service loads Test	0.5 - 1 s
Time constant of propulsion motor rotor	50 ms – 1 s

According to IEC standard 61000-4-30, power quality in shipboard microgrids is assessed based on deviations from technical benchmarks, with common issues arising from voltage waveform disturbances due to cyclic and non-cyclic load transients [90], [61]. The major problems in power quality of marine microgrids are enlisted in Table 3. Harmonics and frequency deviations primarily affecting AC systems are increasingly prevalent due to the rise in power-electronics-based loads and generators, while voltage deviations impact both AC and DC systems. As ships adopt "more-electric" architectures, maintaining power quality has become more complex, prompting classification societies to standardize acceptable limits to mitigate risks to vessel operation, cargo, and crew [91]. Voltage and frequency limits for marine AC systems are detailed in Table 4, ensuring equipment resilience during deviations [61]. To further enhance system reliability, energy storage systems (ESS) are employed to smooth transients and support real-time power balance, contributing to safer and more robust shipboard power networks [96]. Nonetheless, challenges persist, including outdated standards, limited modeling fidelity, and a lack of real-time monitoring. Proposed improvements include revising classification rules, updating evaluation methods, and enhancing system models to better reflect operational and environmental conditions [97].

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Table 3: *Power quality problems classification in ship microgrid. [61]*

Problem in Quality of Power	Probable Reason(s)
Voltage Sag/Dips	Bow Thruster [92], Electronic Weapons for Rapid-Response [93]
Frequency Drop	Switching of Larger Loads [94]
Voltage Variations (Flickers)	Radar System [63]
Harmonics	Loads and Generator being Power Electronically Interfaced [95]
Voltage Swell	Radar System [63]

Table 4: *Acceptable voltage and frequency alterations in ac systems [61]*

Quantity within Operation	Deviations	
	Permanent (percent)	Transient (Time for Recovery) (percent)
Voltage	+6 to +-10	+-20 (1.5 s)
Frequency	+-5	+-10 (5 s)

The Continuous Need for Improvement

To further enhance system reliability, energy storage systems (ESS) are employed to smooth transients and support real-time power balance, contributing to safer and more robust shipboard power networks [96]. Nonetheless, challenges persist, including outdated standards, limited modeling fidelity, and a lack of real-time monitoring. Proposed improvements include revising classification rules, updating evaluation methods, and enhancing system models to better reflect operational and environmental conditions as shown in Table 5 [97].

Table 5: *Improvements required in ship power systems [97]*

Problems	Possible Improvement(s)
Insufficient rules of ship classification, unclear definitions of basic quantities.	Newer and clearer rules should be presented by ship classification societies
Inappropriate standardized methods for power quality evaluation and signal processing tools	Definition of up to date assessment methods and tools
Inefficiencies in the shipboard power system	Integration of real-time power quality monitoring capabilities into power management system (PMS)
Faults in ship's designing, trial and exploitation phases	Suitably refined models of upcoming ship systems should be prepared
Issues occurring in systems modeling of ship or development of assessment techniques	Environmental states impact and system's real aspects should be considered

Numerous studies have demonstrated the advantages of AI-based control in marine systems. Applications include optimal energy scheduling, fault detection, load forecasting, and adaptive control using neural networks. These studies have reported improvements in fuel economy, emission reduction, and fault resilience. However, challenges remain in generalization, explainability, and hardware integration.

Artificial Intelligence Methods for Shipboard Microgrid Optimization

Artificial Intelligence (AI) encompasses various subfields, including Machine Learning (ML), Deep Learning (DL), and Rule-Based Systems (RBS) [99]., each offering unique advantages for the optimization and control of shipboard microgrids. The choice of AI technique depends on the nature of the application, data availability, and required precision.

A.Machine Learning Techniques

Machine Learning (ML) enables computer systems to improve performance on specific tasks through data-driven experience. It involves designing algorithms that can learn from historical data and make predictions or decisions without being explicitly programmed. For instance, a diagnostic ML system trained on medical records can enhance its accuracy in detecting cancer as it learns from more patient data. Applications of ML span diverse domains including robotics, intelligent personal assistants, pattern recognition, data mining, traffic prediction, healthcare diagnostics, cybersecurity, agriculture, and natural language processing [98].

Types of Machine Learning Algorithms

1. Supervised Learning

Supervised learning involves training algorithms on labeled datasets to predict outcomes or classify inputs. Figure 7 a) shows the basic workflow of the supervised learning models. Key algorithms include:

Decision Trees: These are hierarchical models that recursively partition data based on feature values. They are interpretable and handle both numerical and categorical data well, but can be sensitive to overfitting and data variability [101], [102].

Naïve Bayes (NB): Based on Bayes' theorem, NB classifiers assume feature independence and are particularly effective in text classification tasks. They are computationally efficient but may perform poorly when classes are highly imbalanced or dependent [102].

Support Vector Machines (SVMs): SVMs seek optimal hyperplanes for separating classes in high-dimensional space. They perform well with structured data but scale poorly with very large datasets and noisy features [103].

Regression Analysis: This technique models relationships between dependent and independent variables. Widely used for forecasting and trend analysis, its efficacy depends on correct model selection and sufficient data [102], [103].

Figure 7: *Supervised learning and Unsupervised Learning workflow (a) Supervised learning workflow [101])*

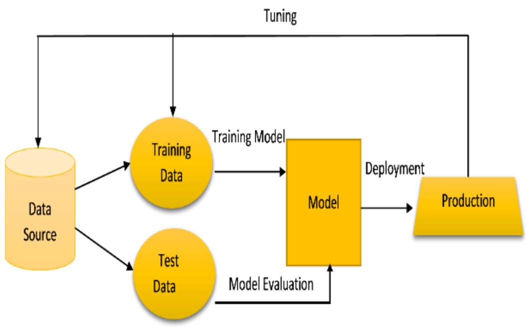
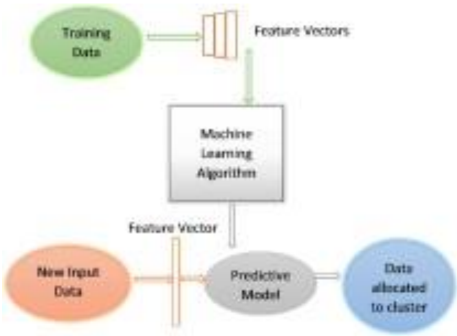


Figure 8: *Supervised learning and Unsupervised Learning workflow (b) Unsupervised Learning workflow [103]*



2. Unsupervised Learning

Unsupervised learning operates on unlabeled data, identifying intrinsic structures or patterns as shown in Figure 7 b). The two fundamental unsupervised learning algorithms are K-means clustering and Principal Component Analysis (PCA).

K-Means Clustering: It partitions data into K predefined clusters by minimizing intra-cluster variance. While efficient, its performance depends heavily on the choice of K and cluster shapes [102], [103].

Principal Component Analysis (PCA): PCA reduces data dimensionality by transforming correlated variables into orthogonal components, aiding in visualization and preprocessing [101].

3. Semi-Supervised Learning

Semi-supervised learning leverages a small amount of labeled data with a larger unlabeled dataset. It is effective when labeling is costly. K-Nearest Neighbors (KNN), a non-parametric method that assigns class labels based on proximity to labeled instances. Though simple and intuitive, its computational cost increases with dataset size and dimensionality [102].

4. Reinforcement Learning

Reinforcement learning models learn through interaction with the environment, using reward and penalty signals. These are well-suited for sequential decision-making tasks such as control systems and gaming applications [103].

5. Ensemble Learning

Ensemble learning integrates multiple models to enhance accuracy and robustness. Random Forest (RF), an ensemble of decision trees built on random data subsets using bagging. RF improves generalization and reduces overfitting, making it effective for both classification and regression tasks [103].

Applications of AI Methods

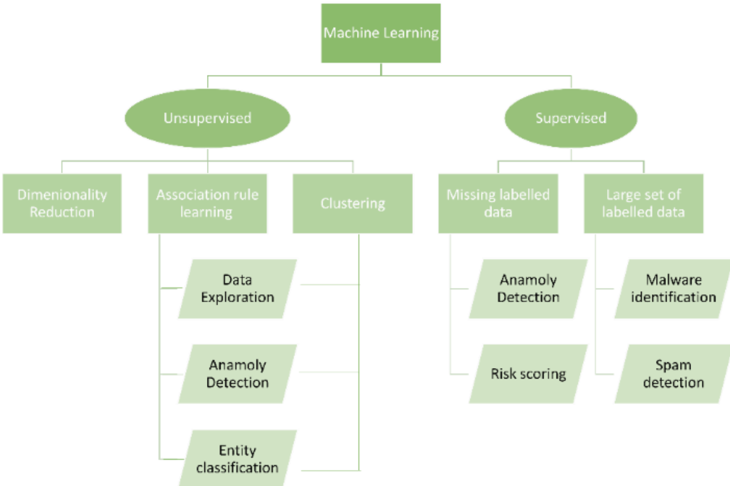
1. General Applications Across Domains

Machine learning (ML) has found widespread application across multiple domains. In drug discovery, ML supports processes such as target validation, identification of prognostic biomarkers, and analysis of digital pathology records in clinical trials [109]. Since the 2010s, the emergence of advanced ML techniques has significantly enhanced intelligent fault diagnosis (IFD) by enabling end-to-end prognostic models that link real-time monitoring data to machine health states using deep learning approaches [110]. ML is also increasingly employed in risk assessment, offering data-driven enhancements to traditional methods, particularly as large volumes of socio-technical system data become available. This trend supports the real-time industrial adoption of ML for more accurate and timely decision-making [111]. In the domain of Customer Relationship Management (CRM), ML has transformed customer interaction strategies through predictive analytics. Techniques such as neural networks, decision trees, support vector machines (SVM), and logistic regression are commonly used to improve CRM efficiency and customer feedback analysis [112]. Agricultural technology has also benefited from ML, where integration with sensor data and high-performance computing has led to AI-enabled farm management systems, improving productivity and decision-making [113]. Within industrial environments, ML plays a critical role in evolving traditional manufacturing systems towards Industry 4.0. Applications span maintenance, quality control, production planning, and supply chain management, with quality management receiving the most attention due to its direct impact on profitability [114]. In structural design and performance assessment (SDPA), ML aids in structural condition monitoring, risk-informed decision-making, and performance forecasting by extracting patterns from complex, high-dimensional data. This is particularly important for aging infrastructure and modern construction systems requiring robust and scalable analytical frameworks [114].

2. Applications in Electric and Marine Systems

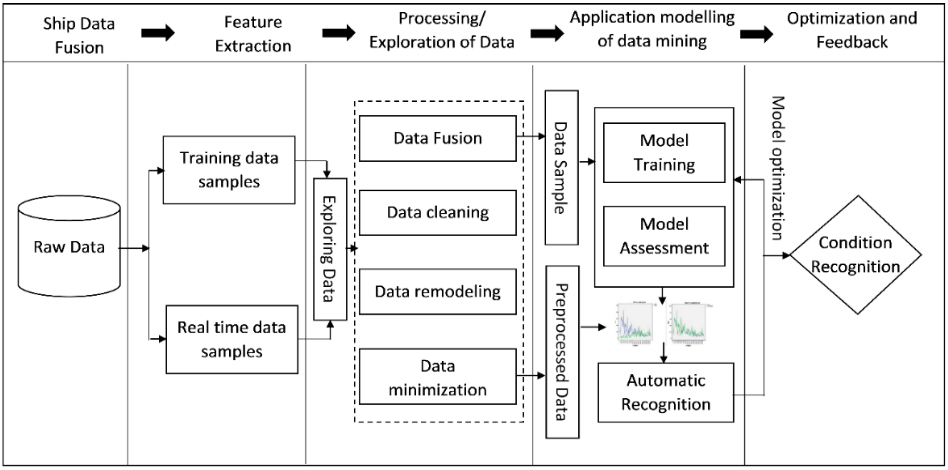
The integration of machine learning (ML) into electric and marine systems has emerged as a promising area of research and application. In the evolving landscape of smart grids, where Internet of Things (IoT)-enabled devices generate vast volumes of data, ML offers effective tools for data analysis and anomaly detection. These tools are essential for handling cyber threats and ensuring secure grid operation through both supervised and unsupervised learning methods as elaborated in Figure 8 [115]. The rise of AI 2.0, a data-driven phase of artificial intelligence, further enhances smart energy and electric power systems (Smart EEPS), particularly in Smart Grids (SG) and Energy Internet (EI), where ML is leveraged to make predictive decisions from historical and synthetic data [116].

Figure 9: *Employing machine learning in smart grid security [115]*



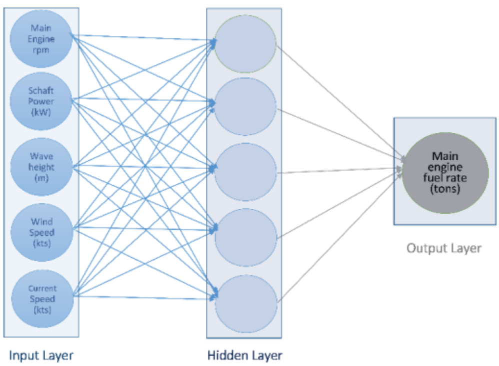
In the marine sector, ML contributes to reducing greenhouse gas emissions and improving energy efficiency by optimizing shipboard electric power systems. Dynamic positioning systems (DPS), which help maintain vessel position in adverse sea conditions, depend on accurate power demand forecasting—an area where ML-based prediction models significantly enhance diesel generator (DG) and energy storage system (ESS) management [117], processing to improve marine energy systems in shown in Figure 9 [117].

