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TOPICAL REVIEW

Energy Management Systems for Maritime Microgrids: A Comprehensive Review of Intelligent Optimization Strategies

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ABSTRACT In modern maritime operations, electric ship power systems (SPSs) play a crucial role as they integrate distributed energy resources to meet stringent environmental targets while ensuring reliability in dynamic and isolated marine environments. Energy management systems (EMS) are critical to optimizing fuel efficiency, reducing emissions, and maintaining power quality under variable load demands and the harsh conditions in which ships operate. This paper presents a comprehensive review of EMS methodologies for SPS, covering traditional methods such as evolutionary algorithms, model predictive control (MPC), fuzzy logic control, and more modern approaches such as machine learning (ML) and deep learning (DL). ML and DL for EMS offer predictive and adaptive capabilities for real-time optimization, but face limitations in data security and centralized computational demands. Federated learning (FL), which is a decentralized, privacy-preserving paradigm, is a viable solution to the disadvantages of the conventional centralized form of training in ML. FL enables collaborative model training across distributed systems without raw data sharing, addressing critical concerns in cybersecurity and communication overhead. However, FL does require individual devices or clients to have enough computational power to carry out distributed optimization locally. A detailed overview of FL, including the FL training process, categories, architectures and various applications of FL in ship and energy systems, is presented in this paper. To further establish the usefulness of conducting energy management (EM) in ship systems, the paper presents a case study on a notional four-zone DC SPS in which FL has been utilized to collaboratively train DL models across multiple generators without sharing sensitive local data. The results demonstrate better generator output power prediction and effective load management in comparison to the conventional centralized learning setup, indicating the potential of FL to enhance energy efficiency and reliability in ship systems. Finally, some challenges and possible research gaps in applying FL to ship systems are discussed.

INDEX TERMS Deep learning, energy management, federated learning, machine learning, microgrid, ship power system.

NOMENCLATURE

ADMM	Alternating Direction Method of Multipliers.
AMI	Advanced Metering Infrastructure.
ANFIS	Adaptive Neuro-Fuzzy Inference System.
ANN	Artificial Neural Network.
APGM	Auxiliary Power Generator Module.
c_i	Cost function of generator i.
CL	Centralized Learning.
CLMD	Common Layer Mean Detection.
CNN	Convolutional Neural Network.
DDPG	Deep Deterministic Policy Gradient.
DL	Deep Learning.
DRL	Deep Reinforcement Learning.
EDG	Electrostatic Discharge Gun.
EEDI	Energy Efficiency Design Index.
EMS	Energy Management System.
ESS	Energy Storage System.
FDRL	Federated Deep Reinforcement Learning.
FedAvg	Federated Averaging.
FedMA	Federated Matched Averaging.
FedProx	Federated Proximal.
FDI	False Data Injection.
FFNN	Feed-Forward Neural Network.
FL	Federated Learning.
FRL	Federated Reinforcement Learning.
FSVRG	Federated Stochastic Variance Reduced Gradient.
GHG	Greenhouse Gas.
GRU	Gated Recurrent Unit.
GWO	Grey Wolf Optimization.
HII	Controller Hijacking.
HIL	Hardware-in-the-Loop.
IID	Independent and Identically Distributed.
IEM	Integrated Energy Microgrid.
IMO	International Maritime Organization.
kNN	k-Nearest Neighbors.
LSTM	Long Short-Term Memory.
MAPE	Mean Absolute Percentage Error.
MG	Microgrid.
ML	Machine Learning.
MPC	Model Predictive Control.
MPGM	Main Power Generator Module.
MSE	Mean Squared Error.
MVDC	Medium Voltage DC.
OPF	Optimal Power Flow.
P_i	Output power of generator i.
P_{ji}	Power transferred from generator j to generator i.
$P_{L,i}$	Load demand for generator i.
P2P	Peer-to-Peer.
PFL	Personalized Federated Learning.
PINNs	Physics-Informed Neural Networks.
PMM	Propulsion Motor Module.
PPL	Pulsed Power Load.
PPO	Proximal Policy Optimization.
RFR	Random Forest Regression.
RL	Reinforcement Learning.
RNN	Recurrent Neural Network.
SEEMP	Ship Energy Efficiency Management Plan.
SOC	State of Charge.
SPS	Ship Power System.
STLF	Short-Term Load Forecasting.

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I. INTRODUCTION

Electric Ship Power Systems (SPS) represent a significant advancement in maritime technology, combining power generation, distribution, and propulsion within an integrated framework. Electric ship systems rely on electric power generators and various energy storage systems (ESS) such as battery banks, fuel cells and capacitors. Moreover, they facilitate the integration of renewable energy sources into maritime operations, which if used effectively through advanced energy storage systems and battery technologies, can significantly reduce the reliance on fossil fuels. Electric propulsion systems also produce substantially less pollution compared to traditional engines that burn heavy oil, helping reduce greenhouse gas emissions and other pollutants. Therefore, the electric SPS is a key solution in meeting the International Maritime Organization's (IMO) target of reducing ship greenhouse gas (GHG) emissions by 50% by the year 2050 [1]. Figure 1 illustrates the emission gap between the IMO GHG strategy target and business-as-usual (BAU) emissions in the time period spanning from the year 2008 to 2050, highlighting the significant difference between the expected emissions and the IMO target. The SPS mainly operates as an islanded Microgrid (MG) and has no provision to take in power from the main grid. The resources available within the system have to be used efficiently to meet the load demand in an optimal manner. In addition, unpredictable and rough sea conditions make the operation of ship MGs more challenging than other MGs. The operation of naval SPS is even more demanding due to the operation of advanced weapons and navigation systems in addition to dynamic maneuvering requirements during battle scenarios [2]. All these factors make the IMO target very challenging to achieve, however, this is a challenge that has to be taken in order to make marine transportation more sustainable and reduce its harmful effects on the environment.

The IMO has identified a few key measures through which their goal of reducing GHG emissions can be achieved. These include improving logistics, increasing energy efficiency, implementing speed reduction, improving fuel efficiency and carrying out pathway optimization. Out of these possible solutions, energy efficiency has been identified as one

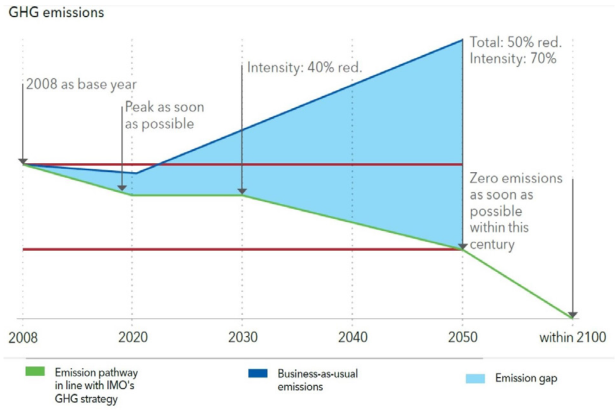

FIGURE 1. GHG emission gap between IMO GHG strategy and BAU emissions [1].

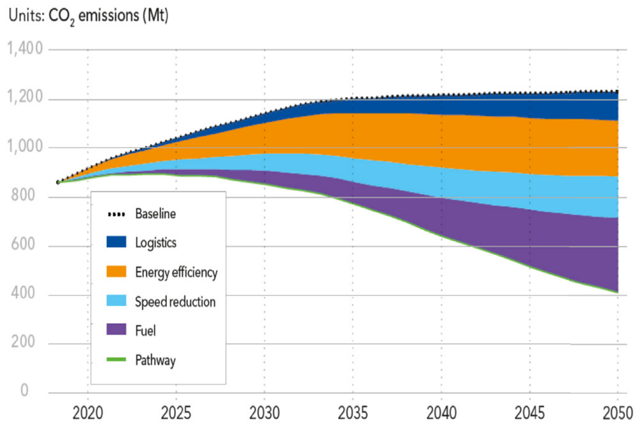

FIGURE 2. Possible measures for achieving the IMO GHG strategy [1].

of the most effective ways of reducing carbon emissions from ship systems, as illustrated in Figure 2. Therefore to improve energy efficiency and meet the challenging operating conditions of the SPS, an effective energy management system (EMS) is crucial. The primary goal of an EMS is to supply the required amount of energy at a minimal cost. It is required to utilize the generation resources of the ship MG efficiently and in a cost-effective manner to meet the desired objectives while satisfying the underlying system constraints. An effective EMS is crucial for optimizing fuel consumption, reducing emissions, maintaining power quality and ensuring a reliable supply of power. Using data analysis and forecasting models, an EMS can also predict future energy demand based on historical data and operational patterns, allowing proactive measures to mitigate potential energy shortages or inefficiencies [3]. The EMS is also required to facilitate the monitoring and control of energy flows within the system in real-time. This capability is essential to respond promptly to changes in energy demand or supply conditions, ensuring reliable energy distribution and usage.

There are many strategies through which the EMS of ship systems and other MGs are implemented. These include evolutionary algorithms, model predictive control (MPC), fuzzy logic, linear programming, etc. Machine Learning (ML) and Deep Learning (DL) techniques are increasingly being applied in energy systems to improve efficiency and optimize operations. These techniques can process large amounts of data, identify patterns, and make real-time predictions. Despite their promise in EMS, conventional ML and DL systems with centralized training face challenges in the distributed and dynamic operating environments of the SPS. Data privacy concerns, high computational complexity, and reduced response times are some of these challenges. In modern ship systems, controllers responsible for system monitoring and automated control are prime targets for cyberattacks, making cyber-physical security and data privacy key concerns [4]. Federated learning (FL) can mitigate these problems by enabling collaborative training of ML models in a distributed manner without directly sharing sensitive data.

Several recent review articles have explored EMS methodologies for MGs and ship systems. In the context of MGs, articles [5] and [6] provided a systematic analysis of control strategies and optimization techniques, while EMS architectures were classified, with an emphasis on centralized and decentralized optimization in paper [3]. Ali et al. [7] addressed challenges specific to DC MGs in residential applications, and the fundamental principles and optimization objectives for MG EMS were outlined in papers [8] and [9]. For ship systems, the article [10] reviewed hybrid energy system modeling and optimization, whereas challenges in ship EMS design, particularly optimization under dynamic maritime conditions, were evaluated in papers [11] and [12]. Recent studies such as [13] and [14] emphasized energy storage integration and ML applications for ship systems. Jaurola et al. [15] covered the power management of ships, especially focusing on numerical optimization methods, and optimization-based energy and power management systems of ships were covered in the article [16]. For the use of FL in energy systems, Grataloup et al. [17] surveyed renewable energy applications, while studies [18] and [19] analyzed FL frameworks in smart grids, highlighting privacy and scalability challenges. Maritime-specific FL reviews, including studies [20] and [21], focused on predictive maintenance and cybersecurity but lacked detailed discussions on EMS integration.

Past review articles provide comprehensive analyses of hierarchical control and optimization techniques for terrestrial MGs; however, they lack emphasis on the unique challenges of isolated maritime environments. Similarly, ship-focused reviews evaluate traditional optimization and ML-based EMS but overlook decentralized learning paradigms necessary for privacy preservation in multi-zone

SPSs. Although FL applications in energy systems have been surveyed, these predominantly focus on smart grids and residential MGs, failing to address the computational constraints, communication latency, and heterogeneous data distributions characteristic of maritime FL deployments. Moreover, reviews on maritime applications of FL conducted so far prioritize predictive maintenance and cybersecurity but neglect systematic evaluations of FL architectures for EMS optimization. In contrast, this paper focuses on the control and optimization of ship EMSs, focusing on the unique challenges introduced by the isolated nature of these MGs. Traditional optimization and ML-based EMS solutions are reviewed, and their drawbacks in ship applications are highlighted. The potential and benefits of FL in ship applications while ensuring privacy and cyber resilience, which are key concerns in modern maritime applications, are explored. Furthermore, previous works lack validation of FL in multi-zone ship EMSs; this study fills that gap through a detailed case study of a four-zone DC SPS, demonstrating FL's potential in achieving distributed EM optimization without compromising data privacy. This review also highlights challenges such as data heterogeneity and computational bottlenecks in applying FL to ship systems and provides novel solutions and future research directions to achieve more scalable and secure EMS implementations in dynamic marine environments.