Figure 10: *Basic modeling process of applying machine learning on ship data [117]*



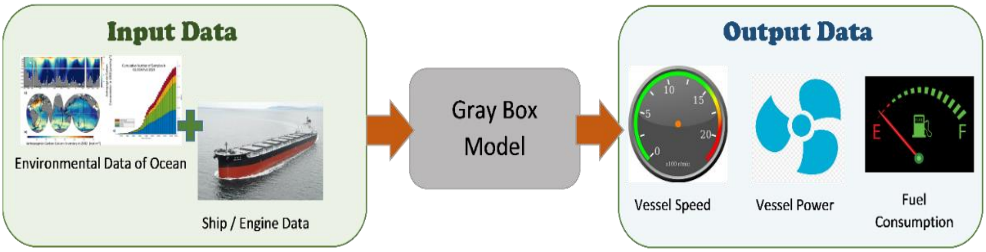
Artificial neural networks (ANNs) and rule-based learning have also been used to optimize shipboard power performance [118]–[121]. Fuel consumption prediction is another critical application, where ML models based on real-time engine data offer accurate forecasting without the need for additional sensors, reducing operational costs and enhancing energy modeling [122]–[124]. A simple representation of machine learning based fuel consumption estimation model is presented in Figure 10. Predictive maintenance, driven by ML, allows early detection of potential faults, thereby improving reliability and reducing energy inefficiencies [125]

Figure 11: *Machine learning for estimation of Fuel consumption [124]*



In terms of cybersecurity, ML aids in detecting false data injection attacks that can mislead energy management systems (EMS) and compromise grid operations [126]. Moreover, for naval and maritime security, ML-based surveillance and classification systems outperform traditional radar technologies by improving threat detection, vessel identification, and situational awareness [127], [128]. Smart surveillance systems are essential for securing coastal regions and harbors against unauthorized intrusions [129].Finally, ML supports collision risk prediction in marine traffic through the computation of the Collision Risk Index (CRI), enhancing navigational safety and decision-making efficiency as elaborated in Figure 11 [130]..

Figure 12: *Gray box model for ship power prediction [125]*



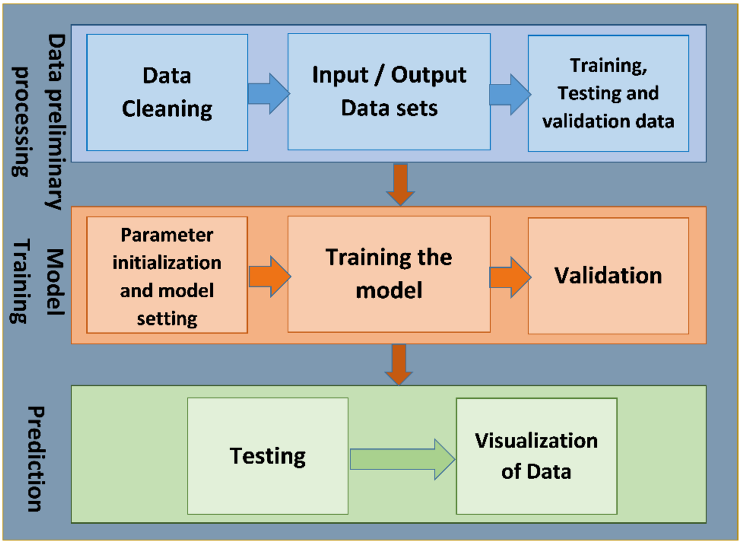
Choice of Learning Technique

The selection of an appropriate learning technique—be it machine learning, deep learning, or rule-based algorithms—depends on the specific requirements and constraints of the system under consideration. Key factors influencing this decision include the type and structure of input data, the availability of labeled or unlabeled data, and the nature of the desired output. Among the various techniques, artificial neural networks (ANNs) have been identified as the most widely used in the modeling of shipboard power systems. However, a diverse set of algorithms, including subcategories of ANNs and other learning paradigms, are also employed depending on the application context and complexity.

Data Preparation and Feature Selection

Effective machine learning modeling requires meticulous data preparation and feature selection. When data is sourced from various case studies, it often contains redundant or irrelevant information that must be filtered out. Figure 13 illustrates a generic flowchart for ship load forecasting using ML, outlining the main steps in data preparation [163]. All data entries with invalid or unscalable values should be removed, as such data can distort distance-based computations crucial to many ML algorithms. Relevant data must be mapped to appropriate class labels according to the specific system under study, ensuring accurate classification during training. To avoid temporal bias, data should be sorted by class and then randomized before dividing into training and testing sets. Datasets should be partitioned into mutually exclusive training and testing subsets of appropriate sizes to balance precision and training efficiency. Any data variation and justification for sample sizing should be reported in the results. Finalized data should be formatted and compiled into designated training and testing files that meet the simulation or algorithmic requirements.

Figure 13: *A generic flowchart for ship load forecasting using ML [163]*



Literature Review of Machine Learning-Based Marine Microgrids

An optimized EMS for diesel-electric vessels is proposed in [132], employing unsupervised learning algorithms (k-means and k-medoids) to extract patterns from historical data, combined with mixed-integer linear programming (MILP) to minimize fuel consumption. The system integrates a predefined optimal ESS charging state as a reference for the PI controller. Evaluated on a hybrid-electric ferry operating cyclically in an urban environment, the system demonstrated accuracy ranging from 87% to 99%.

A fault diagnosis method for MVDC marine power systems is presented in [119], using Noise-Assisted Multivariate Empirical Mode Decomposition (NA-MEMD) for signal decomposition and Multilevel Iterative LightGBM (MI-LightGBM) for classification. Intrinsic Mode Functions (IMFs) extracted from voltage signals are used to compute energy moments, forming the fault feature vector. Simulations conducted using AppSIM validated its high precision and engineering applicability.

In [133], several ML techniques including Bayesian networks, radial basis function networks, decision trees, support vector machines (SVMs), and nearest neighbor classifiers are compared for fault detection in shipboard electronic components. The study provides early-stage comparative insights into their effectiveness.

The authors in [122] utilize ridge regression, LASSO, multiple linear regression, boosting, tree-based algorithms, and support vector regression to predict marine fuel consumption. K-fold cross-validation and error metrics such as MAE, RMSE, and R2R^2R2 were employed. Engine RPM, shaft indicators, and scavenged air parameters were identified as key features. Multiple linear and ridge regression models achieved the best performance with an MAE of 0.002, RMSE of 0.0001, and R2R^2R2 of 99.9%.

A study in [134] applies an online sequential extreme learning algorithm with an adaptive kernel to manage signal uncertainty in real-time ship power systems. Using data from two sea conditions, the method employs three adaptive factors to control kernel scaling, resulting in accurate real-time predictions. In [123], a genetic algorithm is used to optimize both model selection and hyperparameters for fuel consumption prediction using noisy sensor data from a Baltic Sea vessel. Implemented entirely with open-source Python tools, the model shows promise for onboard deployment.

Reference [124] presents another ML-based fuel prediction model using multiple linear regression. Noon report data is split into training and testing sets, and the model's predictions are validated against actual data. In [135], ship speed is predicted using AIS and weather data from 76 vessels over one year. Results indicate the ML model's effectiveness in forecasting speed based on selected features. A fault identification method in [125] integrates Expected Behavior Models with Exponentially Weighted Moving Average (EWMA). Using polynomial ridge regression, it accurately predicts faults in exhaust gas and air pressure of the main engine, supporting preventive maintenance. An optimal shipboard PMS is proposed in [136], utilizing Naive Bayes classification to determine operational states based on real/reactive power and generator status. The OPF method quantifies load losses, and real-time training updates improve system adaptability. The scheme achieves 97.67% accuracy with a processing time of 25 ms.

Reference [137] assesses ML for incident likelihood prediction during the US Atlantic hurricane season. Support Vector Machines yielded 95% recall and 92% accuracy, highlighting the potential for intelligent vessel routing and maritime risk assessment. A Bayesian ML approach in [138] is integrated with Axiomatic Design principles for sustainable ship propulsion system design. It enables probabilistic evaluation of design parameters and identification of hidden couplings in early design stages. An integrated monitoring methodology is proposed in [117], combining

Gaussian Mixture Models and PCA for fault detection. It uses long-term voyage data to train models, facilitating identification of common operating states and early-stage machinery failures.

In [139], a reinforcement learning-based PMS uses Q-learning to minimize fuel consumption by modeling the ship's power network as a Markov Decision Process. Applied to cruise ship data from the Baltic Sea, the model achieves approximately 0.9% fuel savings, equating to 32 tons annually. Reference [140] explores the feasibility of predictive fuel modeling using Azure ML Studio.

The multiple linear regression model processes IoT ship data with an R2R^2R2 value of 0.9707, validating its effectiveness for real-world applications. A hybrid voyage optimization model is presented in [141], combining semi-empirical methods and ML via XGBoost. It predicts additional resistance using metocean, ship profile, and motion data. Case studies across three ships show ML reducing discrepancy from over 40% to below 1%. Data gap analysis in [142] compares single ML models and meta-models using real ship operation data. Meta-models achieved <5% MAPE and RRMSE, offering accurate anomaly detection and condition monitoring.

In [143], ML algorithms (SVM, MLP, GLM, RF) are evaluated for predicting LPG ship energy efficiency. Random Forest achieved the lowest RAE (2.304%) and RMSE (17.2632), demonstrating its superior regression performance. An intrusion detection system using image processing and SVM is proposed in [129], aimed at detecting unauthorized ships in dynamic coastal environments, enhancing maritime security. Reference [126] presents a defense mechanism against false data injection attacks (FDIA) in ship power systems. Using deep learning and importance indices, the model outperforms traditional techniques with 90% higher accuracy.

Another IDS for the NAVFAC smart grid is introduced in [144], using a KNN-based classifier to detect web, DOS/DDOS, and port scan attacks. Optimizing the k-value improves response classification while minimizing SOC load. An intelligent video surveillance system (AIVS3) is proposed in [127] using computer vision and ML for shipboard security. It identifies, classifies, and tracks threats, triggering alerts to a man-in-the-loop (MITL) interface.

In [130], ML is integrated with Dempster–Shafer (D-S) theory for Collision Risk Index (CRI) prediction. Gradient Boosting Regression enhances speed and accuracy. Simulations show the model’s compliance with COLREGs and high reliability. Bayesian Networks trained on AIS data are used in [145] for anomaly detection, combining static and dynamic models. The hybrid approach increases performance and interpretability. Sea Spotter, a third-generation naval IRST system in [146], integrates custom ML for target acquisition and tracking. The study discusses design constraints and implementation methodology, showing improved imaging and threat recognition. Table 6 summarizes the reviewed works, categorizing them by algorithm type and marine system components involved in ML-based optimization.

Table 6: *Summary of machine learning algorithms applied to vessel energy systems and hardware platforms*

	ML Algorithm Used	**Hardware component improved**	**Objective/ Description**
[132]	k-means or k-medoids	Diesel engines and ESS (energy storage system)	Optimizing the ESS of Hybrid-Electric ships containing Cyclic Operations
[119]	Noise-Assisted Multivariate Empirical Mode Decomposition (NA-MEMD) and Multilevel Iterative LightGBM (MI LightGBM)	Medium-voltage DC (MVDC) power system cable	Fault diagnosis of medium-voltage DC shipboard power system
[133]	Decision trees; radial basis function networks; Bayesian networks; nearest neighbor classifiers; and support vector machines	MVDC power system cable	Diagnosis and spotting of faults in marine power systems by automated monitoring of power electronic components
[122]	Multiple linear regression, Ridge & LASSO regression, Kernel Ridge regression, Bayesian Ridge regression, Support Vector regression, K-Nearest Neighbors, Multi-Layer Perceptron regression, Decision tree regression, Random Forest regression, Ada Boost regression, Gradient Boosting regression, Hist Gradient Boost regression	Main engine	Comparison of different machine learning algorithms to improve ship fuel usage
[134]	Adaptive kernel based online sequential extreme learning machine	Thrusters, generators, Converters	Model presented to provide accurate prediction of online shipboard electric power fluctuations
[123]	Auto machine learning (AML)	Main engine	Optimization of prediction of Ship Fuel Consumption
[124]	Multiple linear regression	Main engine	Optimized forecasting of Ship Fuel Consumption

[135]	Decision Tree Regressor, Random Forest Regressor, Extra Trees Regressor, Gradient Boosting Regressor, Extreme Gradient Boosting Regressor	Engines	Comparison of multiple ML Approaches for prediction of ship speed
[125]	Optimal regression model (Multiple linear ridge regression, Ordinary Least Squares (OLS) single linear regression, multiple polynomial ridge regression. And OLS single polynomial regression)	Main engine	Fault detection in ship systems operations
[136]	Naive Bayes Network(NBN)	MVAC power system cable	Diagnosis Support of marine power systems controls
[137]	Support Vector Machines (SVM)	Propeller, Main engine	Monitoring approach for ship safety in extreme weather conditions
[138]	Bayesian Network Model	Main propulsion engine, Main diesel engine, hull	Theoretical design of a ship's traditional propulsion system is presented using sustainable engineering principles
[117]	Gaussians Mixture Model (GMM), EM (expectation–maximization) Algorithm	Main engine	Design approach of Ship Monitoring System is given
[139]	Reinforcement learning (RL)	Main engine, power system	Optimization of autonomous control of marine auxiliary power networks.
ML Algorithm Used	**Hardware component improved**	**Objective/ Description**	**ML Algorithm Used**
[140]	Multiple regression model (MLR)	Main engine	Model proposed for predictive modeling of vessel fuel consumption
[141]	XGBoost algorithm	Propeller, Main engine	Designing speed-power models for optimization of ship's voyage

[142]	Generalized linear model (GAM), gradient boosting regressor (GBR), and multivariate adaptive regression splines (MARS)	Main engine, Navigation sensor	Method proposed for detection of abnormal data among collected real time marine data.
[143]	Multilayer preceptor (MLP), Generalized linear model (GLM) regression, random forest (RF), support vector machine (SVM),	Main propulsion engine, Main diesel engine	Prediction of energy efficiency of seagoing vessels by applying different ML algorithms

Table 7 provides an overview of the related literature in terms of components involved in the papers that used machine learning to avoid intrusions and faults in marine power systems.

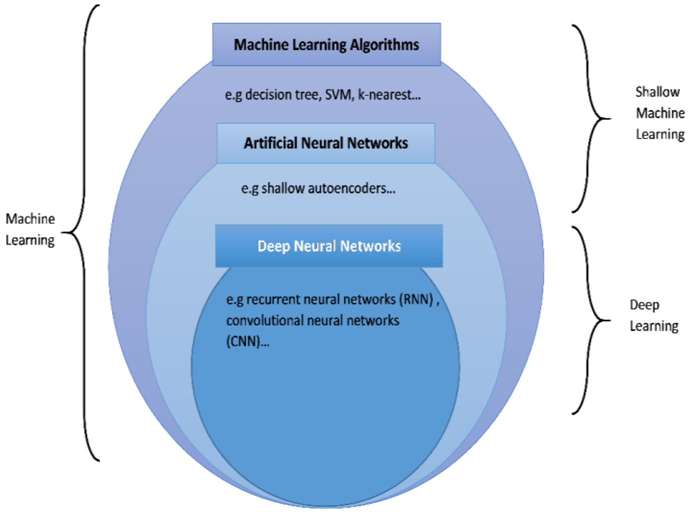
Table 7: *Ml algorithms for ship power systems focused on intrusion and fault mitigation*

	ML Algorithm Used	**Attack on/ Fault in?**	**Objective/ Description**
[129]	Support Vector Machines (SVM)	Intrusion detection system	Ship's Intrusion Detection System is presented
[126]	Support Vector Machines (SVM)	Power grid system	Research presented for detecting fake data injection attack in smart ship power systems
[144]	K-Nearest Neighbors Machine Learning	Smart grid	Detection of cyberattack on a navy smart grid
[127]	Support vector machine (SVM), multi-class Naïve Bayes Classifier.	Attack by terrorists and pirates	Intelligent automated marine video surveillance system is given
[130]	Gradient boosting regression (GBR)	Lessen risks of ship collision	Ship collision risk estimation model is presented
[145]	Bayesian Networks	Deviation from route	Model for anomaly detection in ship tracks
[146]	Offline Supervised Learning model	Target acquisition and tracking	Infrared warning model for navy surface vessels is given

DEEP LEARNING METHODS IN SHIP MICROGRIDS

DL techniques, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, are highly effective in handling non-linear time-series data and dynamic system behavior. These methods excel in tasks such as propulsion system load forecasting and condition monitoring. Deep Learning (DL), a subdomain of Machine Learning (ML), is fundamentally built upon artificial neural networks (ANNs) and surpasses conventional ML and shallow learning techniques in numerous complex applications [147]. With the advent of advanced learning algorithms and refined pre-processing techniques, deep neural network architectures have emerged as powerful tools for learning complex patterns, collectively known as Deep Learning [148], [149]. A hierarchical depiction of the relationship among ML, ANNs, and Deep Neural Networks is illustrated in Fig. 12 [148].

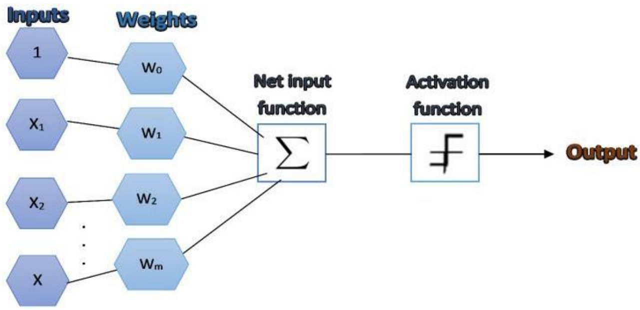
Figure 14: *A generic flowchart for ship load forecasting using ML [163]*



Artificial Neural Networks are biologically inspired algorithms primarily used in supervised learning. Modeled after the brain's structure, they consist of interconnected units called neurons, mimicking the behavior of biological neurons—each composed of dendrites (input receivers), soma (processing unit), nucleus (central control), and axon (output transmitter). ANNs typically operate over three layers: input, hidden, and output. The network is trained through iterative adjustment of weights associated with interconnections, enabling parallel distributed processing. Various DL architectures have evolved from ANNs, including Extreme Learning Machines (ELM), Recurrent Neural Networks (RNN), and Deep Neural Networks (DNN). A schematic representation of a neural network's operation is provided in Fig. 13 [101].

Figure 14: *Working of neural networks [101]*

Applications of Deep Learning Algorithms



Deep neural networks (DNNs) have demonstrated significant capabilities across various domains. In computing, DNNs have been applied for bot detection on social platforms. A model combining Long Short-Term Memory (LSTM) and DNNs is proposed in [150] for accurate identification of bots on platforms like Facebook and Twitter. Similarly, [151] integrates Convolutional LSTM (CLSTM) with DNNs for robust anomaly detection in web traffic based on user activity and data transmission volumes. In the medical domain, DL models have shown efficacy from drug identification to disease diagnosis. In [152], a DNN employing Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) is proposed for brain tumor classification using MRI data. Likewise, [153] uses deep convolutional networks for diagnosing dental issues, while [154] presents a CNN-based method for retinal alignment offering a cost-effective and non-invasive solution.

Deep Learning Applications in Marine Microgrids

Deep learning algorithms play a significant role in enhancing the performance of marine microgrids. Waterborne transportation, being a cost-effective mode of global trade, demands advanced systems for navigation, energy management, and vessel performance optimization [155]. Deep learning techniques have been extensively applied to shipboard power systems to improve their efficiency. For instance, power consumption forecasting using deep neural networks has facilitated economic dispatch and operational scheduling under sea disturbances by employing nonlinear regression-based models [12]. Hybrid-electric vessels (HEVs), which integrate internal combustion engines with energy storage systems (ESS), are gaining traction in maritime transport due to their potential to reduce fuel consumption and CO_2 emissions [156], [157], [20].

In alignment with the Paris Agreement under the United Nations Framework Convention, shipbuilders are increasingly focusing on reducing greenhouse gas (GHG) emissions [158]. Electrification of ship systems is a key strategy in this regard. All-Electric Ships (AES) power both propulsion and auxiliary systems from a unified energy source, contributing to reduced GHG emissions and enhanced renewable energy integration [159]–[161]. Naval ships, in particular, benefit from these architectures due to their varied and mission-critical load demands, including sensors and weaponry.

The full electrification of marine systems requires Integrated Power Systems (IPS), which often incorporate hybrid energy setups comprising diesel engines, batteries, fuel cells, supercapacitors, and renewable sources such as solar energy. These hybrid systems address challenges such as slow dynamic response of certain sources (e.g., fuel cells), resource intermittency (e.g., solar unavailability during nighttime), and the weight and cost constraints of energy storage devices. To manage these complexities, fuzzy logic controllers are implemented in real-time power management schemes to prevent issues like battery overcharging from regenerative braking [162]. Accurate forecasting of solar power is critical for shipboard PV systems, which face more variability than onshore installations due to weather changes and vessel motion. Deep learning-based hybrid models can provide interval forecasts for PV power output. An example of such a model is illustrated in Fig. 4.3 [163].

Ensuring a continuous power supply is vital for electric vessels operating under dynamic and hostile environmental conditions. Anomalies in the marine power system can disrupt power delivery and damage electrical equipment. Fast and reliable fault detection and isolation are crucial to prevent outages and maintain operational integrity [164]. Additionally, forecasting maritime traffic is essential for safe navigation and efficient management of maritime transport. Many existing models offer localized, short-term predictions. However, deep learning-based systems enable long-term traffic forecasting over large regions, which is vital for vessel traffic service (VTS) operations in congested harbor areas [165], [166].

Medium Voltage DC (MVDC)-based shipboard power systems can be considered as isolated microgrids, powered by distributed generators (DGs). While efficient, these systems are more vulnerable to faults, often causing high fault currents and posing severe safety threats. Fault diagnosis in MVDC systems is still in its infancy, with both conventional methods—such as directional protection, overcurrent protection (AC/DC), and current differential protection—and advanced techniques including wavelet transforms (WT) [169], short-time Fourier transform (STFT) [170], and artificial neural networks (ANNs) [114] being explored [167], [168]. False Data Injection Attacks (FDIA) also pose a serious risk to shipboard microgrids. These attacks compromise data integrity by altering state estimates, which can disrupt operations, lead to system failure, and potentially cause total blackouts. FDIA was first introduced by Yao Liu in [171].

Literature Review of Deep Learning in Marine Microgrids

An intelligent technique based on Artificial Neural Networks (ANNs) was introduced in [172] for controlling a ship's hybrid power system using past operational data. The proposed electric power system utilizes a fuel cell as the DC power source, with photovoltaic (PV) modules serving as the primary energy source during sufficient daylight conditions. Upon the absence of sunlight, the fuel cell is engaged to meet power demands. MATLAB simulations demonstrated the system's ability to select the energy source and compute power output dynamically according to shipload requirements.

In [12], a deep learning approach was developed for Dynamic Positioning (DP) ships to predict the power consumption of thrusters under varying sea conditions. Nonlinear regressive neural networks were used to forecast the power demands of generators during disturbances. The predicted data was integrated with Power Management Systems (PMS) and Dynamic Positioning Systems (DPS), improving engine performance and reducing both fuel consumption and greenhouse gas (GHG) emissions. Mixed-Integer Nonlinear Programming (MINLP) was conducted using GAMS, with simulations executed in MATLAB.

A control system proposed in [173] applied both ANN and Extreme Learning Machine (ELM) methods to optimize a marine loading arm plant. Temperature and gas sensors (DHT11 and MQ for ammonia detection) were employed to regulate a safety device. Simulation results revealed that ELM outperformed ANN, achieving an error rate of less than 0.4%, thereby making it viable for safety enhancement and ammonia gas leakage prevention.

A method for modeling inland ship velocity under dynamic environmental conditions was proposed in [155]. The study employed Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to categorize environmental data, including water levels and wind parameters. A Generalized Regression Neural Network (GRNN) was then used to predict vessel speed. A case study on a ship operating on the Yangtze River confirmed the model's accuracy in estimating ship velocity. In [163], a hybrid ensemble method for interval prediction of onboard solar power was proposed based on a stochastic motion ship model. Machine learning algorithms such as Back Propagation Neural Network (BPNN), Elman Neural Network, Radial Basis Function Neural Network (RBFNN), and ELM were combined with Particle Swarm Optimization (PSO). The model was tested on a solar-equipped oil tanker traveling from Dalian (China) to Aden (Yemen). The results validated the model's reliability in predicting solar energy output under navigation constraints.

A classification model using Long Short-Term Memory (LSTM) auto-encoders and short-time Fourier transform (STFT) was developed in [174] for fault detection in

DC pulsed load monitoring. The system reconstructed pulse signals to detect abnormalities based on residual differences between actual and predicted signals. Trained on 20 coil gun pulses sampled at 10 kHz, the model achieved 97.88% classification accuracy.

An ANN-based technique for fault categorization and localization in shipboard MVDC systems was proposed in [164]. It used transient waveform data of voltage and current to train and validate multiple ANN modules. The method was simulated in PSCAD on a medium-voltage DC cable system. Results showed effective fault classification and location detection, except in 30 cases of positive rail-to-ground faults. Another fault detection and classification method based on ANN was presented in [175], utilizing Wavelet Transform Multiresolution Analysis (WT-MRA) and Parseval’s theorem for feature extraction. Daubechies 10 (db10) was selected as the mother wavelet with a decomposition level of 9. The model demonstrated the ability to classify various fault types, including DC/AC bus faults and ground faults, when simulated in MATLAB.

A Generative Adversarial Network (GAN)-based method was proposed in [176] for fault detection and localization under imbalanced datasets. Synthetic training samples were generated using a deep convolutional GAN, and feature extraction techniques were used to minimize input dimensionality. A Random Forest (RF) classifier trained on both real and synthetic data achieved a classification accuracy of 99%, using real-time simulation data from a PSCAD/EMTDC power system model. An intelligent Energy Management System (EMS) was introduced in [177] for marine vessels, developed using an Adaptive Neuro-Fuzzy Inference System (ANFIS). The power source included a Proton Exchange Membrane Fuel Cell (PEMFC) and a battery bank as energy storage. Simulations were conducted in MATLAB using hardware-in-the-loop testing, demonstrating the system's capability in reducing GHG emissions and enhancing power system reliability.

In [178], three machine learning models—Nonlinear Partial Least Squares Regression (NL-PLSR), Nonlinear Principal Component Regression (NL-PCR), and probabilistic ANN—were employed to analyze hydrodynamic performance using onboard data from two sister ships. These models were used to detect performance trends influenced by propeller and hull cleaning, with the probabilistic ANN yielding the highest accuracy. A fuel consumption forecasting model for a 13,000 TEU container ship was presented in [179], integrating operational data and domain knowledge to select relevant input features. Both Multiple Linear Regression (MLR) and ANN were applied, with ANN achieving prediction accuracies ranging from 0.9709 to 0.9936. Sensitivity analysis determined an optimal draught of 14.79 m under standard conditions, closely aligning with the ship’s design draught. In [180], a Radial Basis Function Neural Network (RBFNN) model was used to estimate resistance for a

13,500 TEU vessel at various drafts. Ship features were normalized, and prediction performance was compared across five ML algorithms, including SVM, BPNN, Random Forest, and XGBoost. The RBFNN exhibited superior predictive accuracy for the total resistance coefficient.

A large-scale integrated dataset comprising Automatic Identification System (AIS) data and European Centre for Medium-Range Weather Forecasts (ECMWF) data was used in [181] to train ML models for vessel propulsion power forecasting. The dataset, processed on a Spark cluster, included records from 228 vessels over 50 months. Performance across different deep learning models was compared, identifying the best-performing architectures for this task. A fuel oil consumption prediction system based on a backpropagation ANN algorithm was introduced in [182], trained using real operational data from a Vietnamese bulk carrier. The input was derived from two years of noon-log reports. The probabilistic system demonstrated its potential to enhance EMS efficiency on ships. A ship powering estimation model was proposed in [183] for use during preliminary ship design, integrating graph theory with a Multilayer Perceptron (MLP) neural network. Following hull parameter analysis, the ML model exhibited an average absolute error of 23%, compared to 17.5% for an analytical model, indicating its applicability in early design stages.