A. CONTRIBUTIONS AND STRUCTURE OF THE PAPER

The main contributions of this survey include:

- A systematic review of control strategies, including a detailed analysis of hierarchical (primary, secondary, tertiary) and supervisory (centralized, decentralized, distributed) control architectures in SPS.
- Evaluation of traditional EM strategies, including evolutionary algorithms, MPC, and fuzzy logic, highlighting their strengths and limitations.
- Exploration ML and DL techniques in EMS, including supervised, unsupervised, and reinforcement learning applications for fuel consumption prediction, load forecasting, real-time optimization and various other objectives in ship and energy systems.
- Detailed discussion on FL frameworks, aggregation algorithms, implementation architectures and applications of FL in ship and energy systems for various objectives such as fault diagnosis, fuel efficiency optimization, and cybersecurity.
- A case study of applying FL has to carry out EM in a four-zone SPS by training DL models in a distributed manner and controlling multiple generators without sharing sensitive local data.
- Identification of key challenges in applying FL for ship EMSs with possible solutions and future research directions.

The rest of the paper is organized as follows. Section II examines hierarchical and supervisory control strategies for SPS stability and efficiency. Sections III and IV outline EMS architectures and traditional optimization techniques. ML and DL methods for predictive and adaptive energy management (EM) are discussed in section V. Section VI introduces FL principles, architectures, and aggregation algorithms. FL applications in energy systems and SPS are provided in section VII. Section VIII covers a case study of an FL-based EMS for a four-zone DC SPS. Some research challenges regarding the implementation of FL in ship systems and possible solutions are provided in section IX. Finally, the conclusion is provided in section X.

II. SPS CONTROL

A. HIERARCHICAL CONTROL

Ship systems employ hierarchical control to effectively coordinate multiple energy storage devices, distributed generation units, and loads. This coordination is achieved through a hierarchical structure based on functionality and operating timescale, primarily consisting of three control levels: primary, secondary, and tertiary control (see Figure 3). This hierarchical control structure is particularly crucial for ship MGs, where efficient power and energy management and stability are of utmost importance due to the isolated nature of the system and the presence of critical loads [22].

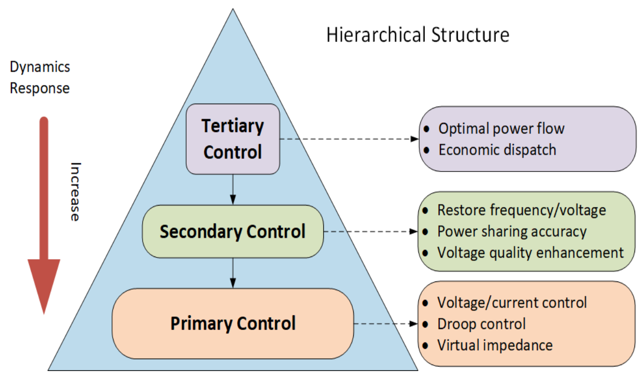

FIGURE 3. Hierarchical control layers of MG [22].

1) Primary control: Primary control, also known as device layer control, is responsible for individual component control. It carries out fundamental objectives such as current sharing, frequency regulation, and voltage control of each individual component or device within the system. It operates on the fastest timescale, typically in the range of microseconds to milliseconds. In ship MGs, primary control plays a crucial role in maintaining power quality and system stability during sudden load changes or faults, which are common in marine environments [23].
2) Secondary control: The secondary control layer carries out power management. It sends reference signals to the

primary control, aiming to improve the overall power quality, voltage regulation, proportional power-sharing, and reliability of the ship's MG. It operates on a slower timescale compared to primary control, typically in the range of milliseconds.

3) Tertiary control: Tertiary control is responsible for EM. It ensures a consistent and efficient flow of energy and economic load dispatch within the system by utilizing all the generating sources and adhering to the system constraints. It operates on the slowest timescale, ranging from a few milliseconds to a few minutes. In ship systems, tertiary control is crucial for optimal EM, especially during long voyages where fuel efficiency and emissions reduction are primary concerns.

The hierarchical control architecture with three control layers of a maritime SPS is illustrated in Figure 4.

B. SUPERVISORY CONTROL

Supervisory control involves the individual monitoring of each system operation and the controller interconnection within the system. It is a critical aspect of managing complex systems such as ship systems. It involves the high-level monitoring, coordination, and optimization of multiple interconnected subsystems to ensure efficient and reliable operation [3]. Supervisory control plays a crucial role in maintaining power quality, managing energy resources, and ensuring the overall stability of the electrical system under varying operational conditions [24].

Based on the implementation of supervisory control, MG control strategies can be broadly categorized into three main types:

1. Centralized Control
2. Decentralized Control
3. Distributed Control

1) CENTRALIZED CONTROL

In the centralized supervisory control structure, a single central controller manages all computing tasks in the system and is responsible for monitoring, analyzing, optimizing, and controlling all the components. The central controller obtains operational data and measurements from the different components and agents through communication lines. It carries out all the necessary calculations and control computations and provides control setpoints back to the agents for execution. The central controller assesses the total generation capacity and the load demand, ensuring that both critical and non-critical loads in the system are met by coordinating the energy sources. Centralized control has a number of advantages. Global optimization can be carried out more easily since the central controller has a comprehensive view of the entire system, allowing for optimal resource allocation and power flow management. It also provides high controllability and observability as the central controller can monitor and control all system parameters, enabling quick response to system-wide changes or disturbances [8].

However, centralized control also has some limitations, such as having a single point of failure. This is because the entire system's operation depends on the central controller, making it vulnerable to failures [22]. Communication bottlenecks can also arise as the system size increases, and communication requirements can become a limiting factor. There are limitations in scalability as well because adding new components or expanding the system can be challenging due to the need to update the central control algorithm. The centralized control structure is more suitable for smaller systems with a limited number of components, as lower computation capacity is required, and the communication network tends to be more manageable [8].

2) DECENTRALIZED CONTROL

In decentralized control, each agent or subsystem in the system has its own local controller, which manages the agent independently by using local data to carry out control computations [8]. Droop control is the most widely used form of decentralized control in MGs, including SPS. The droop controller provides decentralized control over each unit, allowing for autonomous power sharing and voltage regulation without the need for communication between units [22]. Key benefits of decentralized control include reduced communication overhead. By relying on local measurements and control actions, decentralized control significantly reduces the need for extensive communication infrastructure. The absence of a central controller eliminates the single point of failure, improving overall system reliability [8]. Moreover, local controllers can react quickly to local disturbances without waiting for commands from a central entity.

However, decentralized control also faces some challenges, such as limited global optimization; without system-wide information, it's challenging to achieve optimal performance across the entire system. Interactions between independently controlled units can sometimes also lead to stability problems, especially in larger systems. Balancing multiple control objectives, such as economic dispatch, voltage regulation, and frequency control, can become more challenging in a decentralized framework. In SPS, decentralized control is often employed in conjunction with other control strategies to balance the need for local autonomy with system-wide coordination. For example, decentralized droop control might be used for primary frequency and voltage regulation, while higher-level centralized or distributed control handles secondary control objectives and optimization [24].

3) DISTRIBUTED CONTROL

In distributed control, each component is controlled by a local controller. These local controllers communicate with their adjacent controllers in the system through the communication network and produce control decisions and commands by reaching a consensus with the adjacent controllers. It has the

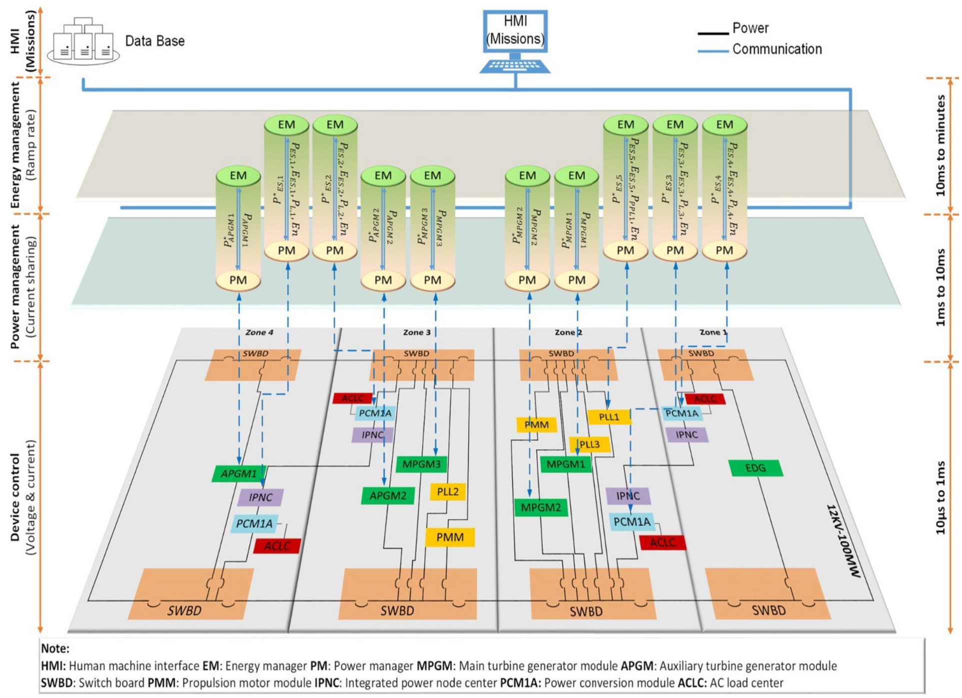

FIGURE 4. Hierarchical control architecture of a maritime SPS [2].

benefits of both centralized and decentralized schemes and also makes up for the drawbacks of those two topologies [8]. The computational and communication requirements of the central controller grow exponentially as centralized systems increase in size. Distributed control systems are a good solution to the growing computational and communication needs of centralized systems, as in the former, sub-system level controllers focus on controlling a smaller portion of the entire system. This maintains a local complexity even if the overall system grows as the overall communication and computational burden is divided among multiple controllers. The ability of the overall system to grow while maintaining low overall complexity is a significant contributing factor to the scalability of distributed systems [25].

Both distributed and decentralized control systems have no central controller but rather have controllers for each sub-system; however, the key difference between the two is that in distributed systems, the controllers communicate with one another, whereas, in decentralized schemes, they do not [25]. Distributed control systems can provide more effective and efficient use of resources. They can maximize resource allocation and reduce operational bottlenecks by splitting up control tasks across several units, each in charge of a particular subset of tasks [26]. In addition, as compared to decentralized control systems, distributed control systems frequently show better scalability and modularity. This is because the distributed architecture makes it easier to integrate new components or subsystems, increasing the system's flexibility in response to expansions and changes [27]. Another key benefit of distributed control is the elimination of a single point of failure because several interconnected controllers share the responsibility for control collectively. This makes distributed control architectures more resilient to cyber-attacks [28].

The centralized, decentralized and distributed supervisory control schemes are compared against each other with respect to their architecture, communication strategy, optimization strategy, scalability, fault tolerance, response time and typical use case in Table 1.

III. ENERGY MANAGEMENT SYSTEM (EMS)

The primary goal of an EMS is to ensure an adequate supply of energy at minimal cost. It has to utilize all the generating resources in the system, such as generators, energy storage units and renewable sources in such a way that the system load demand is met at all times under all kinds of operating scenarios. While doing so, it has to ensure that constraints such as generator maximum and minimum power limits and generator and energy storage ramp rates are met. The IEC standard 61970, which deals with the application of EM programs in power systems, describes EMS as a computer system comprised of a software platform that offers fundamental support services and a collection of applications that provide the functionality required for the efficient operation of electrical generation and transmission facilities in order to guarantee an adequate supply of energy at the minimum cost [29], [30]. EMS employs various techniques such as optimization, forecasting, data analysis, and Human-Machine Interface (HMI) to execute optimal decisions that are communicated to the components in the

TABLE 1. **Comparison of centralized, Decentralized, and Distributed control schemes.**

Control Scheme	Centralized Control	Decentralized Control	Distributed Control
Architecture	Single central controller	Independent local controllers	Local controllers with neighbor communication
Communication	All components with central controller	No inter-controller communication	Local controllers share data with neighbors
Optimization	Global optimization possible	Local optimization only	Consensus-based global optimization
Scalability	Poor	Moderate	Excellent (modular)
Fault Tolerance	Low (Single point of failure)	High	High
Response Time	Slow (central processing)	Fast (local decisions)	Moderate (requires coordination)
Typical Use Case	Small systems with simple topology	Droop control in MGs	Large networked MGs with critical loads

system with the help of communication protocols. The objective function of EMS depends on factors such as the mode of operation, the type of supervisory control, economic aspects, and the dynamic behavior of the components in the system. Other factors such as reliability, power loss and security also play an important role. The EMS is required to facilitate real-time monitoring and control of energy flows within the system. This capability is essential for promptly responding to changes in energy demand or supply conditions, thus ensuring reliable energy distribution and usage. It has to ensure that it can meet the computational limitations of the physical system while maintaining the desired performance standards [31]. The basic operating principle of a typical EMS is illustrated in Figure 5. Here, a centralized EMS controller gathers information from generators, ESSs, and loads, finds the optimal operation setpoints for the components through optimization, and sends the reference setpoints back via the communication bus.

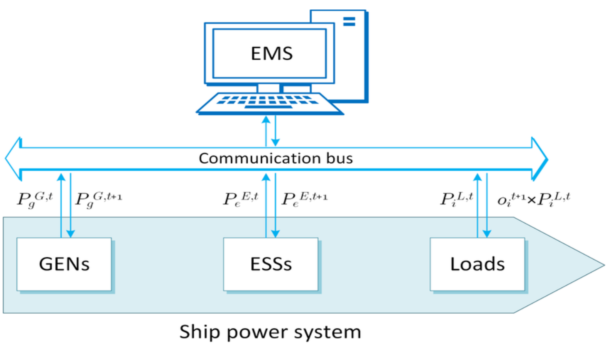

FIGURE 5. **EMS structure [32].**

In islanded MG systems such as SPS, an EMS is essential due to unique operational challenges like isolation from external power grids and the necessity for high reliability. It is critical to maintain DC bus voltage, power quality, and a steady supply to the load. It is the job of the EMS to utilize the generation resources of the ship MG efficiently and in a cost-effective manner to meet the desired objectives while satisfying the underlying system constraints. The time required to execute a new decision is a very important factor that must be carefully chosen to establish an efficient and effective EMS [33]. The EMS in ship systems is usually required to operate in the range of a few milliseconds to a few minutes to respond to changes in the dynamic operating conditions. Energy saving and the efficient use of energy within the system fall under the scope of the EMS, and it is crucial in the reduction of fuel consumption emissions from these systems. An effective EMS can significantly decrease fuel consumption and emissions by optimizing the operation of generators and integrating ESS [34]. The IMO emphasizes reducing emissions from ship systems and has carried out comprehensive studies to decrease emission effects like the Energy Efficiency Design Index (EEDI) and Ship Energy Efficiency Management Plan (SEEMP) [35]. By utilizing data analytics and forecasting models, an EMS can also predict future energy demand based on historical data and operational patterns, allowing for proactive measures to mitigate potential energy shortages or inefficiencies [3].

Energy storage units such as battery banks are used as a controllable source to maintain stability in MGs. They are used as a backup power source when the generators are not sufficient to meet the system load. The ESS is also very crucial during high-power pulsed load operations during battle scenarios in military ships, which require a very high amount of power in a relatively short amount of time. Conventional generators cannot increase their power output by such large amounts in a very short period of time due to their ramp rate limitations and are unable to meet these load demands. Efficient EM and control strategies are crucial for such operations as they coordinate the combined operation between the ESS and the generators depending on the requirements of the system. It is the EMS that assesses the system condition and the load demand and sends operational set points to the generating units and the ESS. EMS must also take into account the power losses of the storage devices, their SoC and response time and the power-energy constraints. In order to maximize the size, rating, and use of ESS, extend their lifespan, and supply power to key loads, the EMS is crucial.

Alongside EM, Power Management (PM) is another essential component necessary for the functioning and reliable operation of DC MGs in both grid-connected and islanded operation modes [36]. The fuel cost, maintenance expenses, capital cost and lifetime of the systems, are essential factors for EM while, for PM strategies, the parameters that have an impact on the instantaneous operating conditions such as current, voltage, and power are important. Voltage regulation and real-time power dispatching among several power sources in MG are examples of PM techniques. PM mostly pertains to the MG's power converter interface and control. Therefore, power management is primarily related to the technical aspects of the systems, whereas EM is primarily related to the economics of the systems [37].

IV. EM STRATEGIES

The main objective of an EMS is to optimize the usage of different resources within an MG system to achieve specific goals under some system constraints through a centralized, distributed or decentralized control system. The workflow of an EMS usually involves obtaining data from the system, feeding the data into the EM optimization algorithm and then finally producing operational set points which are to be implemented by the real-time control system. Several methods can be applied to carry out the optimization in an EMS, examples of such methods include meta-heuristic processes such as evolutionary algorithms, fuzzy logic, model predictive control, mathematical programming and a few others [8]. Some of these methods are discussed below.

A. EVOLUTIONARY ALGORITHMS

Evolutionary algorithms are a type of meta-heuristic algorithm that mimics the process of natural selection, in which the fittest individuals are chosen for reproduction to create offspring of the following generation. Swarm optimization algorithms such as Particle Swarm Pptimization (PSO) and cuckoo search algorithm are examples of evolutionary algorithms. These algorithms attempt to enhance a candidate solution in relation to a particular quality measure iteratively in order to optimize a problem [8].

Authors in [38] used the PSO algorithm to optimize the EM strategy of a fuel cell hybrid electric ship under varying operational conditions. The ship had a composite energy storage system comprising batteries, super-capacitors, and fuel cells. The simulations conducted revealed that the application of the PSO algorithm led to a significant enhancement in the EM strategy, enabling the battery to sustain a stable output current for prolonged periods of operation. The bus voltage fluctuation, in particular, was reduced by more than 40%. However, the study also identified certain limitations associated with the PSO approach, such as its computational intensity, slow convergence and the challenges it poses in achieving real-time performance. An EMS based on the PSO algorithm was used for a ship's hybrid solar energy generation system consisting of PV panels, battery storage, and diesel generators in study [39]. The authors aimed to minimize the ship's fuel consumption and maximize the efficiency of the diesel generators by employing a multi-objective optimization model solved using the PSO algorithm. This strategy was tested under various loading scenarios and battery SOC conditions and achieved a reduction in overall fuel consumption and CO_2 emissions. In another instance, the PSO algorithm was used to optimize power controllers within a distributed power and energy management architecture of a DC ship system [40]. The objective was to utilize PSO for real-time optimization and ensure appropriate power sharing among different sources and loads. The effectiveness of the proposed distributed control architecture and PSO-based optimization was validated through simulation studies, and it managed to achieve enhanced current sharing and voltage stability. However, in both these examples, no real-time simulation was carried out to further validate the effectiveness of these methods.

Zhou et al. [41] addressed the inefficiencies in ship EM by constructing a dynamic optimization model using a bus voltage coordination control strategy and an improved cuckoo search algorithm, with population feature feedback. The simulation results demonstrated that the optimized system reduced fuel consumption by 11.09% and increased the state of charge (SOC) of the battery by 1.81% compared to unoptimized systems. However, the study's limitations include the need for real-world validation beyond simulations and potential challenges in applying the strategy to different ship configurations.

Similarly, a distributed crow search algorithm was utilized by the EMS of a Medium Voltage DC (MVDC) ship to increase generator efficiency in paper [42]. The distributed crow search algorithm works by optimizing the generator output power in each subsystem and leverages ADMM to enable neighboring subsystems to share information with each other and reach a consensus point. Experimental results showed that the proposed method reduced fuel consumption and increased system efficiency. However, having a large number of subsystems can take a long time to reach consensus and achieve the desired levels of accuracy.

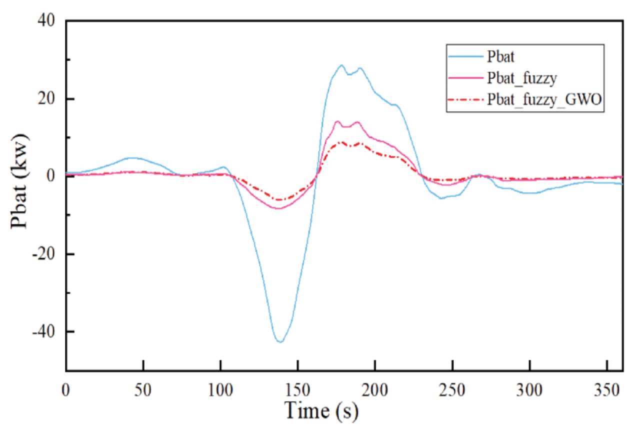

FIGURE 6. Power output fluctuation of lithium battery [43].

The grey wolf optimization (GWO) algorithm was implemented in study [43] to improve EM in a hybrid ship by optimizing the fuzzy logic controller's membership functions. By integrating GWO with fuzzy control, the study achieved a significant reduction in power fluctuations and instability, particularly lowering the peak power and fluctuations experienced by the lithium battery by up to 28.7% as shown in Figure 6. This optimization led to a more stable SOC near the ideal 0.75 value, improving battery life and system efficiency leading to the reduction of energy consumption in the overall power system by 4.272%. However, despite the improvements, the reliance on simulation models and the inherent complexity of implementing advanced control strategies in real-world scenarios are the limitations of this approach.

Authors in [44] proposed a multi-objective EMS for a multi-MG (MMG) system, primarily aiming to minimize the cost of energy (COE) and loss of power supply probability (LPSP), thereby reducing operating costs, enhancing reliability, and achieving zero emissions. Day-ahead scheduling was done for four grid-connected MGs, explicitly considering uncertainties in renewable energy generation, load demand, and energy prices. The optimization was performed using the multi-objective multi-verse optimizer (MOMVO), which demonstrated superior performance compared to multi-objective grey wolf optimization (MOGWO) and multi-objective salp swarm algorithm (MSSA). MOMVO achieved an optimum COE and an LPSP, significantly reducing daily operating costs by 40.32% from the base case and ensuring optimal utilization of distributed energy resources with zero emissions.

B. MODEL PREDICTIVE CONTROL (MPC)

The fundamental idea behind Model Predictive Control (MPC) is to predict the system's behavior over a given time horizon and then calculate an optimal control input that minimizes a predefined cost function while ensuring that the system constraints are met. MPC solves the optimization problem at each control time step, which involves predicting future states of the system based on the current state and control inputs [3].

Study [45] presented an MPC framework designed to optimize EM in hybrid ships to reduce fuel consumption while ensuring safe and efficient battery operation. An advanced EMS was developed that integrated both short-term and mission-scale predictions to control the ship's generating units. The framework effectively managed constraints imposed by onboard batteries, such as capacity and SoC, and adapted to changing mission profiles through dynamic, real-time adjustments. The MPC framework, validated through simulations, demonstrated a fuel consumption reduction of up to 3.5% compared to traditional methods. Despite its effectiveness, the framework assumed perfect predictions for disturbances, which may not always be achievable in real-world scenarios. Furthermore, the computational demands of MPC, especially in real-time applications, could be a limitation for ships with limited processing capabilities.

Authors in [46], presented a hierarchical distributed MPC approach for optimizing hybrid EM on ships under variable operating conditions. A two-layer control structure was employed, with the upper layer for strategic decision-making and the lower layer for real-time control, utilizing a distributed framework to enhance responsiveness and efficiency. Simulation results indicated significant reductions in fuel consumption and emissions and improved responsiveness to changes in operating conditions. However, the complexity of the hierarchical control structure may increase computational demands, and there may be challenges related to the scalability of the approach when applied to larger and more complex systems.

A hybrid control approach combining MPC and heuristics to optimize the coordination of distributed energy storage devices and power generators for all-electric ships was introduced by the authors in [47]. Simulations and experimental results obtained showcased the efficacy of the proposed method in handling the challenges of high-power ramp rate demands in SPS. However, limitations in the ramp rates of the ESS were not considered by the authors. The authors in [48], used MPC with load prediction to manage the power and energy of generators and the ESS in ship systems. The goal was to meet the power needs of the system load while considering the ramp rate limitations of the generators and the ESS and also reach a specific SOC for the ESS. The control framework was validated in a real-time simulation environment and demonstrated promising results. However, the high computational burden of the MPC method created challenges for fast real-time operation.