A study [184] presented a comparative analysis of multiple regression data-driven algorithms to predict fuel oil consumption by ship main engines, based on two different shipboard data acquisition schemes: noon reports and Automated Data Logging and Monitoring (ADLM) systems. Several regression algorithms were evaluated, including Extra Trees Regressors (ETRs), Artificial Neural Networks (ANNs), Random Forest Regressors (RFRs), Support Vector Machines (SVMs), and ensemble methods. Among these, ETRs and RFRs yielded the highest accuracy for both acquisition schemes, with the ADLM system improving prediction accuracy by up to 7% and reducing data collection time by 90%. These approaches demonstrated the ability to forecast fuel consumption accurately across various sailing conditions.

An ANN and Multi-Regression (MR) based model was proposed in [185] for the estimation of ship power and fuel consumption. The model is designed for real-time operational environments and is developed using intensive datasets rather than traditional noon reports. This model was further applied in a Just-In-Time (JIT) voyage scenario to predict potential fuel savings. In [186], machine learning techniques were employed to estimate ship power performance using functional data to build regression models. These models integrate domain knowledge based on physical laws to minimize overfitting during regression. Environmental uncertainty was also considered to assess prediction reliability. The developed models can predict ship speed and engine power under various operational and meteorological conditions.

The Levenberg–Marquardt algorithm, a nonlinear recurrent neural network (RNN) approach, was used in [187] to predict thruster power consumption under challenging sea states. The model utilizes real-time dynamic positioning (DP) load and parametric weather data for comparison with three conventional forecasting methods. Numerical analyses confirmed the superior accuracy of the proposed technique for future DP load behavior prediction. A regional traffic forecasting approach based on a multiple hexagon-based convolutional neural network (mh-CNN) was introduced in [165]. This model incorporates both flow dynamics and atmospheric conditions and was applied in the South Atlantic State region to predict traffic flow. It proved effective for daily forecasts during normal conditions and hourly forecasts during hurricanes.

A deep reinforcement learning (DRL)-based model was proposed in [188] to develop a cost-effective, zero-emission energy management system (EMS) for fully electric ferry boats. The system integrates batteries and fuel cells for energy storage. Loss of Load Expectation (LOLE) was used as a reliability index in a multi-objective EMS framework. Standards DNVGL-ST-0033 and DNVGL-ST-0373 were considered to validate the commercial applicability of the model. Performance was verified using a real-time Hardware-in-the-Loop (HIL) simulation. A synthetic aperture radar (SAR)-based ship detection method was introduced in [189], featuring a new 3-class SAR dataset for improved ship classification performance. The proposed model, evaluated using this dataset, achieved the highest mean classification accuracy of 96.67% and significantly reduced false positives compared to other existing methods.

In [190], a deep feedforward neural network (DFN) was used to forecast ship power by identifying data patterns. Ocean environmental parameters and ship operational data were used as inputs, with ship power as the label. Several steps were taken to improve prediction accuracy, including preprocessing environmental parameters relative to ship velocity, adjusting the DFN structure based on input characteristics, and analyzing forecast precision. K-means clustering was also used to examine the effect of environmental and operational conditions, and model performance was compared across various forecasting strategies. A deep neural network (DNN)-based model named Ship Traffic Extraction Network (STENet) was proposed in [166] for medium- and long-term ship traffic prediction in caution zones. The system is guided by AIS sensor data and structured into modules, each with specific responsibilities. Performance comparisons were made with four methods, including VGGNet and support vector regression (SVR)-based techniques. The proposed model outperformed others with a relative improvement of approximately 50.65% for medium-term predictions and 57.65% for long-term predictions. Table 8 gives an oversight in terms of deep learning algorithms used in each paper included in this review.

Table 8: *Deep learning algorithms to improve ship power systems concerning hardware*

	Deep Learning Algorithm Used	Hardware component improved	Objective/ Description
[172]	Artificial neural network (ANN)	Fuel cell, photovoltaic array	Improvement in EMS of hybrid power system of vessel using renewable resources of energy
[12]	RNN (recurring neural network)	Diesel generators	Optimization of shipboard microgrids for dynamic positioning in offshore support vessels
[173]	Comparison of Neural Network (NN) and Extreme Learning Machine (ELM)	Temperature sensor Safety device	Ammonia leakage monitoring and safety device prototype is given
[155]	Generalized Regression Neural Network (GRNN)	Propeller, Main engine, multi-source sensors	Inland ship speed estimation method proposed for dynamic navigation environment
[163]	Back propagation neural network (BPNN), a radial basis function neural network (RBFNN), an extreme learning machine (ELM) and an Elman neural network	Solar power system	Model presented for Solar Power Output Interval Prediction in Shipboard Power Systems
[174]	Recurrent neural network (RNN)	DC pulsed load monitoring cable	A neural network is proposed for Fault classification and detection in dc pulsed load monitoring
[164]	Artificial neural network (ANN)	MVDC power system cable	Fault location and classification model given for MVDC shipboard power systems
[175]	Artificial neural network (ANN)	MVDC power system cable	Fault detection and classification model for medium voltage dc power systems of ships
[176]	GAN-RF (deep convolutional neural networks + random forest)	Generators, propulsion motors, DC converters, loads and buses	Model proposed for real-time fault detection and localization of an all-electric shipboard MVDC power system
[177]	Adaptive Neuro-Fuzzy Inference System (ANFIS)	Fuel cell	Designing and implementing an improved energy management system for

			electric ship power system is presented
[178]	Artificial neural network (ANN), NL-PCR (Non-linear Principal Component Regression), NL-PLSR (Non-linear Partial Least Squares Regression)	Propeller shaft	Ship performance monitoring optimization
[179]	artificial neural network (ANN), multiple linear regression (MLR)	Main engine	Fuel consumption forecasting model given, that uses ship's in-service data
[180]	Radial Basis Function neural network (RBFNN)	Engines	Research presented for accurately predicting resistance of a container ship
[181]	MLP (Multi-Layer Perceptron) (category of ANN)	Propeller, Main engine	Comparison is performed on various prediction models for vessel propulsion power and most suitable one is discussed in detail
[182]	Artificial neural network (ANN)	Main diesel engine	Comparative analysis of the fuel consumption forecast models
[183]	Multilayer Perceptron (MLP) (category of ANN)	Hull, Propeller, Main engine	Estimation improvement method for ship powering in preliminary ship design is presented
[184]	SVMs, Random Forest Regressors (RFRs), Extra Trees Regressors (ETRs), ANNs, ensemble methods	Main engine	Comparative study of several ML methods for predicting Fuel Oil Consumption
[185]	ANN and Multi-Regression (MR)	Main engine	Model proposed for estimation of ship's power and fuel usage in different operational states
[186]	DQN (deep reinforcement learning)	Fuel cell and battery	An optimal power scheduling model is provided for all-electric ships
[187]	RNN (recurring neural network)	Ship thrusters, DP (dynamic positioning) controller	Method suggested for short-term DP load forecasting in marine microgrids
[165]	convolutional neural network (mh-CNN) based on multiple hexagon	Propeller, Main engine	Traffic flow prediction optimization
[188]	DQN (deep reinforcement learning)	Fuel cell and battery	An optimal power scheduling model is

			provided for all-electric ships
[189]	Long Short Term Memory Network (type of RNN)	Synthetic Aperture Radar	A Synthetic Aperture Radar (SAR) sensor optimization method is proposed
[190]	Deep feed forward neural network (DFN)	Main engine	Ship power prediction optimization
[166]	Deep neural network	AIS sensor	Caution area traffic prediction optimization

RULE BASED METHOD

Rule-based systems operate using "if-then" statements derived from a set of predefined declarations. These rules dictate system behavior and are fundamental to expert systems, which aim to replicate human decision-making [191], [192]. Widely applied in AI, rule-based methods often use graph rewriting techniques. They offer flexibility and adaptability across diverse domains [193], [194].

Applications of Rule-Based Methods

Rule-based systems are valued for their declarative nature, allowing focus on what to solve rather than how. This makes them easier to prototype and modify iteratively [196]. Their applications span software development [197], [198], maintenance, and security [199]–[201], as well as scientific fields like chemistry, biology, and social sciences [202]. In remote healthcare, rule-based techniques manage big, heterogeneous patient data to improve Healthcare-as-a-Service (HaaS) [203]–[205]. Agriculture also benefits from RB systems for crop, pest, and disease management, irrigation control, and yield forecasting [221]–[229].

Marine applications include optimizing shipboard microgrids, integrating renewables, and reducing emissions [213]–[217]. Rule-based learning has also been used for estimating ship fuel consumption [214]. In traffic management, AI-based rule systems apply traffic rules and evidential reasoning to handle congestion more effectively [218]–[220]. In energy systems, they guide EMS development and power distribution strategies in hybrid and microgrid setups [206]–[212].

Literature Review of Rule-Based Methods in Ship Microgrids

A rule-based, task-aware energy management scheme for marine power systems is proposed in [120], aiming at the optimal dispatch of production and storage units to meet task-dependent objectives and minimize fuel consumption. Initially, operational tasks and classification society regulations are used to make rule-based decisions. These decision variables are then utilized in the optimization phase to formulate and update the functional constraints and objectives. The optimization problem is modeled as a mixed-integer linear programming (MILP) problem, which is solved using an exhaustive search algorithm. The effectiveness of this dispatch strategy is demonstrated through four case studies involving different ship configurations and operational task cycles.

An energy management strategy based on rule-based control is presented in [128] to compensate for power fluctuations caused by tidal motion. The hybrid energy storage model incorporates a vanadium redox flow battery (VRB), which mitigates low-frequency oscillating power due to tides and compensates for power discrepancies between grid commands and grid-connected energy sources. A 3 MW vessel power system simulation, incorporating real ship current-velocity data, is developed to validate the proposed strategy, demonstrating improved system reliability.

In [121], a DC hybrid power system is modeled using the bond graph technique. Key system components are individually modeled and integrated with varying levels of dynamic accuracy. The system is simulated using a rule-based EMS to investigate load-sharing schemes and system robustness under diverse operational scenarios. Simulation results are validated through experiments conducted on a full-scale DC hybrid laboratory testbed, confirming the model's capability to represent real system behavior accurately.

A fuzzy rule-based (FRB) scheme is proposed in [213] within a game-theoretic optimization framework to minimize greenhouse gas (GHG) emissions in marine systems. This approach employs fuzzy IF–THEN rules to manage uncertainty in the optimization environment. Sensitivity analyses conducted on a numerical case study reveal that, despite increased emission-related costs, the model enhances overall cost efficiency for the involved companies.

In [214], the authors analyze the integration of a hybrid power system (HPS) with DC distribution and a battery energy storage system (BESS) in short-distance cargo vessels, replacing the conventional AC system. Two optimization strategies are compared: a traditional rule-based (RB) control method and a meta-heuristic Grey Wolf Optimization (GWO) technique. Simulation results indicate that the HPS achieves 2.91% and 7.48% reductions in fuel consumption using the RB and GWO schemes, respectively. The study concludes that HPS combined with advanced meta-heuristic control provides better emission reduction and fuel efficiency, with diesel generators operating at higher efficiency. Table 9 provides a comparative overview of the discussed studies employing rule-based approaches in shipboard microgrids.

Table 9: *Overview of rule based ship energy systems with respect to hardware*

	Algorithm Used	Hardware component improved	Objective/ Description
[120]	Exhaustive search algorithm	Diesel-electric engines, Main engines, energy	Task-aware EMS for ship power systems is presented

		storage systems, propellers, generators	
[128]	Fuzzy logic control algorithm	Vanadium redox flow battery (VRB), energy storage systems	An energy management control strategy is proposed that is based on different rules for compensating the fluctuating power caused due to tidal motion
[121]	Exact control algorithm not known	Generator Set, Propulsion Unit, Propulsion Unit, Current Converters, Circuit Breakers, DC bus	A rule-based EMS is proposed that simulates the entire system and investigates the system stability and load sharing strategies in several operating conditions
[213]	Fuzzy logic control algorithm	Generator	An approach is presented to reduce GHG emissions optimally
[214]	Meta-heuristic optimization algorithm	Diesel engine generator, battery, inverter, DC-DC converter, Rectifier, propeller	Hybrid systems power management optimization in electric ferries

SIMULATION AND HARDWARE PLATFORMS

Most machine learning models developed for maritime microgrids utilize MATLAB as the primary simulation environment. For solving optimization problems, various algorithms are implemented using the General Algebraic Modeling System (GAMS), while BARON (Branch-And-Reduce Optimization Navigator) solvers are employed to enhance GAMS's high-level modeling capabilities for efficiently solving objective functions [172], [29]. Visual Studio is also used in certain systems for monitoring purposes [173].

In marine vessel direct current (MVDC) shipboard power systems, real-time fault simulations are conducted using digital simulators, with initial data analysis frequently performed in MATLAB [175]. Python is another widely adopted programming environment due to its flexibility and extensive library support, making it suitable for developing and simulating machine learning-based marine power systems [119], [139], [130].

Various real-time simulation tools are also employed. For instance, an MVDC power system model has been developed using the AppSIM Real-Time Simulator to replicate fault scenarios, with NA-MEMD applied for preprocessing fault voltage data. In another case, the Real Time Digital Simulator (RTDS) is used to execute high-fidelity simulations of marine power systems and generate datasets for fault detection and classification. The RTDS platform provides high-speed, real-time performance suitable for general power system analysis and control system validation [230], [231].

RTDS utilizes advanced hardware with parallel processing capabilities and is operated via a graphical interface called RSCAD. RSCAD acts as the primary tool for interacting with RTDS hardware, allowing users to build, simulate, and analyze interactive models. It also facilitates efficient data collection for post-processing [133]. Owing to its near real-time performance and broad I/O channel support, RTDS has gained widespread adoption in various power system applications [232]. It is particularly effective for system design, testing, and algorithm verification in safety-critical and control-sensitive environments [136].

PSCAD is another widely used software for simulating MVDC shipboard power system models [155]. Real-time fault detection algorithms are implemented in PSCAD/EMTDC to evaluate electrical behavior under transient conditions [176]. Moreover, numerous rule-based systems applied in marine microgrids are simulated using MATLAB/Simulink for power optimization and energy management [128], [214]. Finally, several studies have adopted Hardware-in-the-Loop (HIL) frameworks based on real-time simulation to validate the performance and effectiveness of proposed optimization strategies for shipboard microgrids [48], [117].