Another instance of MPC applied to ship systems was in study [49], where the authors aimed to minimize fuel consumption and achieve optimal power distribution among generators and batteries. A two-level MPC EM strategy, consisting of two optimization stages, was proposed to determine the power distribution. The first stage focused on minimizing fuel consumption and the second stage further optimized power distribution for high-frequency components like the ultra-capacitor. The strategy managed to effectively reduce fuel consumption, achieve clear power frequency division between battery and ultra-capacitor, and approach global optimization performance. However, the authors acknowledged limitations in parameter selection and interpolation methods using the second stage optimization.

Study [50] presented an EM control system for a DC SPS to coordinate multiple energy storage units and generators to meet load demands. MPC was used to determine the optimal power setpoints for the energy storage units when the generators' ramp rates were insufficient to meet the load demand. Simulations showed that load demand was met for different load profiles, including charging of the ESS, changes in propulsion load, and during high power ramp rate pulsed load operation. However, there was a slight overshoot during the initial charging stage, and the centralized nature of the MPC control implemented makes it prone to cyber-attacks. An MPC-based EMS for an isolated electro-thermal MG with limited electricity access was proposed in the article [51]. MPC was used to optimally manage diverse energy sources, including photovoltaic and diesel generators,

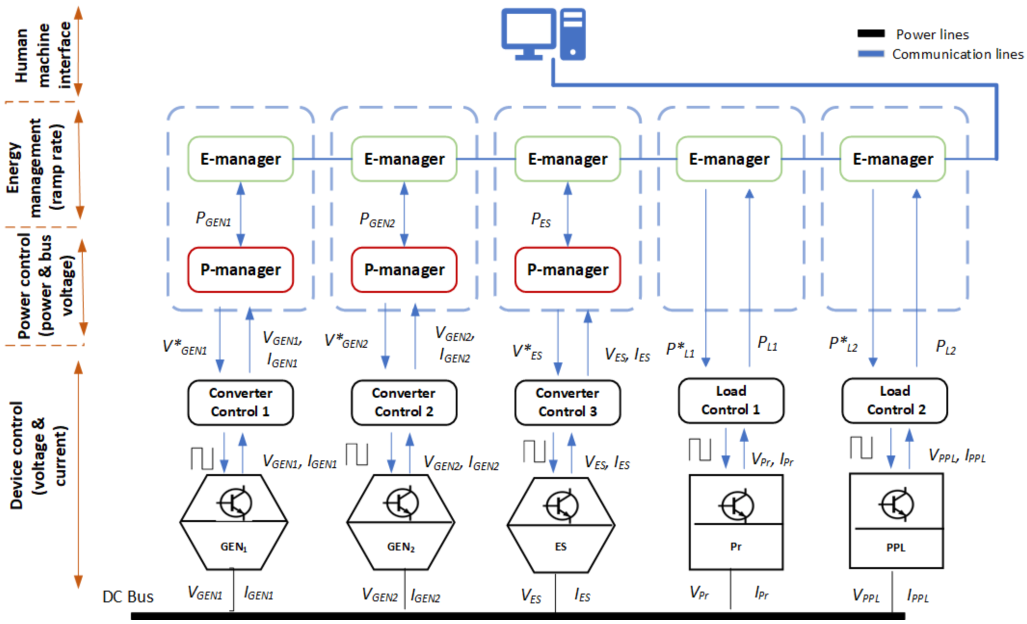

FIGURE 7. **Distributed control architecture for the notional electric ship [47].**

along with a lithium-ion battery energy storage system (BESS), and a domestic hot water system. The primary goals were to minimize operational costs, reduce greenhouse gas emissions, prolong the battery's lifespan, and ensure user comfort. The study highlighted MPC's advantages over the unit commitment approach through simulations and HIL validation, managing to reduce operation costs by 5.86%. A notable limitation, as mentioned by the authors, is the assumption of an ideal scenario with no prediction errors in generation and consumption.

C. FUZZY LOGIC CONTROL

Fuzzy logic control is a form of control system that employs fuzzy logic principles to handle the uncertainty and imprecision present in complex systems. Fuzzy logic is an approach to processing variables that allows for multiple possible truth values to be processed through the same variable.

Authors of [52] aimed to develop an enhanced EM strategy utilizing fuzzy logic control for a hybrid power system that integrated fuel cells, PV systems, batteries, and super-capacitors. Fuzzy logic was employed to optimize energy flow among the system components, model the hybrid power system and adapt to real-time conditions and demands. The results indicated that the strategy significantly improved energy utilization efficiency, system stability, and reliability, while also reducing fuel consumption and operational costs compared to traditional methods. The fuzzy logic controller was able to reduce the hydrogen fuel consumption by a decent 14.39% and was able to maintain constant SOC for the battery system. However, there were limitations, including the complexity of tuning the fuzzy logic model for various operational scenarios and the potential challenges posed by varying weather conditions and unexpected demand spikes.

Study [53], proposed an intelligent EMS for a ship powered by renewable energy using fuzzy logic controllers to manage the energy sources based on their availability. Two interlinking converters were used to connect the AC and DC buses of the MG, and fuzzy logic controllers were used to control the power flow between them. The performance of the proposed strategy was validated under various operating conditions and results demonstrated that the system could handle the uncertainty in renewable sources and provide a continuous power supply to the ship system. Another case of applying a fuzzy logic EM strategy was explored in paper [54], for a hybrid ship. Fuzzy logic was utilized to optimize the distribution of power generation between the solar panels, diesel generators, and battery, based on the load demand, the variability of solar energy generation, and the battery SOC. Simulation results demonstrated that the approach could improve the overall performance of the hybrid power system, reduce fuel consumption, and minimize emissions. However, for both these methods, only simulation results were used to validate the effectiveness of the method, and no real-time experiments were conducted.

An energy storage management system based on fuzzy logic for batteries and super-capacitors to efficiently meet both steady and transient power demands in an MVDC all-electric ship system was introduced in [55]. Simulation and real-time hardware-in-the-loop (HIL) results highlighted the advantages of the fuzzy logic-based system, particularly its ability to manage charging and discharging rates based on the state of charge of the energy storage. Authors in [56] proposed an EM strategy that combined a logic threshold control strategy with a fuzzy logic algorithm for hybrid electric ships to minimize fuel consumption and emissions. The logic threshold strategy was used to determine the optimal operating range of the diesel generator set, while the fuzzy logic algorithm further optimized this strategy based on real-time power demand and battery SOC. The proposed strategy was validated through simulation and demonstrated significant fuel savings compared to conventional methods. However, there is uncertainty about whether fuzzy logic will be able to have good predictive capabilities in the rapidly changing and dynamic operating environments of ship systems.

D. OTHER EMS METHODS

Apart from the MG EMS examples discussed so far in this section, a few more recent use cases are mentioned here. Samal et al. [57] introduced an EMS for a stand-alone hybrid MG with a reduced converter count to enhance system reliability while reducing complexity and costs. A key objective of the EMS was to optimize hydrogen consumption by the fuel cell and extend battery lifespan by managing its SoC within desired limits. The proposed system's performance was validated in real-time across various operating modes, with results demonstrating its efficacy in maintaining stable voltage and frequency and the ability to maintain BESS SOC within desired limits while reducing the converter count to three converters. However, as mentioned by the authors, the charging time of the BESS was slow in order to reduce fuel cell usage. Study [58] proposed a modified redundancy-based EMS for a DC MG, aiming to enhance the reliability of the SoC sharing function and ensure SoC equalization among BESSs. A DC MG configuration utilizing cascaded bidirectional Cuk (CBC) and cascaded bidirectional boost (CBB) converters was developed to interface two BESSs, coordinating them with a DC utility through an SoC-sharing function and droop control. The proposed redundancy in the DC MG enhanced reliability and provided a more stable DC-link voltage, with experimental HIL validation confirming its feasibility and effectiveness and showing faster SoC equalization compared to other methods.

A multifunctional EMS for an isolated network of MGs, with the objectives of reliably supplying energy, minimizing load adjustment, and considering battery degradation was introduced in study [59]. A nonlinear programming optimization problem was formulated to allocate power among renewable generators, battery storage, and load adjustments, optimizing power exchange between MGs. Results showed a substantial reduction in load shedding and dumping compared to isolated operation, enhancing operational flexibility and system resilience even during faults. However, a significant drawback was the continuous charge/discharge cycles of the battery systems due to the lack of access to a main grid and insufficient renewable power penetration. Authors in the study [60] proposed an advanced double-layer adaptive EMS for short-term MG operation scheduling, aiming to mitigate input parameter uncertainty and enable MG operators to balance greater profit with equipment lifetime extension. A reactive scheduling framework consisting of two layers and based on the rolling horizon strategy was employed. The upper layer was implemented for online profit maximization, and the lower layer to perform near real-time dispatch to minimize corrective actions resulting from forecast mismatches. Results demonstrated that the framework effectively mitigated the uncertainty of input parameters and allowed MG operators to implement various operational strategies, optimizing between profit and equipment longevity. Bhatt et al. [61] utilized MILP to establish an EM strategy to minimize the operational cost of a carbon-neutral MG by optimally integrating second-life batteries (SLBs) and crypto mining devices (CMDs). Key results indicated that the incorporation of CMDs and SLBs significantly reduced operational costs, and higher bitcoin prices can further decrease both operational costs and the required capacity of lithium-ion batteries. A drawback noted by the authors was not considering other types of CMDs in the analysis, suggesting the need for further research into environmental impact assessments and risk analysis. A two-layer EM strategy for MG clusters, aiming to minimize operational costs and CO2 emissions by utilizing demand-side flexibility and shared battery energy storage, was presented in [62]. The EM problem was formulated as a mixed-integer quadratic programming (MIQP) optimization, and validated with real-world data from a cluster of three MGs. Results demonstrated a significant reduction in operational costs alongside CO2 emission reduction. However, the strategy was primarily designed for grid-connected MGs, limiting its applicability to isolated systems and it may also face potential scalability challenges for the MIQP approach in more complex systems.

Despite their effectiveness, the aforementioned strategies for EM have various shortcomings and drawbacks. Evolutionary algorithms such as PSO are heavily dependent on parameter settings and incorrect parameter selection can significantly degrade performance and lead to poor results. These algorithms often fail to converge to an optimal solution due to the randomness involved. Moreover, for large and complex systems, the time and computational requirements to reach satisfactory solutions grow drastically. Techniques like MPC require precise mathematical models of the system. The computational demand can become very large as the complexity of the system increases. Although MPC can handle constraints well, defining and managing constraints can be difficult for complex and large systems. Fuzzy Logic Control has complexity in rule formation. It also involves additional fuzzification and defuzzification steps. The drawbacks of these methods are organized in Table 2 for better understanding. Due to the drawbacks of these

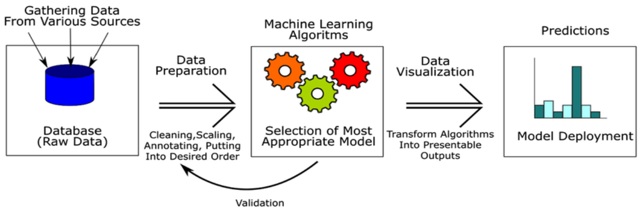

FIGURE 8. General process of learning in an ML model [66].

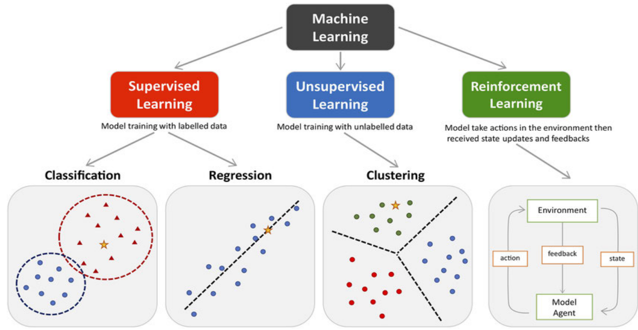

FIGURE 9. Machine Learning Categories [66].

conventional EM strategies, there has been a growing trend in applying Machine Learning (ML) and Deep Learning techniques in energy systems for the purpose of EM.

V. MACHINE LEARNING (ML) AND DEEP LEARNING (DL)

ML is a collection of techniques that enable systems to learn from data, identify patterns, and make decisions with minimal human intervention. Unlike traditional programming, where explicit instructions need to be given, ML algorithms learn from past data and can improve their performance over time through experience and learning from new data (see Figure 8). The accuracy of ML models can be improved by performing actions such as making changes in features or scaling the input data [22]. The general learning process of ML models includes a number of steps, starting from data collection, to data cleaning and preparation, developing models, training the models, visualization of data and finally the evaluation of the models.

ML can broadly be classified into three categories (see Figure 9):

1) Supervised learning: In supervised learning, the algorithm is trained on a labeled dataset, meaning that the input data is paired with the correct output. During the training process, the model learns to map input to output, allowing it to make predictions or classifications on new, unseen data [67].
2) Unsupervised learning: In this category of ML, algorithms are trained on unlabeled data or data where input is not mapped with the corresponding correct output. These models look for patterns and correlations within the input data by grouping or organizing them based on inherent relationships [68].
3) Reinforcement learning: Reinforcement learning (RL) focuses on how agents in an environment should take actions to maximize cumulative rewards over time. It uses the reward system as feedback to learn optimal behaviors. The RL method allows an agent to learn from its past experiences, adjusting strategies based on the rewards received [69].

DL is a subset of ML that utilizes algorithms based on artificial neural networks to process and model complex patterns in data. DL methods mimic the way human brains operate, utilizing multiple layers of information processing to recognize patterns and perform tasks. DL models like neural networks are more efficient and accurate in predicting unstructured data compared to standard ML models [70].

A. USE CASES OF ML AND DL IN EMS

Several studies have used ML and DL to improve the operation of EMS.

The authors in [71] developed a random forest regression model (RFR) to predict the fuel consumption of a ship's main engine using features such as sailing speed, cargo weight, weather and sea conditions. Figure 10 provides an illustration of a decision tree model used by the authors of this paper. The model was able to predict fuel consumption fairly accurately and recorded a Mean Absolute Percentage Error (MAPE) of 7.91%. Predictions from the ML model were fed to a second optimization layer, which was implemented to reduce the fuel consumption by the engines. The prediction results from the RFR model however, had several break-points where the fuel consumption has been predicted to be much lower than it actually is; this is mainly due to the manner in which data splitting is done by decision tree models.

Alexiou et. al. [72] implemented several ML algorithms such as decision trees, RFR, k-nearest neighbors (kNN), linear Regression, artificial neural networks (ANN) and AdaBoost to predict the output power of a ship's main engines. The main objective was to reduce the ship's operational costs and fuel consumption by optimizing its performance by predicting engine power. Using the hybrid model led to a significant reduction in computational time (50% to 99.97%) while maintaining acceptable accuracy, though certain algorithms, particularly ANN, showed increased training times. Even though the algorithms had good prediction accuracy over the entire dataset, there were many instances with high discrepancies between the original and predicted values, indicating room for further improvements.

An ANN model was used to improve energy efficiency by optimizing and predicting fuel consumption in ship systems in [73]. Another use of ANN to improve energy efficiency in ship systems was explored in [73]. A decision support system was introduced to improve ship energy efficiency by optimizing and predicting fuel consumption through a combination of engine optimization models and

TABLE 2. Comparison of drawbacks in EM strategies for SPS.

Method	Key Drawbacks	Ref.
Evolutionary Algorithms	1. Sensitive to parameter selection (poor tuning degrades performance) 2. Randomness may prevent optimal solutions 3. Challenges in real-time implementation (struggles with dynamic conditions) 4. Large systems increase time/resources exponentially	[63]
Model Predictive Control (MPC)	1. Requires precise system models (inaccuracies reduce effectiveness) 2. High computational burden (limits real-time applications) 3. Complex constraint management in large systems 4. Centralized implementations vulnerable to cyber-attacks	[64], [65]
Fuzzy Logic Control	1. Added complexity in rule formation 2. Additional steps (fuzzification/defuzzification) increase overhead 3. Poor predictive capability in rapidly changing environments 4. Tuning difficulty across operational scenarios	[65]

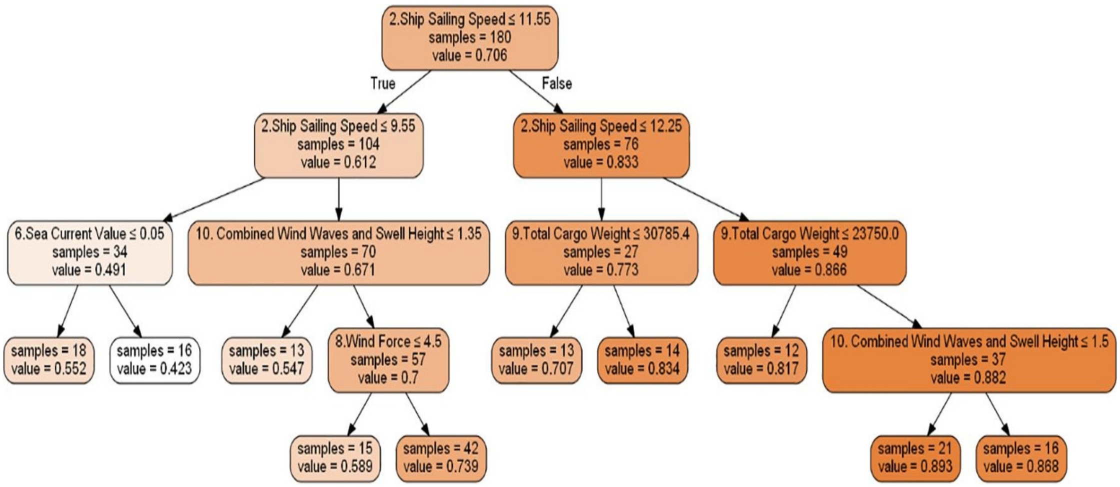

FIGURE 10. Decision Tree model to predict ship fuel consumption [71].

ANN. Results showed that the ANN model was able to predict fuel consumption with high accuracy, enabling the engine optimization model to effectively use this data and minimize fuel consumption. However, weather data was not taken into consideration for the ANN fuel consumption prediction, and this can significantly impact the accuracy of fuel consumption predictions in varying weather conditions.

Parkes et al. [74] used a neural network to predict the shaft power of merchant vessels. The network with two layers and 50 neurons in each layer was able to successfully predict the shaft power and achieved the prediction accuracy within 10% of the results produced by the regression models. However, for speeds above 17 knots, the accuracy of shaft power prediction of the neural network decreases due to the lack of data available at these speeds, which are not very common for such merchant vessels. The authors acknowledged that more analysis is required to verify whether the functions mapped by the neural network represent the actual physical relationships between its inputs and outputs.

In study [75], an intelligent EMS based on the adaptive neuro-fuzzy inference system (ANFIS) was implemented to optimize the power distribution in a hybrid SPS. The ANFIS structure, as shown in Figure 11, is a powerful hybrid system that combines the strengths of artificial neural networks and fuzzy logic to model complex patterns and nonlinear relationships. The ANFIS model took battery SoC and the ship load power as input to compute the fuel cell output power. Compared to the traditional control method, the ANFIS model provided better power management and maintained battery health by efficiently charging and discharging on the basis of the SoC. However, only simulation-based results were provided, and the study lacks validation through real-time experimentation.

DL models, such as feed-forward neural networks (FFNNs) and recurrent neural networks (RNNs) with long short-term memory (LSTM) units, have been utilized to predict ship propulsion power in study [76]. Unlike traditional FFNNs, RNNs and LSTMs are better at processing and predicting sequential data; this is mainly due to having connections in the hidden units that loop back on themselves, allowing them to maintain a memory of previous inputs as illustrated in Figure 12. Results showed that although the FFNN model was faster in making predictions, it was much less accurate than the LSTM models in capturing the dynamics of ship propulsion data.

B. APPLICATIONS OF RL IN EMS

RL algorithms are well-suited to carry out EM of MGs due to their ability to handle the complex, uncertain, and dynamic nature of MG environments. Integration of renewable energy sources, ESSs, and variable loads in MGs introduces significant unpredictability in both power supply and load demand. RL solutions excel in such environments because they do not require explicit modeling of the system's dynamics; instead, these algorithms learn optimal control strategies through direct interaction with the environment, adapting to changing conditions and unpredictable parameters like fluctuating load demand and renewable energy generation. There are many instances of applying RL to solve the EM problem of MGs; for instance, a model-based deep reinforcement learning (MDRL) algorithm was used to solve the energy supply plan in the multi-access edge computing (MEC) networks of microgrids (MGs) [78]. The MDRL model used the energy demand of the MEC base stations and the energy generation from the MGs as inputs to create the optimal energy supply plan. It utilized deep neural networks (DNN) to learn the dynamic behavior of the system from historical data and find the optimal policy by observing the previous optimal policy and the current environment. The proposed method significantly reduced energy consumption by 5.7% and 7.3% compared to greedy and random greedy methods, respectively, while achieving task execution success of around 97%. However, MDRL training is computationally intensive and might not be suitable for real-time CHIL testing.

Yu et al. [79] used a deep deterministic policy gradient (DDPG) algorithm to minimize energy cost for smart homes by optimizing heating, ventilation and air-conditioning (HVAC) systems and ESSs while ensuring minimum temperature deviation. The actor network of the DDPG actor-critic architecture was used to select an action to decide the HVAC input power and the ESS discharging power by evaluating the current environment state, which consisted of parameters such as ESS energy level, outdoor temperature, indoor temperature, etc. The reward function was made up of HVAC energy consumption penalty, ESS depreciation penalty and temperature deviation penalty. The proposed home EMS was able to reduce energy costs by 8.10% and 15.21% compared to two other baseline methods and maintained indoor temperature within the desired range with minimal deviation. Similarly, in a smart home EMS, a hybrid ML model consisting of an LSTM network and a DDPG model was leveraged to achieve an optimal balance between energy cost and temperature deviation [80]. The LSTM network was trained on historical data to predict the energy consumption of the smart home and the energy generated from renewable sources. The DDPG model was tasked with optimizing the HVAC energy consumption and the ESS charging/discharging by utilizing data from the home environment and output from the LSTM network. The hybrid ML model was able to reduce energy cost by 12% and 5% compared to rule-based methods in summer and winter scenarios, respectively. Similarly, there was a reduction in temperature deviation in both scenarios compared to the baseline methods. However, both these approaches have been validated using a simplified smart home model with a limited number of load types, excluding other heavy loads such as electric vehicles, water heaters, etc.

The authors in [81] implemented an effective charging plan for electric vehicles using deep Q learning. The objective was to minimize the electric vehicles' charging time and reduce the origin-to-destination distance. The algorithm used the charging rate constraint, the electricity consumption rate and the maximum travel distance as inputs to find the optimal charging scheduling route. The proposed algorithm could find an optimal charging scheduling route that could reduce average finish charging times by 74.3% and 152.8% compared to nearest neighbor charging routing and earliest start time methods, respectively. Not considering real-world variables such as traffic congestion and battery degradation poses a limitation to the approach. An optimal and cost-saving EMS for an emission-free all-electric ferry ship having battery ESSs and fuel cells was introduced [82]. The goals were to minimize total costs and maximize reliability by reducing the loss of load expectation (LOLE) metric. A multi-objective deep Q network was implemented to achieve the conflicting objectives of cost and reliability. The deep Q network state space was made up of parameters such as battery SOC, LOLE, cold ironing, fuel cell power output and hydrogen level, while the action of the network was to determine the power transfer from the energy sources to the loads. Real-time HIL simulations showed that the proposed EMS was able to reduce operational costs and improve reliability by reducing LOLE.

A deep reinforcement learning (DRL) based optimal control method for DC SPS, specifically designed to accommodate pulsed power loads by managing ESS charging was developed by the authors in [83]. To validate the proposed method, the study conducted different case studies involving tests under constant load conditions, random load disturbance, and CHIL real-time simulation. The results showed that the DRL-based control outperformed traditional methods, such as PI controllers and profile-based control (PBC). The DRL method also demonstrated the ability to handle fast dynamics and system uncertainties without requiring an accurate system model. However, one of the drawbacks

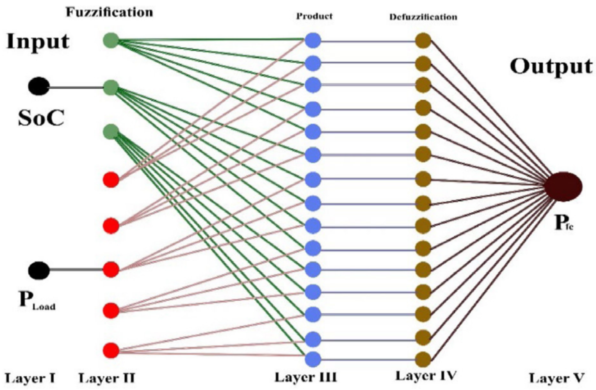

FIGURE 11. ANFIS structure [75].