CASE STUDIES AND PERFORMANCE COMPARISON

Several studies have applied AI models to specific maritime case studies, such as hybrid-electric ferries and cargo vessels. Key results from these studies are summarized below:

A hybrid-electric ferry employing K-means clustering and linear programming for EMS optimization achieved a 12–18% reduction in fuel consumption. LSTM-based forecasting of propulsion load demonstrated 95% prediction accuracy, significantly improving scheduling and generator loading. Rule-based control integrated with ANN-based power prediction was used to prevent blackouts in naval shipboard systems, ensuring 100% uptime in critical operations.

Table 10: *Summarized performance metrics of different ai techniques applied in the reviewed studies*

Technique	Application Area	Accuracy/Benefit	Notes
SVM	Fault Diagnosis	93%	Good generalization, needs labeled data
LSTM	Load Forecasting	95%	Excellent for time-series prediction
Rule-Based + ANN	Power Control	Stable Output	Best for deterministic logic

DISCUSSION

The integration of artificial intelligence (AI) into shipboard microgrid systems marks a significant advancement in enhancing operational efficiency, environmental compliance, and system resilience. AI-driven approaches—particularly machine learning (ML) and deep learning (DL) techniques—have demonstrated considerable potential in tasks such as predictive maintenance, fault detection, load forecasting, and real-time power optimization. These applications directly contribute to reduced fuel consumption and lower greenhouse gas emissions, aligning maritime operations with international sustainability directives.

Despite these advantages, several challenges hinder the widespread adoption of AI-based control in marine environments. One of the primary obstacles is the difficulty of model generalization across diverse vessel types and operating conditions, largely due to heterogeneous system architectures, variable data quality, and inconsistent operational protocols. Additionally, the opaque nature of many deep learning models poses concerns regarding explainability—an essential requirement for safety-critical maritime systems. Other technical barriers include the need for real-time processing, ensuring data privacy, and addressing cybersecurity threats.

To mitigate these issues, hybrid control frameworks that combine data-driven AI models with deterministic, rule-based strategies offer a promising compromise, balancing system adaptability with reliability and interpretability. The continued evolution of such architectures, supported by standardized evaluation protocols and deployment strategies, will be crucial for future development.

Conclusion

This paper presented a comprehensive review of AI methodologies applied to shipboard microgrid systems, with an emphasis on machine learning, deep learning, and rule-based hybrid approaches. Among these, artificial neural networks (ANNs) emerged as the most frequently utilized, alongside techniques such as k-means clustering, support vector machines (SVMs), decision trees, regression models, and fuzzy logic algorithms.The reviewed literature highlights the successful deployment of these intelligent control techniques across diverse maritime applications, including power and energy management, ship design optimization, radar control, fault and anomaly detection, fuel consumption forecasting, and marine traffic regulation. Notable improvements were observed in the efficiency and reliability of onboard components such as propulsion systems, energy storage units, thrusters, converters, generators, radars, and sensors. Simulation platforms such as MATLAB, Python, PSCAD, Real-Time Digital Simulator (RTDS), and hardware-in-the-loop (HIL) systems were commonly employed to evaluate model performance. Overall, the findings underscore that AI-enabled microgrid control strategies offer tangible benefits in terms of energy efficiency, emissions reduction, and operational cost minimization.

Recommendations and Future Work

The insights obtained through this review point to several promising avenues for future research. First, there is significant potential for exploring deep reinforcement learning (DRL) and federated learning approaches to enable more adaptive and decentralized control in marine microgrids. These techniques could be especially valuable in environments characterized by uncertainty, variability, and real-time constraints. Second, the integration of robust cybersecurity mechanisms within AI-based control frameworks remains underexplored. Future efforts should prioritize the development of intelligent intrusion detection and cyber-resilient control systems to protect critical shipboard infrastructure. Third, to ensure safe and explainable AI deployment in maritime settings, greater emphasis should be placed on developing interpretable models that comply with marine safety standards. Hybrid systems that integrate AI with expert systems or rule-based logic may offer a pragmatic solution. Lastly, the creation and public release of standardized, high-fidelity datasets reflecting various operational profiles and vessel types would significantly advance research in this domain. The establishment of benchmark protocols and unified testing frameworks will also be instrumental in accelerating real-world implementation of AI-driven marine microgrid technologies.

References

[1] Arora, N. K. (2019). Earth: 50 years challenge. Environmental Sustainability, 2(1), 1-3.

[2] UNEP, U. (2020). Emissions gap report 2020. UN Environment Programme.

[3] Gulagi, A., Alcanzare, M., Bogdanov, D., Esparcia Jr, E., Ocon, J., & Breyer, C. (2021). Transition pathway towards 100% renewable energy across the sectors of power, heat, transport, and desalination for the Philippines. Renewable and Sustainable Energy Reviews, 144, 110934.

[4] Figueres, C., Schellnhuber, H. J., Whiteman, G., Rockström, J., Hobley, A., & Rahmstorf, S. (2017). Three years to safeguard our climate. Nature, 546(7660), 593-595.

[5] Moreau, V., Dos Reis, P. C., & Vuille, F. (2019). Enough metals? Resource constraints to supply a fully renewable energy system. Resources, 8(1), 29.

[6] Breyer C, Bogdanov D, Gulagi A, Aghahosseini A, Barbosa LSNS, Koskinen O, et al. On the role of solar photovoltaics in global energy transition scenarios. Prog Photovoltaics Res Appl 2017;25(8):727–45.

[7] Breyer C, Bogdanov D, Aghahosseini A, Gulagi A, Child M, Oyewo AS, et al. Solar photovoltaics demand for the global energy transition in the power sector. Prog Photovoltaics Res Appl 2018;26(8):505–23.

[8] Deal, G. (2018). Communication From the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions.

[9] Andersson, Ö., & Börjesson, P. (2021). The greenhouse gas emissions of an electrified vehicle combined with renewable fuels: Life cycle assessment and policy implications. Applied Energy, 289, 116621.

[10] IMO, Prevention of GHG Emissions from Ships, Third IMO GHG Study 2014, Final Report, 2014

[11] Lindstad, H., Asbjørnslett, B. E., & Strømman, A. H. (2012). The Importance of economies of scale for reductions in greenhouse gas emissions from shipping. Energy policy, 46, 386-398.

[12] Mehrzadi, M. (2020). Power management Systems for Dynamic Positioning Offshore Support Vessels: Artificial Intelligence and Optimization for Shipboard Microgrids.

[13] Skjong, E., Volden, R., Rødskar, E., Molinas, M., Johansen, T. A., & Cunningham, J. (2016). Past, present, and future challenges of the marine vessel's electrical power system. IEEE Transactions on Transportation Electrification, 2(4), 522-537.

[14] Kim, S. Y., Choe, S., Ko, S., & Sul, S. K. (2015). A Naval Integrated Power System with a Battery Energy Storage System: Fuel efficiency, reliability, and quality of power. IEEE electrification magazine, 3(2), 22-33.

[15] Petrolium Safety Authority (PTIL) Norway. [Online]. Available: http://www.psa.no/?lang=en US

[16] Norwegian Maritime Authority (NMD). [Online]. Available: https://www.sjofartsdir.no/en

[17] Skjong, E., Johansen, T. A., Molinas, M., & Sørensen, A. J. (2017). Approaches to economic energy management in diesel–electric marine vessels. IEEE Transactions on Transportation Electrification, 3(1), 22-35.

[18] R. H. Lasseter and P. Paigi, “Microgrid: a conceptual solution,” in Proceedings of the IEEE 35th Annual Power Electronics Specialists Conference (PESC 04), pp. 4285–4290, June 2004.

[19] R. H. Lasseter, “Microgrids,” in Proceedings of the IEEE Power Engineering Society Winter Meeting, vol. 1, pp. 305–308, 2002.

[20] S. Parhizi, H. Lotfi, A. Khodaei, and S. Bahramirad, ``State of the art in research on microgrids: A review," IEEE Access, vol. 3, pp. 890-925, Jun. 2015.

[21] F. Nejabatkhah, Y. W. Li, and H. Tian, ``Power quality control of smart hybrid AC/DC microgrids: An overview," IEEE Access, vol. 7, pp. 5229552318, Apr. 2019.

[22] A. Mohammed, S. S. Refaat, S. Bayhan, and H. Abu-Rub, ``AC microgrid control and management strategies: Evaluation and review," IEEE Power Electron. Mag., vol. 6, no. 2, pp. 18-31, Jun. 2019.

[23] D. E. Olivares, A. Mehrizi-Sani, A. H. Etemadi, C. A. Cañizares, R. Iravani, M. Kazerani, A. H. Hajimiragha, O. Gomis-Bellmunt, M. Saeedifard, R. Palma-Behnke, G. A. Jiménez-Estévez, and N. D. Hatziargyriou, ``Trends in microgrid control," IEEE Trans. Smart Grid, vol. 5, no. 4, pp. 1905-1919, Jul. 2014.

[24] E. Hossain, E. Kabalci, R. Bayindir, and R. Perez, ``Microgrid testbeds around the world: State of art," Energy Convers. Manage., vol. 86, pp. 132-153, Oct. 2014.

[25] Z. Jiang and X. Yu, ``Hybrid DC-and AC-linked microgrids: Towards integration of distributed energy resources," in Proc. IEEE Energy Conf., Atlanta, GA, USA, Feb. 2008, pp. 1-8.

[26] C. Marnay, ``Introduction to microgrids," in Proc. Introduction Consor- tium Electr. Rel. Technol. 981 Solutions Berkeley Symp. Microgrids, 2005.

[27] Y. Tan, L. Meegahapola, and K. M. Muttaqi, ``A review of technical challenges in planning and operation of remote area power supply systems," Renew. Sustain. Energy Rev., vol. 38, pp. 876-889, Oct. 2014.

[28] Ahmed, M., Meegahapola, L., Vahidnia, A., & Datta, M. (2020). Stability and control aspects of microgrid Architectures–A comprehensive review. IEEE Access, 8, 144730-144766.

[29] A. Arulampalam, M. Barnes, A. Engler, A. Goodwin, and N. Jenkins, ``Control of power electronic interfaces in distributed generation microgrids," Int. J. Electron., vol. 91, no. 9, pp. 503523, Sep. 2004.

[30] A. T. Elsayed, A. A. Mohamed, and O. A. Mohammed, "Dc microgrids and distribution systems: An overview," Electric Power Systems Research, vol. 119, pp. 407–417, 2015.

[31] Wang, C. (2013). Theoretical analysis and simulation Microgrid.

[32] M. H. Rashid, Power Electronics Handbook: Devices, Circuits and Applications. New York, NY, USA: Academic, 2010.

[33] G. F. Reed, ``DC technologies: Solutions to electric power system advancements [guest editorial]," IEEE Power Energy Mag., vol. 10, no. 6, pp. 10-17, Nov. 2012.

[34] G. W. Arnold, ``Challenges and opportunities in smart grid: A position article," Proc. IEEE, vol. 99, no. 6, pp. 922-927, Jun. 2011.

[35] A. Battaglini, J. Lilliestam, A. Haas, and A. Patt, ``Development of Super-Smart grids for a more efficient utilization of electricity from renewable sources," J. Cleaner Prod., vol. 17, no. 10, pp. 911-918, Jul. 2009.

[36] A. T. Elsayed, A. A. Mohamed, and O. A. Mohammed, "Dc microgrids and distribution systems: An overview," Electric Power Systems Research, vol. 119, pp. 407–417, 2015.

[37] J. Vasquez, J. Guerrero, J. Miret, M. Castilla, and L. de Vicuñanda, “Hierarchical control of intelligent microgrids,” IEEE Ind. Electron. Mag., vol. 4, no. 4, pp. 23–29, Dec. 2010.

[38] H. Kakigano, M. Nomura, T. Ise, “Loss Evaluation of DC Distribution for Residential Houses Compared with AC System,” Proc. IPEC, pp. 480-486, 2010.

[39] P. Wang, L. Goel, X. Liu, and F. Hoong Choo, ``Harmonizing AC and DC: A hybrid AC/DC future grid solution," IEEE Power Energy Mag., vol. 11, no. 3, pp. 76-83, May 2013.

[40] I. Patrao, E. Figueres, G. Garcerá, and R. González-Medina, ``Microgrid architectures for low voltage distributed generation," Renew. Sustain. Energy Rev., vol. 43, pp. 415-424, Mar. 2015.

[41] D. Fregosi, S. Ravula, D. Brhlik, J. Saussele, S. Frank, E. Bonnema, J. Scheib, and E. Wilson, ``A comparative study of DC and AC microgrids in commercial buildings ACross different climates and operating profiles," in Proc. IEEE 1st Int. Conf. DC Microgrids (ICDCM), Atlanta, GA, USA, Jun. 2015, pp. 159-164.

[42] U. Manandhar, A. Ukil, and T. K. K. Jonathan, ``Efficiency comparison of DC and AC microgrid," in Innov. Smart Grid Technol.-Asia (ISGT ASIA), Sep. 2015, pp. 1-6.

[43] Jirdehi, M. A., Tabar, V. S., Ghassemzadeh, S., & Tohidi, S. (2020). Different aspects of microgrid management: A comprehensive review. Journal of Energy Storage, 30, 101457.

[44] N. W. A. Lidula and A. D. Rajapakse, “Microgrids research: a review of experimental microgrids and test systems,” Renewable and Sustainable Energy Reviews, vol. 15, no. 1, pp. 186–202, 2011.

[45] S. Karki, M. Kulkarni, D. Michael, Mann, and S. Hossein, “Efficiency improvement through combined heat and power for on-site distributed generation technologies,” Cogeneration and Distributed Generation Journal, vol. 22, no. 3, pp. 19–34, 2007.

[46] S. Chowdhury, S. P. Chowdhury, and P. Crossley, Microgrids and Active Distribution, Networks, London, UK, 2009.

[47] W. El-Khattam and M. M. A. Salama, “Distributed generation technologies, definitions and benefits,” Electric Power Systems Research, vol. 71, no. 2, pp. 119–128, 2004.