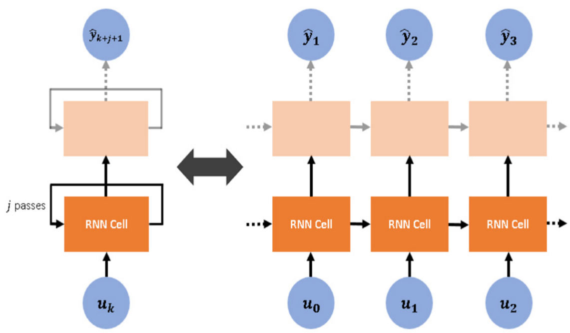

FIGURE 12. Illustration of an RNN layer in compact form (left) and unfolded form (right) [77].

of the proposed method is the significant computational resources that it requires. Chen et al. [84] developed an integrated eco-driving strategy for fuel cell hybrid electric vehicles. A DRL approach using the soft actor-critic (SAC) algorithm was implemented to synchronously optimize both motion trajectory planning and EM in multi-lane highway environments. The aim of the proposed framework was to improve energy efficiency, reduce emissions, and enhance driving comfort and safety by considering factors like hydrogen consumption, battery health, and collision avoidance. Simulation results were used to validate the framework's effectiveness in achieving better driving comfort and reduced costs.

C. LIMITATIONS OF ML AND DL TECHNIQUES AND POSSIBLE SOLUTION

Despite the increasing utilization of ML and DL models in energy systems, they have some drawbacks. Conventionally, for training ML and DL models, all the data from the controllers or individual clients is directly transferred to the server. The server then uses the raw data to train the models. This exposes a huge privacy risk, as sensitive information can easily be extracted during raw data transmission through cyber-attacks. Furthermore, directly transmitting large volumes of data over the communication network can significantly increase communication overhead and cause latencies in the system [85]. Processing such large volumes of data also significantly increases the computational power requirements of the server. This leads to increased cost and can severely hamper the performance of EM systems, which are required to react promptly to changes in operating conditions. An alternative to the conventional centralized form of training ML and DL models is distributed learning, where the training process is distributed across multiple nodes that work collaboratively to train a single model. This is mainly done through data parallelism or model parallelism [86]. In data parallelism, the dataset is split between multiple nodes, and each node trains the model on its local subset of data. The nodes periodically synchronize their model parameters with a central server or among themselves. In model parallelism, the model itself is split into layers between multiple nodes, with each node responsible for computing a portion of the model. This is less common in practice compared to data parallelism. However, distributed learning focuses on scalability and efficiency in training large models or handling large datasets by leveraging multiple computational resources. It does not necessarily prioritize privacy, and data is commonly shared or replicated between nodes [87]. Split learning [88] is another method to carry out training in a distributed manner, in which raw data is not directly transferred. The model is split into two parts, where the earlier layers are trained by the clients and the later ones are trained by the server. The clients have to send the outputs of their trained layers to the server, and the server has to send the outputs of the later layers back to the clients to conduct backpropagation and complete one epoch of model training. However, this creates a sequential dependency, as the client training cannot be completed until the server can send the later layer activations to the client [89]. Such sequential bottlenecks can slow down training, which is not ideal for EMS requirements of ships and other MGs. Swarm learning combines decentralized training with blockchain technology to reach consensus on model parameters without a central server. However, blockchain operation introduces complexity to the system and also increases computational overhead, which can lead to increased latency and reduced response times [90]. The travelling model [91] is another method to conduct distributed training of models without directly sharing data among clients. In this approach, a single model is trained sequentially from client to client. This approach has only been reported as effective when the dataset size is small and is not suitable for large systems or systems where data accumulation is high due to varying operating conditions. In comparison to the methods mentioned above, FL emerges as a better technique to enable distributed learning of ML and DL algorithms on the controllers themselves without directly sharing raw data. This is explored in more detail in the next section.

VI. FEDERATED LEARNING

Federated learning (FL) is a technique for training ML and DL models in a distributed manner. A global server

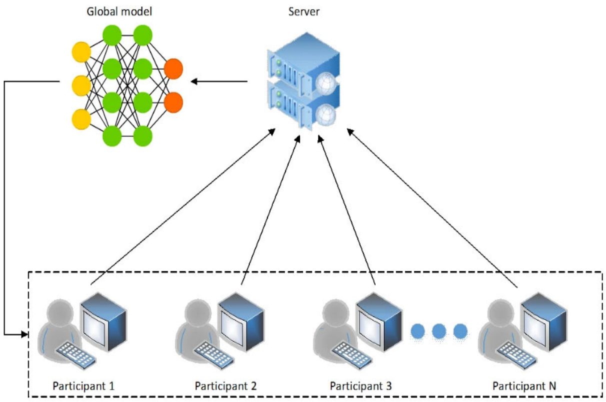

FIGURE 13. The basic FL framework [92].

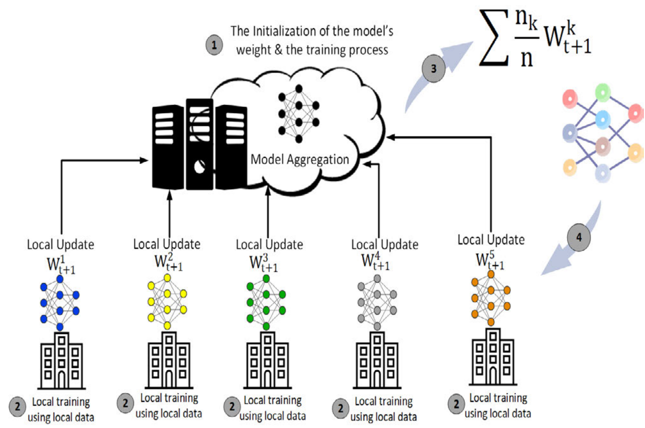

FIGURE 14. FL training steps [19].

coordinates the independent training of models by some distributed clients utilizing their individual local data. The server then combines the trained models to create the final global model. Like most other ML techniques, the training in FL is conducted in an iterative manner where the local models are updated, and the global model is aggregated until the model reaches convergence or a predetermined number of training iterations have been conducted [18]. Figure 13 illustrates the structure of a basic FL framework.

FL was first introduced by Google in 2016 to anticipate user text input on Android devices while still keeping user data secure on end devices [93]. The federated method of learning was mainly developed to solve the privacy concern arising from multiple distributed end devices participating in shared learning. This is because, in the FL training process, the model updates are sent to the main server, and the raw data remains securely on the local devices. Apart from improved privacy, FL has other advantages, such as lower computational requirements and more resiliency towards cyber-attacks and threats. Since only model updates are transmitted between devices instead of vast amounts of training data, there is also a significant reduction in network overhead. Conventional centralized ML and DL models require high computational resources since a single central server has to train huge amounts of data coming in from all the end devices, commonly referred to as clients, in the system. Meanwhile, in FL, the server only has to aggregate the model updates from the clients, which is much less in volume than the total training data. This significantly reduces the computational burden for the server in FL architectures. At the same time, since no raw data is being transferred over the communication network between the server and the clients, the risk of cyber-attacks that could occur during the transmission of data over the network is eliminated [18]. However, in FL, the individual devices or clients need to have sufficient copmputational resources to be able to train local models by themselves.

A. FL TRAINING PROCESS

At the beginning of the FL training process, the server creates an initial global model based on the model architecture selected before. After this, the following steps are carried out:

1) The server selects the clients in the network to participate in training for the current round. At times, all the clients participate in a training round, and at other times, only a certain number of clients are selected. The selection of clients to participate in an FL round can be done randomly, or they can be selected based on their computing capabilities or the heterogeneity of the data distribution among themselves [94]. The parameters of the global model are sent from the server to all participating clients on the network.
2) Clients train the global model using their own individual local datasets and calculate the model update or gradient by minimizing a loss function using optimization techniques. The clients then send each of their updated model parameters back to the server.
3) The server aggregates the model updates from all clients and uses an aggregation algorithm to compile a new global model.
4) The newly aggregated global model is then sent by the server back to the clients.

The above steps comprise one single round or iteration of FL. They will be carried out on every iteration of FL until a termination condition is reached in the process. The FL training process can be illustrated by Figure 14.

FL revolves around supervised learning, where to make predictions, input values x_i are mapped to output labels y_i. The goal is to compute the model parameter w by minimizing the loss function $fi(w)$ for the input-output pair of data (x_i, y_i) of size n. The function of the supervised optimization algorithm can be expressed as:

$$f(w) = \frac{1}{n}\sum_{i=1}^{n} f(x_i, y_i, w) \tag{1}$$

$$f(w) = \frac{1}{n}\sum_{i=1}^{n} f(w) \tag{2}$$

In an FL system, the goal is to calculate the model parameter w by minimizing the loss function $F_k(w)$ for each client. $F_k(w)$ is calculated using (3) where $f_i(w)$ presents the loss function for a single data point i given the model parameters w, K is the total number of clients participating in the FL round, k is the client index with each client having a local dataset with a set of indices P_k and n_k data samples from a total dataset size of n across all clients in the system. Using the FedAvg aggregation algorithm, the overall loss function $f(w)$, which represents the global loss across the entire system, is calculated as the weighted sum of the loss function $F_k(w)$ for each client (4). The weight update across the global optimization can be expressed as (5), where w_{new} is the newly updated weight parameter of the global model and w_k is the model weight parameter of client k.

$$F_k(w) = \frac{1}{n_k}\sum_{i \in P_k} f_i(w) \tag{3}$$

$$f(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w) \tag{4}$$

$$w_{new} = \sum_{k=1}^{K} \frac{n_k}{n} w_k \tag{5}$$

The primary goal of FL is to train and generate a high-quality global model using distributed high-dimensional data on devices through the learning rounds. The aggregation algorithm plays a crucial role in combining model updates from all the clients to compile the global model. The performance of the final model is directly influenced by the aggregation algorithm that has been implemented [18]. There are various kinds of aggregation algorithms that can be implemented in the FL process; some of them are mentioned below:

1. **Federated averaging (FedAvg)**: In FedAvg, each client that has been chosen for training receives the global model from the main server. The clients then send updated models back to the server after they have trained the global model using their individual local data. The server averages the parameters of all the local model updates it receives from the clients to create a new global model.
2. **FedProx**: FedProx, proposed in [95], aims to overcome FL heterogeneity by providing an enhanced version of FedAvg. In FL training rounds, FedProx considers variances in data distribution, processing power, and many other aspects of the clients involved. A proximal term is introduced to the loss function in FedProx to address inconsistent local updates and influence convergence towards the global model.
3. **Federated Matched Averaging (FedMA)**: FedMA utilizes hierarchical matching and averaging of parameters in neural networks, to aggregate the global model. The global model is built one layer at a time by matching local model parameters having similar characteristics. FedAvg is more suited to independent and identically distributed (IID) client data, where client data have similar distributions, and experiences lower accuracy on non-IID data, where clients have data from different distributions. However, FedMA has better accuracy than FedAvg in non-IID settings [96].
4. **Federated Dynamic Regularization (FedDyn)**: Often in FL, the minima of the local client-level empirical loss are inconsistent with the global empirical loss. FedDyn improves FL efficiency by aligning local device training with the global objective using dynamic regularization. A dynamic regularizer is introduced for each client to prevent clients from overfitting to their local data and to ensure that local updates account for past gradients, aligning them with the global objective. The server calculates the average of all received local models and maintains a state variable that accumulates the average of all client gradients over time. This state variable adjusts the global update to account for differences in local data distributions [97].
5. **Stochastic Controlled Averaging for Federated Learning (SCAFFOLD)**: In SCAFFOLD, the server maintains a global model and a global control variate, which helps align local updates. Each client also has its control variate, and in local training, instead of using just their local gradient, the clients adjust it by adding the difference between the local and the global control variates. This correction term reduces drift caused by non-IID data. The server averages the differences between the clients' updated models and the original server model, and also averages the changes in clients' control variates to update the global control variate [98].
6. **Model-Contrastive Federated Learning (MOON)**: In MOON, clients train the global model received from the server on their local data. Unlike standard FL, MOON adds a model-contrastive loss to the training objective. This loss pulls the local model's feature representations closer to the global model's representations and pushes them away from the previous local model's representations. This ensures the local model aligns better with the global model, even if local data is skewed. The server aggregates the local models by averaging their parameters, weighted by the size of each party's dataset [99].
7. **Federated Stochastic Variance Reduced Gradient (FSVRG)**: FSVRG operates on the principle of doing a single, costly, full gradient calculation centrally and then performing several distributed stochastic updates

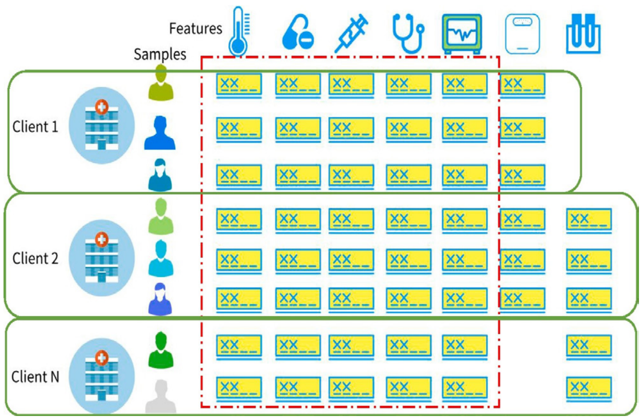

FIGURE 15. Horizontal FL [103].

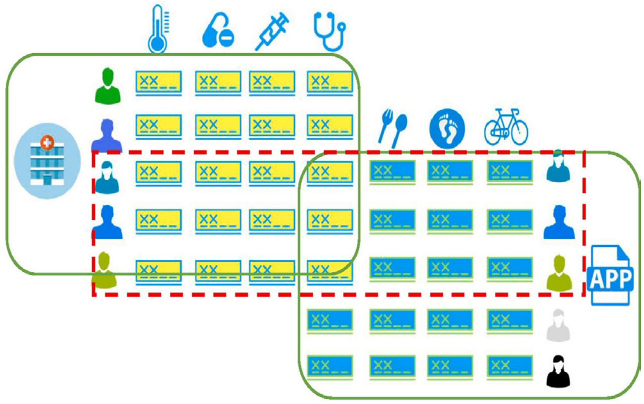

FIGURE 16. Vertical FL [103].

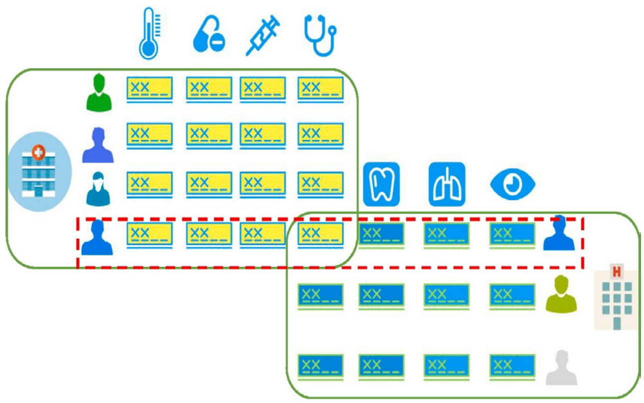

FIGURE 17. Federated transfer learning [103].

for every client. To execute a stochastic update, a random permutation of the local data is iterated over, with one update for each data point [100]

8. **CO-OP method**: The CO-OP method in federated learning proposes an asynchronous approach where any received client model is immediately merged with the global model. Each client model and the global model have an associated age, and the difference in ages is used to compute a merging weight. This approach accounts for the fact that clients may be training on models of varying recency, ensuring more effective integration of updates from different clients [101].

B. FL CATEGORIES

FL can be categorized into three classes based on how the data is partitioned among the clients:

1. **Horizontal FL**: In horizontal FL (see Figure 15), there is an overlap between the data of the clients in the feature space, while the data is different in the sample space. This means that most of the data in the clients have the same features or attributes, but they mainly have different samples of data. Horizontal FL can increase the number of samples taking part in training as in this type of FL; the data is split horizontally among the clients such that all the data having the same features are included in the training [102].
2. **Vertical FL**: In vertical FL (see Figure 16), clients mostly overlap in the sample space and rarely have any similarity among each other in the feature space. In this type of scenario, the clients have similar samples of data but have different features for their data. Therefore, to carry out FL between all the clients, the datasets are split vertically to include the part of the data that has the same samples to use for training. This vertical splitting of data increases the feature dimension of training data [102].
3. **Federated Transfer Learning**: In the third and final kind of scenario in data partitioning, the clients hardly have any overlap either in the sample space or in the feature space (see Figure 17). The datasets in the clients do not have common features or attributes, nor do they have similar samples of data. Transfer learning, in which knowledge from one domain is used in another, is ideal in this kind of scenario rather than splitting or segmenting the data [102].

C. FL ARCHITECTURES

The architecture in an FL system determines how the client and servers in the network are connected to each other and how they communicate between themselves. FL architecture can be mainly categorized into centralized FL, decentralized FL and semi-decentralized FL [104]. The three different types of FL architectures are briefly discussed below and their differences are illustrated in Figure 18.

A. **Centralized FL:** In centralized FL, a single server is connected to all clients in the network. During each communication round, the server collects model updates from all the clients and aggregates a global model, which is later passed on to all the clients. Although having a single central server eases the control and communication within the system, this creates a single point of failure, making the system vulnerable to any

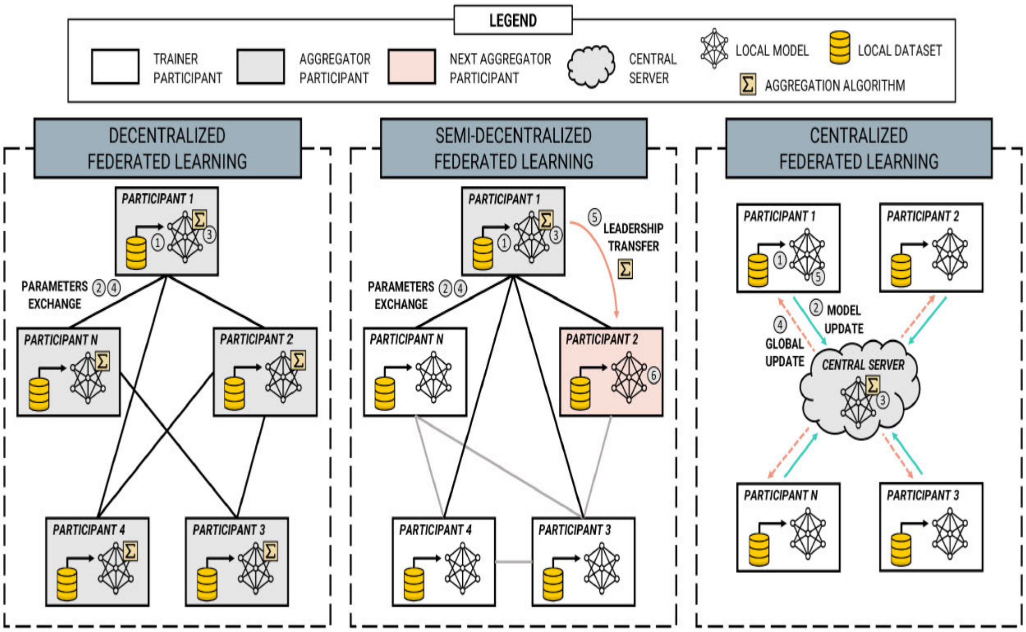

FIGURE 18. Federated learning architectures [104].

possible faults or cyber-attacks that the server might face. Moreover, sending all the model updates to a single entity can create possible communication bottlenecks and increase the system latency.

B. **Decentralized FL:** In decentralized FL, however, there is no central server. Each client collects model updates from neighboring clients and carries out aggregation separately. This can reduce the chances of communication bottlenecks as the communication overhead is evenly distributed among the clients. Moreover, distributed aggregation also leads to better utilization of resources since the computing power required to aggregate the model updates is shared among the clients. However, there are risks of weak and intermittent connections between some clients. The clients in this setup can mainly be connected in three types of topologies. They can be fully connected, i.e., direct communication links between all the clients. There can be partially connected networks where direct connections only exist between some clients, or, in a third scenario, the clients are grouped into clusters based on the similarity of model parameters [105].

C. **Semi-Decentralized FL**: The semi-decentralized FL is a hybrid of centralized FL and decentralized FL. Instead of having a fixed server, the role of the aggregator is rotated among the participating clients in the network. At each round, the client selected as the aggregator collects model updates from the remaining clients in the network and compiles a new global model by itself. The client to carry out aggregation in each round can be selected randomly or based on computational capacity or some other parameter [106]. The choice of aggregator can have a significant impact on the performance and efficiency of such an architecture.

VII. APPLICATIONS OF FL

A. APPLICATIONS IN ENERGY SYSTEMS

In the field of energy systems, FL is a relatively new topic of study. Applications from the data analysis perspective can be in the form of forecasting, analysis or decision-making (control and optimization) [18]. FL-based optimization is suitable for energy systems since it does not require different components and clients in the system, like loads and generating units, to have uniform model structures. The use of FL by electricity companies can improve the security of customers' private information. Energy providers can serve customers with customized EM solutions, personalized energy service, energy-saving product recommendations, and many more, while FL ensures that the customer's private information is not shared with the company. A few applications of FL in energy systems, particularly in MGs and smart grids, are presented below.

To carry out short-term load forecasting (STLF) in a smart grid, Taïk and Cherkaoui [107] assessed the effectiveness of LSTM using FedAvg. The training data comprised data from 200 houses. A multi-access edge computing (MEC) server and clients (houses equipped with edge devices like smart meters) were the two primary components of the proposed system. For STLF, a global LSTM-based model was constructed using FL. The results from the study confirmed that, while maintaining accuracy, the models could reduce networking overhead and data security hazards. However, such a model significantly relies on the hardware capabilities of the local edge devices in the consumer households. FL for multi-energy demand forecasting for integrated energy microgrids (IEMs) was explored in [108]. Utilizing a CNN-Attention-LSTM model, the research showed that FL permits distributed model training while maintaining data privacy, resulting in predicting accuracy that is either equivalent to or better than that of conventional centralized models. The model, however, is vulnerable to false data injection attacks (FDIA) and has lower accuracy during such events. In study [109], FTL was applied to improve the energy efficiency in smart buildings by predicting energy consumption while also addressing privacy concerns and data scarcity. Representative clients for FL were selected by clustering buildings according to their physical and geospatial attributes. This allowed for model training without sharing sensitive data. The findings show that the FTL approach improved prediction accuracy when compared to scenarios that use FL and transfer learning separately. Nevertheless, the study is limited by the fact that it only looks at a small subset of buildings, and there may be difficulties in applying the model to a wide range of conditions and building types.

Fekri et al. [110] demonstrated the effectiveness of FL in distributed load forecasting using smart meter data, showing that the FedAVG approach achieved better accuracy and efficiency compared to other methods. A privacy-preserving FL approach was proposed in study [111], for predicting distributed energy resource generation and consumption, leveraging IoT nodes to transmit models without revealing consumer data. This approach was validated on the Pecan Street dataset, demonstrating its practicality for real-world applications. Furthermore, FL has been integrated with edge computing and advanced metering infrastructure (AMI) to enable non-intrusive load monitoring and improve EM. Hudson et al. [112] proposed a framework combining edge computing, edge intelligence, and AMI for distributed deep learning via FL, achieving efficient non-intrusive load monitoring in smart distribution grids. Furthermore, a secure FL framework for AMI, using LSTM models for short-term load forecasting while ensuring communication efficiency and data privacy, was introduced in [113].