[48] Mariam, L., Basu, M., & Conlon, M. F. (2013). A review of existing microgrid architectures. Journal of engineering, 2013.

[49] Zhou, Y., & Ho, C. N. M. (2016, May). A review on microgrid architectures and control methods. In 2016 IEEE 8th International Power Electronics and Motion Control Conference (IPEMC-ECCE Asia) (pp. 3149-3156). IEEE.

[50] X. Wang, J. M. Guerrero, and Z. Chen, “Control of grid-interactive AC microgrids,” Proc. IEEE ISIE 20010, pp. 2211-2216.

[51] J. Rocabert, A. Luna, F. Blaabjerg, and P. Rodríguez, “Control of power converters in AC microgrids,” IEEE Trans. Power Electron., vol. 27, no. 11, pp. 4734–4749, Nov. 2012.

[52] T. S. Ustun et al., “Recent developments in microgrids and example cases around the world—A review,” Renewable and Sustainable Energy Reviews, vol.15, pp. 4030–4041, 2011.

[53] I. J. Balaguer, Q. Lei, S. Yang, U. Supatti, and F. Z. Peng, “Control for grid-connected and intentional islanding operations of distributed power generation,” IEEE Trans. Ind. Electron., vol. 58, no. 1, pp. 147–157, Jan. 2011.

[54] V. Verma and G. G. Talpur, “Decentralized master–slave operation of microgrid using current controlled distributed generation sources,” Proc. IEEE Int. Conf. Power Electron. Drives Energy Syst. (PEDES), Bangalore, India, pp. 1–6, 2012.

[55] Z. Xiao, J. Wu, and N. Jenkins, “An Overview Of Microgrid Control,” Intelligent Automation & Soft Computing, vol. 16, pp.199–212, 2010.

[56] J. M. Guerrero, J. C. Vasquez, J. Matas, L. G. de Vicuna, and M. Castilla, “Hierarchical control of droop-controlled AC and DC microgrids: A general

approach toward standardization," IEEE Trans. Ind. Electron., vol. 58, no. 1, pp. 158–172, Jan. 2011.

[57] N. Cai and J. Mitra, "A Decentralized control Architecture for a Microgrid with Power Electronic Interfaces" Proc. of the 42th Annual North American, Alinton, TX, Sep. 2010.

[58] T. Dragicevic, J. Guerrero, J. Vasquez, and D. Skrlec, "Supervisory control of an adaptive-droop regulated dc microgrid with battery management capability," IEEE Trans. Power. Electron., vol. 29, pp. 695–706, Feb. 2014.

[59] X. Lu, K. Sun, J. M. Guerrero, J. C. Vasquez, and L. Huang, "State-of- Charge Balance Using Adaptive Droop Control for Distributed Energy Storage Systems in DC Microgrid Applications," IEEE Trans. Ind. Electron., vol. 61, no. 6, pp. 2804–2815, Jun. 2014.

[60] C. Ho, V. Cheung, and H. Chung, "Constant-frequency hysteresis current control of grid-connected VSI without bandwidth control," IEEE Trans. Power Electron., vol. 24, no. 11, pp. 2484–2495, Nov. 2009.

[61] Jayasinghe, S. G., Meegahapola, L., Fernando, N., Jin, Z., & Guerrero, J. M. (2017). Review of ship microgrids: System architectures, storage technologies and power quality aspects. inventions, 2(1), 4.

[62] Lan, H., Wen, S., Hong, Y. Y., David, C. Y., & Zhang, L. (2015). Optimal sizing of hybrid PV/diesel/battery in ship power system. Applied energy, 158, 26-34.

[63] Musolino, V.; Piegari, L.; Tironi, E. Technical and economical evaluation of storage systems in naval applications. In Proceedings of the 2013 International Conference on Clean Electrical Power (ICCEP), Alghero, Italy, 11–13 June 2013; pp. 120–127.

[64] Musolino, V.; Piegari, L.; Tironi, E. Storage systems for transportation, land handling and naval applications. In Proceedings of the Electrical Systems for Aircraft, Railway and Ship Propulsion (ESARS), Bologna, Italy, 16–18 October 2012; pp. 1–9.

[65] Guerrero, M.A.; Romero, E.; Barrero, F.; Milanes, M.I.; Gonzalez, E. Supercapacitors: Alternative Energy Storage Systems. Prz. Elektrotech. 2009, 85, 188.

[66] Akinyele, D.O.; Rayudu, R.K. Review of Energy Storage Technologies for Sustainable Power Networks. Sustain. Energy Technol. Assess. 2014, 8, 74–91. [CrossRef]

[67] Adhikari, S.; Lei, Z.; Peng, W.; Tang, Y. A battery/supercapacitor hybrid energy storage system for DC microgrids. In Proceedings of the 2016 IEEE 8th International Power Electronics and Motion Control Conference (IPEMC-ECCE Asia), Hefei, China, 22–26 May 2016; pp. 1747–1753.

[68] Vechiu, I.; Etxeberria, A.; Camblong, H.; Vinassa, J.M. Three-level Neutral Point Clamped Inverter Interface for flow battery/supercapacitor Energy Storage System used for microgrids. In Proceedings of the 2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe), Manchester, UK, 5–7 December 2011; pp. 1–6.

[69] Xiao, J.; Wang, P.; Setyawan, L. Hierarchical Control of Hybrid Energy Storage System in DC Microgrids. IEEE Trans. Ind. Electron. 2015, 62, 4915–4924. [CrossRef]

[70] Ghenai, C., Bettayeb, M., Brdjanin, B., & Hamid, A. K. (2019). Hybrid solar PV/PEM fuel Cell/Diesel Generator power system for cruise ship: A case study in Stockholm, Sweden. Case Studies in Thermal Engineering, 14, 100497.

[71] N. Olmer, B. Comer, B. Roy, X. Mao, and D. Rutherford, ``Greenhouse gas emissions from global shipping, 20132015," in International Council on Clean Transportation. 2017, pp. 1-38.

[72] McCoy, T.J. Trends in ship electric propulsion. In Proceedings of the 2002 IEEE Power Engineering Society Summer Meeting, Chicago, IL, USA, 21–25 July 2002; Volume 1, pp. 343–346.

[73] Baldi, F., Ahlgren, F., Nguyen, T. V., Thern, M., & Andersson, K. (2018). Energy and exergy analysis of a cruise ship. Energies, 11(10), 2508.

[74] Pico, H. N. V., Aliprantis, D. C., & Sudhoff, S. D. (2015, June). Reachability analysis of shipboard power systems with uncertain pulsed loads. In 2015 IEEE Electric Ship Technologies Symposium (ESTS) (pp. 395-402). IEEE.

[75] Van der Burgt, J. J. A., Van Gelder, P., & Van Dijk, E. (1999, June). Pulsed power requirements for future naval ships. In Digest of Technical Papers. 12th IEEE International Pulsed Power Conference.(Cat. No. 99CH36358) (Vol. 2, pp. 1357-1360). IEEE.

[76] QUEEN MARY II Technical Information. Available online: http://www.cunard.com/documents/press% 20kits/queen%20mary%202/queen_mary_2_technical.pdf (accessed on 12 November 2016).

[77] IEEE Industry Applications Society. 1709–2010—IEEE Recommended Practice for 1 kV to 35 kVMedium-Voltage DC Power Systems on Ships; IEEE Standard: New York, NY, USA, 2010; pp. 1–54.

[78] Feng, X.; Butler-Purry, K.L.; Zourntos, T. Multi-Agent System-Based Real-Time Load Management for All-Electric Ship Power Systems in DC Zone Level. IEEE Trans. Power Syst. 2012, 27, 1719–1728. [CrossRef]

[79] Hein, K., Yan, X., & Wilson, G. (2020). Multi-objective optimal scheduling of a hybrid ferry with shore-to-ship power supply considering energy storage degradation. Electronics, 9(5), 849.

[80] Chen, X.; Wang, X. A novel wound rotor BDFIG for ship shaft generator application—Control and prototype tests. In Proceedings of the 2014 17th International Conference on Electrical Machines and Systems (ICEMS), Hangzhou, China, 22–25 October 2014; pp. 1196–1200.

[81] Jiang,W.; Fang, R.; Khan, J.; Dougal, R. Performance Prediction and Dynamic Simulation of Electric Ship Hybrid Power System. In Proceedings of the 2007 IEEE Electric Ship Technologies Symposium, Arlington, VA, USA, 21–23 May 2007; pp. 490–497.

[82] Bosich, D.; Vicenzutti, A.; Pelaschiar, R.; Menis, R.; Sulligoi, G. Toward the future: The MVDC large ship research program. In Proceedings of the 2015 AEIT

International Annual Conference (AEIT), Naples, Italy, 14–16 October 2015; pp. 1–6.

[83] Jin, Z.; Sulligoi, G.; Cuzner, R.; Meng, L.; Vasquez, J.C.; Guerrero, J.M. Next-Generation Shipboard DC Power System: Introduction Smart Grid and dc Microgrid Technologies into Maritime Electrical Networks. IEEE Electrif. Mag. 2016, 4, 45–57. [CrossRef]

[84] Vijlee, S.Z.; Ouroua, A.; Domaschk, L.N.; Beno, J.H. Directly-Coupled Gas Turbine Permanent Magnet Generator Sets for Prime Power Generation on Board Electric Ships. In Proceedings of the 2007 IEEE Electric Ship Technologies Symposium, Arlington, VA, USA, 21–23 May 2007; pp. 340–347.

[85] Mashayekh, S.; Wang, Z.; Qi, L.; Lindtjorn, J.; Myklebust, T.A. Optimum sizing of energy storage for an electric ferry ship. In Proceedings of the 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012; pp. 1–8.

[86] Schwoerer, F.;Witzig,W.F. Nuclear power today and tomorrow. IEEE Spectr. 1964, 1, 120–130. [CrossRef]

[87] Donnelly,W. Nuclear Power and Merchant Shipping; U.S. Atomic Energy Commission, Division of Technical Information: Oak Ridge, TN, USA, 1964.

[88] Guo, C.; Sun, Y.; Yuan, C.; Yan, X.; Wang, Y.; Jiang, Q. Research on power load flow calculation for photovoltaic-ship power system based on PSAT. In Proceedings of the 2015 International Conference on Renewable Energy Research and Applications (ICRERA), Palermo, Italy, 22–25 November 2015; pp. 443–448.

[89] Tsekouras, G.J.; Kanellos, F.D.; Prousalidis, J. Simplified method for the assessment of ship electric power systems operation cost reduction from energy storage and renewable energy sources integration. IET Electr. Syst. Transp. 2015, 5, 61–69. [CrossRef]

[90] IEC 61000-4-30:2015. Electromagnetic Compatibility (EMC)—Part 4-30: Testing and Measurement Techniques Power Quality Measurement Methods; International Electro technical Commission: Geneva, Switzerland, 2015.

[91] American Bureau of Shipping. International Naval Ships, Guide for Building and Classing, Part 4 Vessel Systems and Machinery, American Bureau of Shipping; 2016 International Association of Classification Societies, Requirements Concerning Electrical and Electronic Installations; IACS Req.: Houston, TX, USA, 2016.

[92] Mindykowski, J. Case Study—Based Overview of Some Contemporary Challenges to Power Quality in Ship Systems. Inventions 2016, 1, 12. [CrossRef]

[93] Domaschk, L.N.; Ouroua, A.; Hebner, R.E.; Bowlin, O.E.; Colson, W.B. Coordination of Large Pulsed Loads on Future Electric Ships. IEEE Trans. Magn. 2007, 43, 450–455. [CrossRef]

[94] Hebner, R.E.; Davey, K.; Herbst, J.; Hall, D.; Hahne, J.; Surls, D.D.; Ouroua, A. Dynamic Load and Storage Integration. Proc. IEEE 2015, 103, 2344–2354. [CrossRef]

[95] Evans, I.C.; Hoevenaars, A.H.; Eng, P. Meeting Harmonic Limits on Marine Vessels. In Proceedings of the 2007 IEEE Electric Ship Technologies Symposium, Arlington, VA, USA, 21–23 May 2007; pp. 115–121.

[96] Al-Falahi, M. D., Tarasiuk, T., Jayasinghe, S. G., Jin, Z., Enshaei, H., & Guerrero, J. M. (2018). AC ship microgrids: control and power management optimization. Energies, 11(6), 1458.

[97] Tarasiuk, T., Jayasinghe, S. G., Gorniak, M., Pilat, A., Shagar, V., Liu, W., & Guerrero, J. M. (2021). Review of Power Quality Issues in Maritime Microgrids. IEEE Access.

[98] Alzubi, J., Nayyar, A., & Kumar, A. (2018, November). Machine learning from theory to algorithms: an overview. In Journal of physics: conference series (Vol. 1142, No. 1, p. 012012). IOP Publishing.

[99] Ray, S. (2019, February). A quick review of machine learning algorithms. In 2019 International conference on machine learning, big data, cloud and parallel computing (COMITCon) (pp. 35-39). IEEE.

[100] Sheikh, S. S. (2019). BATTERY HEALTH MONITORING USING MACHINE LEARNING (Doctoral dissertation, National University of Sciences and Technology).

[101] Mahesh, B. (2020). Machine Learning Algorithms-A Review. International Journal of Science and Research (IJSR).[Internet], 9, 381-386.

[102] Smola, A., & Vishwanathan, S. V. N. (2008). Introduction to machine learning. Cambridge University, UK, 32(34), 2008.

[103] Bishop, C. M. (1995). Neural networks for pattern recognition. Oxford university press.

[104] Mohapatra, B. N., & Panda, P. P. (2019). Machine learning applications to smart city. ACCENTS Transactions on Image Processing and Computer Vision, 5(14), 1.

[105] Watson, D. S., Krutzinna, J., Bruce, I. N., Griffiths, C. E., McInnes, I. B., Barnes, M. R., & Floridi, L. (2019). Clinical applications of machine learning algorithms: beyond the black box. Bmj, 364.

[106] Triantafyllidis, A. K., & Tsanas, A. (2019). Applications of machine learning in real-life digital health interventions: review of the literature. Journal of medical Internet research, 21(4), e12286.

[107] Cruz, J. A., & Wishart, D. S. (2006). Applications of machine learning in cancer prediction and prognosis. Cancer informatics, 2, 117693510600200030.

[108] Kushwaha, S., Bahl, S., Bagha, A. K., Parmar, K. S., Javaid, M., Haleem, A., & Singh, R. P. (2020). Significant applications of machine learning for COVID-19 pandemic. Journal of Industrial Integration and Management, 5(04), 453-479.

[109] Vamathevan, J., Clark, D., Czodrowski, P., Dunham, I., Ferran, E., Lee, G., ... & Zhao, S. (2019). Applications of machine learning in drug discovery and development. Nature Reviews Drug Discovery, 18(6), 463-477.

[110] Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., & Nandi, A. K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. Mechanical Systems and Signal Processing, 138, 106587.

[111] Hegde, J., & Rokseth, B. (2020). Applications of machine learning methods for engineering risk assessment–A review. Safety science, 122, 104492.

[112] Chagas, B. N., Viana, J., Reinhold, O., Lobato, F. M., Jacob Jr, A. F., & Alt, R. (2020, January). A literature review of the current applications of machine learning and their practical implications. In Web Intelligence (Vol. 18, No. 1, pp. 69-83). IOS Press.

[113] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.

[114] Bertolini, M., Mezzogori, D., Neroni, M., & Zammori, F. (2021). Machine Learning for industrial applications: A comprehensive literature review. Expert Systems with Applications, 175, 114820.

[115] Hossain, E., Khan, I., Un-Noor, F., Sikander, S. S., & Sunny, M. S. H. (2019). Application of big data and machine learning in smart grid, and associated security concerns: A review. Ieee Access, 7, 13960-13988.

[116] Cheng, L., & Yu, T. (2019). A new generation of AI: A review and perspective on machine learning technologies applied to smart energy and electric power systems. International Journal of Energy Research, 43(6), 1928-1973.

[117] Guanglei, L., Hong, Z., Dingyu, J., & Hao, W. (2018, June). Design of Ship Monitoring System Based on Unsupervised Learning. In International Conference on Intelligent and Interactive Systems and Applications (pp. 270-276). Springer, Cham.

[118] William, E. J., Manic, M., & Johnson, B. K. (2007, September). Ann relays used to determine fault locations on shipboard electrical distribution systems. In 2007 39th North American Power Symposium (pp. 143-147). IEEE.

[119] Liu, S., Sun, Y., Zhang, L., & Su, P. (2021). Fault diagnosis of shipboard medium-voltage DC power system based on machine learning. International Journal of Electrical Power & Energy Systems, 124, 106399.

[120] Hein, K., Xu, Y., Senthilkumar, Y., Gary, W., & Gupta, A. K. (2021). Rule-based operation task-aware energy management for ship power systems. IET Generation, Transmission & Distribution, 14(25), 6348-6358.

[121] Ghimire, P., Zadeh, M., Pedersen, E., & Thorstensen, J. (2020). Dynamic Modeling, Simulation, and Testing of a Marine DC Hybrid Power System. IEEE Transactions on Transportation Electrification, 7(2), 905-919.

[122] Uyanık, T., Karatuğ, Ç., & Arslanoğlu, Y. (2020). Machine learning approach to ship fuel consumption: A case of container vessel. Transportation Research Part D: Transport and Environment, 84, 102389.

[123] Ahlgren, F., & Thern, M. (2018). Auto machine learning for predicting ship fuel consumption. In ECOS 2018-the 31st International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, 17-21 June, 2018, Guimarães.

[124] Uyanik, T., Arslanoglu, Y., & Kalenderli, O. (2019, April). Ship fuel consumption prediction with machine learning. In Proceedings of the 4th International Mediterranean Science and Engineering Congress, Antalya, Turkey (pp. 25-27).

[125] Cheliotis, M., Lazakis, I., & Theotokatos, G. (2020). Machine learning and data-driven fault detection for ship systems operations. Ocean Engineering, 216, 107968.

[126] Wang, G., & Zhu, J. (2020, August). Research on Fake Data Injection Attack Detection in Intelligent Ship Power System. In Journal of Physics: Conference Series (Vol. 1607, No. 1, p. 012129). IOP Publishing.

[127] Wei, H., Nguyen, H., Ramu, P., Raju, C., Liu, X., & Yadegar, J. (2009, May). Automated intelligent video surveillance system for ships. In Optics and Photonics in Global Homeland Security V and Biometric Technology for Human Identification VI (Vol. 7306, p. 73061N). International Society for Optics and Photonics.

[128] Han, J., Li, X., & Tang, T. (2021). Energy Management Using a Rule-Based Control Strategy of Marine Current Power System with Energy Storage System. Journal of Marine Science and Engineering, 9(6), 669.

[129] Dugad, S., Puliyadi, V., Palod, H., Johnson, N., Rajput, S., & Johnny, S. (2017, January). Ship intrusion detection security system using image processing & SVM. In 2017 International Conference on Nascent Technologies in Engineering (ICNTE) (pp. 1-7). IEEE.

[130] Abebe, M., Noh, Y., Seo, C., Kim, D., & Lee, I. (2021). Developing a Ship Collision Risk Index estimation model based on Dempster-Shafer theory. Applied Ocean Research, 113, 102735.

[131] Aslam, S., Herodotou, H., Mohsin, S. M., Javaid, N., Ashraf, N., & Aslam, S. (2021). A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids. Renewable and Sustainable Energy Reviews, 144, 110992.

[132] Mohammadzadeh, N., Baldi, F., & Boonen, E. J. (2018, October). Application of Machine Learning and Mathematical Programming in the Optimization of the Energy Management System for Hybrid-Electric Vessels Having Cyclic Operations. In International Naval Engineering Conference and Exhibition (No. CONF).

[133] Mair, A. J., Davidson, E. M., McArthur, S. D. J., Srivastava, S. K., Schoder, K., & Cartes, D. A. (2009, April). Machine learning techniques for diagnosing and locating faults through the automated monitoring of power electronic components in shipboard power systems. In 2009 IEEE Electric Ship Technologies Symposium (pp. 469-476). IEEE.

[134] Peng, X., Wang, B., Zhang, L., & Su, P. (2021). Adaptive Online Sequential Extreme Learning Machine with Kernels for Online Ship Power Prediction. Energies, 14(17), 5371

[135] Abebe, M., Shin, Y., Noh, Y., Lee, S., & Lee, I. (2020). Machine learning approaches for ship speed prediction towards energy efficient shipping. Applied Sciences, 10(7), 2325.

[136] Amgai, R., Shi, J., Santos, R., & Abdelwahed, S. (2013, April). Machine learning based diagnosis support for shipboard power systems controls. In 2013 IEEE Electric Ship Technologies Symposium (ESTS) (pp. 405-410). IEEE.

[137] Rawson, A., Brito, M., Sabeur, Z., & Tran-Thanh, L. (2021). A machine learning approach for monitoring ship safety in extreme weather events. Safety science, 141, 105336.

[138] Fardelas, G., & Kim, S. G. (2021, August). Data-driven sustainable ship design using Axiomatic Design and Bayesian Network Model. In IOP Conference Series: Materials Science and Engineering (Vol. 1174, No. 1, p. 012003). IOP Publishing.

[139] Huotari, J., Ritari, A., Ojala, R., Vepsäläinen, J., & Tammi, K. (2019). Q-Learning Based Autonomous Control of the Auxiliary Power Network of a Ship. IEEE Access, 7, 152879-152890.

[140] Kee, K. K., & Simon, B. Y. L. (2019, February). Cloud-based iot solution for predictive modeling of ship fuel consumption. In Proceedings of the 2019 8th International Conference on Software and Computer Applications (pp. 44-49).

[141] Lang, X. (2021). Development of Speed-power Performance Models for Ship Voyage Optimization. Chalmers Tekniska Hogskola (Sweden).

[142] Jeon, M., Noh, Y., Jeon, K., Lee, S., & Lee, I. (2021). Data gap analysis of ship and maritime data using meta learning. Applied Soft Computing, 101, 107048.

[143] Vorkapić, A., Radonja, R., & Martinčić-Ipšić, S. (2021). Predicting seagoing ship energy efficiency from the operational data. Sensors, 21(8), 2832.

[144] Chan, V. C. (2020). Using a K-Nearest Neighbors Machine Learning Approach to Detect Cyberattacks on the Navy Smart Grid. NAVAL POSTGRADUATE SCHOOL MONTEREY CA.

[145] Mascaro, S., Nicholso, A. E., & Korb, K. B. (2014). Anomaly detection in vessel tracks using Bayesian networks. International Journal of Approximate Reasoning, 55(1), 84-98.

[146] Engel, M., Navot, A., Saban, I., Engel, Y., Arad, E., & Shahar, N. (2013, June). Sea Spotter: A fully staring naval IRST system. In Infrared Technology and Applications XXXIX (Vol. 8704, p. 87040K). International Society for Optics and Photonics.

[147] Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. Electronic Markets, 31(3), 685-695.

[148] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT press.

[149] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444 https://doi.org/10.1038/nature14539.

[150] Kudugunta, S., & Ferrara, E. (2018). Deep neural networks for bot detection. Information Sciences, 467, 312-322.

[151] Kim, T. Y., & Cho, S. B. (2018). Web traffic anomaly detection using C-LSTM neural networks. Expert Systems with Applications, 106, 66-76.

[152] Mohsen, H., El-Dahshan, E. S. A., El-Horbaty, E. S. M., & Salem, A. B. M. (2018). Classification using deep learning neural networks for brain tumors. Future Computing and Informatics Journal, 3(1), 68-71.

[153] Lee, J. H., Kim, D. H., Jeong, S. N., & Choi, S. H. (2018). Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. Journal of dentistry, 77, 106-111.

[154] Nair, L. R. (2020). RetoNet: a deep learning architecture for automated retinal ailment detection. Multimedia Tools and Applications, 79(21), 15319-15328.

[155] Yuan, Z., Liu, J., Zhang, Q., Liu, Y., Yuan, Y., & Li, Z. (2021). A practical estimation method of inland ship speed under complex and changeful navigation environment. IEEE Access, 9, 15643-15658.

[156] Mohamed, M. R., Sharkh, S. M., & Walsh, F. C. (2009, September). Redox flow batteries for hybrid electric vehicles: Progress and challenges. In 2009 IEEE Vehicle Power and Propulsion Conference (pp. 551-557). IEEE.

[157] Vrijdag, A., Stapersma, D., & Van Terwisga, T. (2010). Control of propeller cavitation in operational conditions. Journal of Marine Engineering & Technology, 9(1), 15-26.

[158] S. UNFCCC, "Report of the Conference of the Parties on its twenty-first session, held in Paris from 30 November to 13 December 2015. Addendum. Part two: Action taken by the Conference of the Parties at its twenty-first session."

[159] Prousalidis, J., Hatzilau, I. K., Michalopoulos, P., Pavlou, I., & Muthumuni, D. (2005, July). Studying ship electric energy systems with shaft generator. In IEEE Electric Ship Technologies Symposium, 2005. (pp. 156-162). IEEE.

[160] Paul, D. (2020). A history of electric ship propulsion systems [history]. IEEE Industry Applications Magazine, 26(6), 9-19.

[161] Gaber, M., El-Banna, S. H., Eldabah, M., & Hamad, M. S. (2019, December). Model and control of naval ship power system by the concept of all-electric ships based on renewable energy. In 2019 21st International Middle East Power Systems Conference (MEPCON) (pp. 1235-1240). IEEE.

[162] Hemi, H., Ghouili, J., & Cheriti, A. (2014). A real time fuzzy logic power management strategy for a fuel cell vehicle. Energy conversion and Management, 80, 63-70.

[163] Wen, S., Zhang, C., Lan, H., Xu, Y., Tang, Y., & Huang, Y. (2019). A hybrid ensemble model for interval prediction of solar power output in ship onboard power systems. IEEE Transactions on Sustainable Energy, 12(1), 14-24.

[164] Chanda, N. K., & Fu, Y. (2011, August). ANN-based fault classification and location in MVDC shipboard power systems. In 2011 North American Power Symposium (pp. 1-7). IEEE.

[165] Wang, X., Li, J., & Zhang, T. (2019). A machine-learning model for zonal ship flow prediction using AIS data: A case study in the south atlantic states region. Journal of Marine Science and Engineering, 7(12), 463.

[166] Kim, K. I., & Lee, K. M. (2018). Deep learning-based caution area traffic prediction with automatic identification system sensor data. Sensors, 18(9), 3172.

[167] Li, H., Li, W., Luo, M., Monti, A., & Ponci, F. (2011). Design of smart MVDC power grid protection. IEEE Transactions on Instrumentation and Measurement, 60(9), 3035-3046.

[168] Satpathi K, Ukil A, Pou J. Short-circuit fault management in DC electric ship propulsion system: protection requirements, review of existing technologies and future research trends. IEEE Trans Transp Electrif 2018;4(1):272–91.

[169] Silva, K. M., Souza, B. A., & Brito, N. S. (2006). Fault detection and classification in transmission lines based on wavelet transform and ANN. IEEE Transactions on Power Delivery, 21(4), 2058-2063.

[170] Lima, É. M., dos Santos Junqueira, C. M., Brito, N. S. D., de Souza, B. A., de Almeida Coelho, R., & de Medeiros, H. G. M. S. (2018). High impedance fault detection method based on the short-time Fourier transform. IET Generation, Transmission & Distribution, 12(11), 2577-2584.

[171] Liu, Y., Ning, P., & Reiter, M. K. (2011). False data injection attacks against state estimation in electric power grids. ACM Transactions on Information and System Security (TISSEC), 14(1), 1-33.

[172] Gaber, M., Hamad, M. S., El-banna, S. H., & El-Dabah, M. (2021). An intelligent energy management system for ship hybrid power system based on renewable energy resources. Journal of Al-Azhar University Engineering Sector, 16(60), 712-723.

[173] Hanggara, P. O., Syai'in, M., Paradisa, P. F., Arifin, M. Z., Sarena, S. T., Syaiin, M., ... & Soeprijanto, A. (2017, October). Prototype control and monitoring system safety device from leakage ammonia at marine loading arm with comparison of Neural Network (NN) and Extreme Learning Machine (ELM) method. In 2017 International Symposium on Electronics and Smart Devices (ISESD) (pp. 85-89). IEEE.

[174] Ma, Y., Maqsood, A., Corzine, K., & Oslebo, D. (2020, June). Long short-term memory autoencoder neural networks based dc pulsed load monitoring using short-time fourier transform feature extraction. In 2020 IEEE 29th International Symposium on Industrial Electronics (ISIE) (pp. 912-917). IEEE.

[175] Li, W., Monti, A., & Ponci, F. (2014). Fault detection and classification in medium voltage DC shipboard power systems with wavelets and artificial neural networks. IEEE Transactions on Instrumentation and Measurement, 63(11), 2651-2665.

[176] Liu, Q., Liang, T., & Dinavahi, V. (2020). Deep learning for hardware-based real-time fault detection and localization of all electric ship mvdc power system. IEEE Open Journal of Industry Applications, 1, 194-204.

[177] Gaber, M., El-Banna, S., El-Dabah, M., & Hamad, M. (2021). Designing and implementation of an intelligent energy management system for electric ship power system based on adaptive Neuro-Fuzzy inference system (ANFIS). Advances in Science, Technology and Engineering Systems Journal, 6(2), 195-203.

[178] Gupta, P., Rasheed, A., & Steen, S. (2021). Ship performance monitoring using machine-learning. arXiv preprint arXiv:2110.03594.

[179] Kim, Y. R., Jung, M., & Park, J. B. (2021). Development of a fuel consumption prediction model based on machine learning using ship in-service data. Journal of Marine Science and Engineering, 9(2), 137.

[180] Yang, Y., Tu, H., Song, L., Chen, L., Xie, D., & Sun, J. (2021). Research on accurate prediction of the container ship resistance by rbfnn and other machine learning algorithms. Journal of Marine Science and Engineering, 9(4), 376.

[181] Liang, Q., Tvete, H. A., & Brinks, H. W. (2020, November). Prediction of vessel propulsion power from machine learning models based on synchronized AIS-, ship performance measurements and ECMWF weather data. In IOP Conference Series: Materials Science and Engineering (Vol. 929, No. 1, p. 012012). IOP Publishing.

[182] Tran, T. A. (2021). Comparative analysis on the fuel consumption prediction model for bulk carriers from ship launching to current states based on sea trial data and machine learning technique. Journal of Ocean Engineering and Science, 6(4), 317-339.

[183] Maimun, A., Hiekata, K., Jauhari, K., Siow, C. L., & Ali, A. (2021). Estimation of ship powering in preliminary ship design using graph theory and machine learning method. In International Conference on Design and Concurrent Engineering 2021 & Manufacturing Systems Conference. September (pp. 3-4).

[184] Gkerekos, C., Lazakis, I., & Theotokatos, G. (2019). Machine learning models for predicting ship main engine Fuel Oil Consumption: A comparative study. Ocean Engineering, 188, 106282.

[185] Farag, Y. B., & Ölçer, A. I. (2020). The development of a ship performance model in varying operating conditions based on ANN and regression techniques. Ocean Engineering, 198, 106972.

[186] Yoo, B., & Kim, J. (2019). Probabilistic modeling of ship powering performance using full-scale operational data. Applied Ocean Research, 82, 1-9.

[187] Mehrzadi, M., Terriche, Y., Su, C. L., Xie, P., Bazmohammadi, N., Costa, M. N., ... & Guerrero, J. M. (2020). A deep learning method for short-term dynamic positioning load forecasting in maritime microgrids. Applied Sciences, 10(14), 4889.

[188] Hasanvand, S., Rafiei, M., Gheisarnejad, M., & Khooban, M. H. (2020). Reliable power scheduling of an emission-free ship: Multiobjective deep reinforcement learning. IEEE transactions on transportation electrification, 6(2), 832-843.

[189] Schwegmann, C. P., Kleynhans, W., Salmon, B. P., Mdakane, L. W., & Meyer, R. G. (2016, July). Very deep learning for ship discrimination in synthetic aperture radar imagery. In 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS) (pp. 104-107). IEEE.

[190] Lee, J. B., Roh, M. I., & Kim, K. S. (2021). Prediction of ship power based on variation in deep feed-forward neural network. International Journal of Naval Architecture and Ocean Engineering, 13, 641-649.

[191] Domínguez Olmedo, J. L., Mata Vázquez, J., Pachón Álvarez, V., & López Guerra, J. L. (2018). A rule-based method applied to the imbalanced classification of radiation toxicity.

[192] Lengyel, L. (2015). Validating rule-based algorithms. Acta Polytech. Hung, 12(4), 17.

[193] Hayes-Roth, F. (1985). Rule-based systems. Communications of the ACM, 28(9), 921-932.

[194] Ringland, G. A., & Duce, D. A. (Eds.). (1988). Approaches to knowledge representation: an introduction. Research Studies Press Ltd.

[195] Zheng, M., Cheng, S., & Xu, Q. (2016). Context-based mobile user interface. Journal of Computer and Communications, 4(09), 1.

[196] Calimeri, F., Germano, S., Ianni, G., Pacenza, F., Perri, S., & Zangari, J. (2018, September). Integrating rule-based AI tools into mainstream game development. In International Joint Conference on Rules and Reasoning (pp. 310-317). Springer, Cham.

[197] Shigarov, A., Khristyuk, V., & Mikhailov, A. (2019). TabbyXL: Software platform for rule-based spreadsheet data extraction and transformation. SoftwareX, 10, 100270.

[198] Liviu, T. (2018, October). FPGA Implementation of a Fuzzy Rule Based Contrast Enhancement System for Real Time Applications. In 2018 22nd International Conference on System Theory, Control and Computing (ICSTCC) (pp. 117-122). IEEE.

[199] Kumar, R., Baz, A., Alhakami, H., Alhakami, W., Agrawal, A., & Khan, R. A. (2021). A hybrid fuzzy rule-based multi-criteria framework for sustainable-security assessment of web application. Ain Shams Engineering Journal, 12(2), 2227-2240.

[200] Agrawal, A., Alenezi, M., Kumar, R., & Khan, R. A. (2019). Measuring the sustainable-security of Web applications through a fuzzy-based integrated approach of AHP and TOPSIS. IEEE Access, 7, 153936-153951.

[201] Li, G., Zhou, H., Feng, B., Li, G., Li, T., Xu, Q., & Quan, W. (2017). Fuzzy theory based security service chaining for sustainable mobile-edge computing. Mobile Information Systems, 2017.

[202] Bustos, Á., Fuenzalida, I., Santibáñez, R., Pérez-Acle, T., & Martin, A. J. (2018). Rule-based models and applications in biology. In Computational Cell Biology (pp. 3-32). Humana Press, New York, NY.

[203] Jindal, A., Dua, A., Kumar, N., Das, A. K., Vasilakos, A. V., & Rodrigues, J. J. (2018). Providing healthcare-as-a-service using fuzzy rule based big data analytics in

cloud computing. IEEE Journal of Biomedical and Health informatics, 22(5), 1605-1618.

[204] Cheng, C. W., Chanani, N., Venugopalan, J., Maher, K., & Wang, M. D. (2013). icuARM-An ICU clinical decision support system using association rule mining. IEEE Journal of Translational Engineering in Health and Medicine, 1, 4400110-4400110.

[205] Forkan, A., Khalil, I., & Tari, Z. (2014). CoCaMAAL: A cloud-oriented context-aware middleware in ambient assisted living. Future Generation Computer Systems, 35, 114-127.

[206] Wang, Y., Sun, Z., & Chen, Z. (2019). Development of energy management system based on a rule-based power distribution strategy for hybrid power sources. Energy, 175, 1055-1066.

[207] Lopez, G. L., Rodriguez, R. S., Alvarado, V. M., Gomez-Aguilar, J. F., Mota, J. E., & Sandoval, C. (2017). Hybrid PEMFC-supercapacitor system: Modeling and energy management in energetic macroscopic representation. Applied Energy, 205, 1478-1494.

[208] Xiong, R., Duan, Y., Cao, J., & Yu, Q. (2018). Battery and ultracapacitor in-the-loop approach to validate a real-time power management method for an all-climate electric vehicle. Applied energy, 217, 153-165.

[209] Du, J., Zhang, X., Wang, T., Song, Z., Yang, X., Wang, H., ... & Wu, X. (2018). Battery degradation minimization oriented energy management strategy for plug-in hybrid electric bus with multi-energy storage system. Energy, 165, 153-163.

[210] Pippia, T., Sijs, J., & De Schutter, B. (2019). A single-level rule-based model predictive control approach for energy management of grid-connected microgrids. IEEE Transactions on Control Systems Technology, 28(6), 2364-2376.

[211] Sun, C., Joos, G., Ali, S. Q., Paquin, J. N., Rangel, C. M., Al Jajeh, F., ... & Bouffard, F. (2020). Design and real-time implementation of a centralized microgrid control system with rule-based dispatch and seamless transition function. IEEE Transactions on Industry Applications, 56(3), 3168-3177.

[212] Restrepo, M., Cañizares, C. A., Simpson-Porco, J. W., Su, P., & Taruc, J. (2021). Optimization-and rule-based energy management systems at the canadian renewable energy laboratory microgrid facility. Applied Energy, 290, 116760.

[213] Rafigh, P., Akbari, A. A., Bidhendi, H. M., & Kashan, A. H. (2021). A fuzzy rule-based multi-criterion approach for a cooperative green supplier selection problem. Environmental Science and Pollution Research, 1-14.

[214] Al-Falahi, M. D., Nimma, K. S., Jayasinghe, S. D., Enshaei, H., & Guerrero, J. M. (2018). Power management optimization of hybrid power systems in electric ferries. Energy conversion and management, 172, 50-66.

[215] Khooban, M. H., Gheisarnejad, M., Vafamand, N., Jafari, M., Mobayen, S., Dragicevic, T., & Boudjadar, J. (2019). Robust frequency regulation in mobile microgrids: HIL implementation. IEEE Systems Journal, 13(4), 4281-4291.

[216] Heydari, R., Gheisarnejad, M., Khooban, M. H., Dragicevic, T., & Blaabjerg, F. (2019). Robust and fast voltage-source-converter (VSC) control for naval shipboard microgrids. IEEE Transactions on Power Electronics, 34(9), 8299-8303.

[217] Mashayekh, S., & Butler-Purry, K. L. (2015). An integrated security-constrained model-based dynamic power management approach for isolated microgrids in all-electric ships. IEEE Transactions on Power Systems, 30(6), 2934-2945.

[218] Albatish, I. M., & Abu-Naser, S. S. (2019, October). Modeling and controlling smart traffic light system using a rule based system. In 2019 International Conference on Promising Electronic Technologies (ICPET) (pp. 55-60). IEEE.

[219] Ezzat, A. A., Farouk, H. A., El-Kilany, K. S., & Abdelmoneim, A. F. (2014, January). Development of a stochastic genetic algorithm for traffic signal timings optimization. In Proceedings of the 2014 Industrial and Systems Engineering Research Conference, Montreal, QC, Canada (Vol. 10).

[220] Liu, Y., Liu, L., & Chen, W. P. (2017, October). Intelligent traffic light control using distributed multi-agent Q learning. In 2017 IEEE 20th international conference on intelligent transportation systems (ITSC) (pp. 1-8). IEEE.

[221] Bannerjee, G., Sarkar, U., Das, S., & Ghosh, I. (2018). Artificial intelligence in agriculture: A literature survey. International Journal of Scientific Research in Computer Science Applications and Management Studies, 7(3), 1-6.

[222] Pasqual, G. M., & Mansfield, J. (1988). Development of a prototype expert system for identification and control of insect pests. Computers and Electronics in Agriculture, 2(4), 263-276.

[223] Batchelor, W. D., McClendon, R. W., Adams, D. B., & Jones, J. W. (1989). Evaluation of SMARTSOY: An expert simulation system for insect pest management. Agricultural Systems, 31(1), 67-81.

[224] Boyd, D. W., & Sun, M. K. (1994). Prototyping an expert system for diagnosis of potato diseases. Computers and electronics in agriculture, 10(3), 259-267.

[225] Balleda, K., Satyanvesh, D., Sampath, N. V. S. S. P., Varma, K. T. N., & Baruah, P. K. (2014, January). Agpest: An efficient rule-based expert system to prevent pest diseases of rice & wheat crops. In 2014 IEEE 8th International Conference on Intelligent Systems and Control (ISCO) (pp. 262-268). IEEE.

[226] Sicat, R. S., Carranza, E. J. M., & Nidumolu, U. B. (2005). Fuzzy modeling of farmers' knowledge for land suitability classification. Agricultural systems, 83(1), 49-75.

[227] Si, Y., Liu, G., Lin, J., Lv, Q., & Juan, F. (2007, August). Design of control system of laser leveling machine based on fussy control theory. In International Conference on Computer and Computing Technologies in Agriculture (pp. 1121-1127). Springer, Boston, MA.

[228] Liu, G., Yang, X., & Li, M. (2005, May). An artificial neural network model for crop yield responding to soil parameters. In International Symposium on Neural Networks (pp. 1017-1021). Springer, Berlin, Heidelberg.

[229] Kaul, M., Hill, R. L., & Walthall, C. (2005). Artificial neural networks for corn and soybean yield prediction. Agricultural Systems, 85(1), 1-18.

[230] Kuffel, R., Giesbrecht, J., Maguire, T., Wierckx, R. P., & McLaren, P. (1995, November). RTDS-a fully digital power system simulator operating in real time. In

Proceedings 1995 International Conference on Energy Management and Power Delivery EMPD'95 (Vol. 2, pp. 498-503). IEEE.

[231] Real Time Digital Simulator Tutorial Manual, RSCAD Version, September 2005.

[232] Adhikari, U., Morris, T. H., Dahal, N., Pan, S., King, R. L., Younan, N. H., & Madani, V. (2012, July). Development of power system test bed for data mining of synchrophasors data, cyber-attack and relay testing in RTDS. In 2012 IEEE Power and Energy Society General Meeting (pp. 1-7). IEEE.