Federated reinforcement learning (FRL), which is a combination of FL and RL, has also been explored for the purpose of EM in energy systems. In order to lower power costs while maintaining consumer comfort and privacy, Lee and Choi [114] presented an FRL framework for efficient EM in numerous smart houses equipped with home appliances and distributed energy resources as shown in Figure 19. To optimize appliance operation, the method used is Local Home EMS, which was connected to a global server. Model-free reinforcement learning was used, which protects data privacy by simply communicating the model parameters. Results showed faster convergence of optimal policies, scalability for integrating more agents, and notable cost savings over current approaches. However, there are limitations, such as communication overhead resulting from repeated interaction rounds and reliance on local model quality, which could differ throughout households. Similarly, to enhance

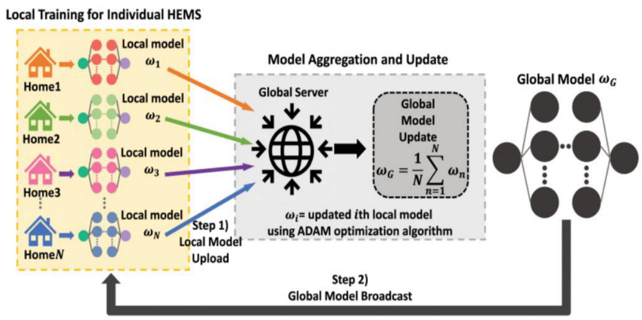

FIGURE 19. Model training and aggregation processes for the FRL-based HEMS involving N homes [114].

EM in smart microgrids, federated deep reinforcement learning (FDRL) was applied to optimize energy trading and consumption among several smart buildings in the paper [115]. The authors proposed a hierarchical architecture that enhances learning efficiency while protecting user privacy. Local building EMSs (BEMS) trained individual DRL models and communicated their experiences with the main server. The results show that this strategy can ensure faster convergence in EM tasks while achieving significant cost and CO2 emission reductions. However, the study can encounter limitations surrounding the federated model's scalability and possible difficulties in application because of diverse data and varying conditions. Furthermore, Li et al. [116] investigated a federated multiagent deep reinforcement learning (F-MADRL) approach to optimize EM in multi-microgrid (MMG) systems while ensuring the protection of user privacy. Using a decentralized architecture, every MG was managed by an agent applying proximal policy optimization (PPO) to augment a physics-informed reward prioritizing energy self-sufficiency and economic efficiency. Findings from the study revealed that the F-MADRL approach performed noticeably better than conventional deep reinforcement learning methods in several scenarios, exhibiting enhanced agent adaptability in a range of MG environments. However, the study highlighted challenges related to the scalability of the FL model and the complexities associated with its real-world implementation.

FL has been extensively applied to solve optimal power flow (OPF) problems in smart grids, where scalability and data privacy are paramount. Reference [117] proposed a novel FL-based approach for distributed OPF solutions, enabling individual grid nodes to perform local computations without sharing raw data. This method preserved data privacy and demonstrated superior accuracy, speed, and scalability compared to conventional OPF methods. Similarly, [118] introduced an FRL framework for distributed optimal energy dispatch in networked microgrids. By formulating the problem as a partially observed markov decision process

(POMDP) and using DDPG, the framework allowed microgrids to train local models and share only model weights, thereby reducing communication overhead and enhancing privacy. To address heterogeneity in multi-task, multi-agent microgrids, [119] applied personalized federated hypernetworks (PFH) to reinforcement learning for energy demand response. The approach enabled decentralized learning and demonstrated significant improvements in learning speed and microgrid profitability compared to FedAvg and local RL control. Additionally, [120] proposed a decentralized FL architecture for networked microgrids, where each microgrid independently trained its local model and exchanged parameters to create a global model. This approach minimized costs and maintained energy self-sufficiency while ensuring data privacy and security.

FL has also been instrumental in peer-to-peer (P2P) energy trading and sharing, where blockchain technology is often integrated to ensure transparency and security. [121] introduced FederatedGrids, an FL and blockchain-assisted platform for P2P energy trading within and across microgrids. The platform utilized convolutional neural networks (CNNs) for energy demand and production prediction, while blockchain-based smart contracts facilitated secure and transparent transactions. Similarly, [122] proposed a blockchain-based distributed FL technique for energy-demand prediction, ensuring data privacy and trust by storing energy data locally and sharing only model parameters on the blockchain.

In the area of cybersecurity, FL has been employed to enhance the resilience of smart grids and microgrids. A secure FL framework for predicting smart microgrid stability, utilizing encryption and authentication mechanisms such as TLS protocols and tree-based group diffie-hellman (TGDH) to protect sensitive information was presented in [123]. Similarly, a conceptual framework for collaborative adaptive cybersecurity in multi-microgrids, integrating FL with blockchain technology to enable decentralized training of predictive models for proactive security incident detection was proposed in [124]. An example of authentication-based FL was implemented in study [125] within an electric vehicle infrastructure between charging stations (CS), which were the clients, and charging station providers (CSP), which were the servers responsible for model aggregation. A key generator center was utilized as a third-party authentication server to generate secret session keys for each of the CS and CSP within the system. These session keys encrypt the model updates before they are transferred. Security analysis verified that the model effectively defended against cyber-attacks such as information exploiting attacks, data poisoning attacks, model poisoning attacks and free-riding attacks.

Another attempt to improve privacy in FL communication involved implementing a differential private FL framework, based on the randomized Gaussian mechanism, to enable secure data transmission between customers and the utility in an advanced metering infrastructure [126]. Differential privacy was used to add random noise to the original data to protect individuals' identification information. An attention-based bi-directional LSTM was used, and it was leveraged to carry out load forecasting using the customer metering data. Simulation results showed that the proposed model could track the load curve precisely and achieved accuracies similar to the centralized model while ensuring higher privacy. To enhance cyber resilience in power grids, study [127] proposed a cyber-secure FL framework for power grids, where entities collaboratively defended against cyber-attacks by sharing machine learning models and parameters without exposing local data. This approach enabled iterative updates to a global model for cyber-attack detection, ensuring robust protection against threats.

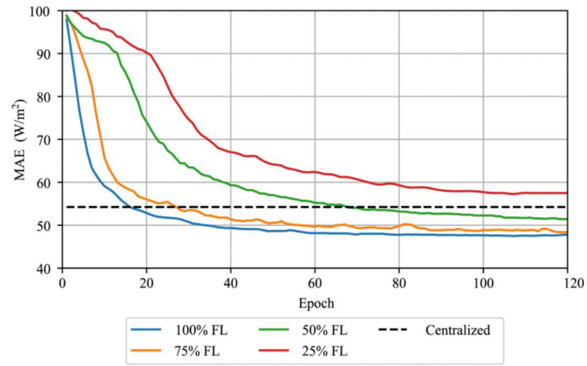

FIGURE 20. Plot of MAE against training epochs with different participation ratio in FL, and in centralized learning [128].

The communication overhead in FL can be further improved by varying the client participation ratio. When the participation ratio is 100%, all the clients in the system participate in an FL round; however, as the ratio decreases, fewer clients participate in model training. This was explored in study [128], where a secure FL with differential privacy was implemented for solar irradiation prediction to improve the forecasting performance. A Bayes LSTM model was employed to model uncertainties. Prediction results were recorded for conventional centralized and FL models with varying participation ratios. As shown in Figure 20, the centralized model achieved an MAE of 54.25 W/m^2 whereas, the FL models with participation ratios 25%, 50%, 75%, and 100% recorded MAE values of 59.2 W/m^2, 51.35 W/m^2, 48.4 W/m^2 and 47.9 W/m^2 respectively. All other parameters were kept the same for the FL models with different participation ratios. These results indicate that, along with reducing communication overhead, the accuracy of FL models still remains high, with only the FL model having a 25% participation ratio performing inferior to the centralized model.

B. APPLICATION IN SHIP SYSTEMS

The FL framework is also increasingly being applied in ship systems, both electric and non-electric. Some applications of FL in ship systems for objectives such as fault diagnosis, fuel

TABLE 3. Summary of federated learning applications in energy systems.

Reference	Application	FL Algorithm	Drawbacks
[107]	Short-term load forecasting	FedAvg	Relies on edge device hardware in local households.
[108]	Multi-energy demand forecasting	FedAvg, FedYogi, and FedAdam.	Vulnerable to FDI attacks, lower accuracy during attacks.
[109]	Energy consumption prediction in buildings.	FTL	Dependency on clustering strategy.
[110]	Distributed load forecasting	FedAvg, FedSGD	High computational cost for training individual models.
[111]	DER generation prediction	Weighted gradient aggregation	Assumes flexible loads under direct utility control.
[112]	Non-intrusive load monitoring	FedAvg with weighted aggregation	Limited real-world validation.
[113]	Short-term load forecasting in AMI	FedAvg with weighted averaging	Assumes uniform data distribution.
[114]	Smart home EM	FedSGD	Limited scalability validation.
[115]	Smart MG EM	FedAvg	Slower convergence compared to centralized DRL.
[116]	Multi-microgrid energy optimization	FedAvg	Uncertainty of renewable energy not addressed.
[117]	Optimal power flow in smart grids	FedAvg	High communication bandwidth for a single server.
[118]	Optimal energy dispatch in networked MGs	FedAvg	Power flow constraints between MGs are not considered.
[119]	Optimized energy pricing in MGs	PFH	Absence of real-time hardware validation.
[120]	EM in networked MGs	FedAvg with weighted averaging	Reliance on effective coalition formation.
[121]	P2P energy trading betweens MGs	FedAvg via blockchain smart contracts	Complexity in managing smart contracts.
[122]	Energy demand prediction	FedAvg via blockchain smart contracts	Higher computational costs due to blockchain integration.
[123]	MG stability prediction	FedAvg	Lower accuracy than centralized approach.
[124]	Cyber-attack detection	FedAvg	Lacks performance validation.
[125]	EV energy demand prediction	FedAvg with authentication	Evaluated on non-EV datasets.
[126]	Load forecasting	FedAvg with Differential Privacy	Reduction in accuracy due to DP integration.
[127]	Cyber-attack detection	FedAvg	Limited robustness against data poisoning.
[128]	Solar irradiation forecasting	FedAvg with Differential Privacy	Communication overhead with high client participation.

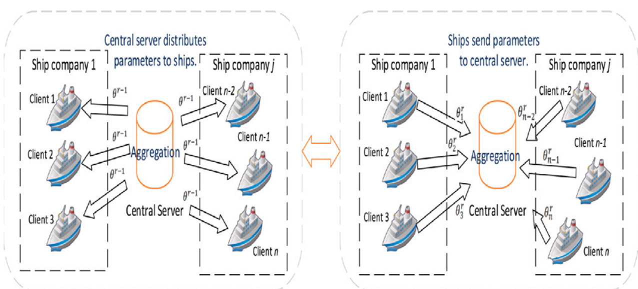

FIGURE 21. FL framework for fuel consumption prediction [131].

efficiency optimization, predictive maintenance, collision avoidance, and cyber-attack detection are discussed below.

An FL approach that enables collaborative fault diagnosis among shipping agents while ensuring data privacy was introduced in study [129]. An adaptive model aggregation interval, where the FL aggregation was done in variable time intervals, was used to improve the training efficiency with regard to communication and computational requirements. A pallier-based homomorphic encryption scheme was utilized to ensure the secure transmission of model parameters and prevent data leakage, and the fault diagnosis model was implemented using the CNN architecture. Although the method had a good balance between communication costs and accuracy, the results showed that adding more agents may result in under-fitting and slower convergence. In another study, an FL scheme was employed to predict the primary engine power of ships [130]. Weather and ship-related historical data were used to train five different supervised ML models, multiple linear regressor (MLR), decision tree regressor (DTR), support vector regressor (SVR), random forest regressor (RFR) and ANN as the underlying ML model for the FL scheme. All five ML models achieved good accuracy however, the ANN model with five hidden layers performed the best. Three different learning frameworks were implemented and compared: a conventional centralized method, FL with aggregation of models at the global server and a ship-to-ship FL model where trained models from one ship are passed to the others to reduce the training effort. The FL framework achieved accuracy close to the centralized framework while maintaining the privacy of data, whereas the ship-to-ship FL framework performed noticeably worse than the other two frameworks.

Wang et al. [131] developed an FL framework that predicts ship fuel consumption and optimizes sailing speed. As illustrated in Figure 21, this FL framework enables ships from different shipping companies to share information with each other without revealing original data. The authors employed a two-stage method where FL was used to collaboratively train a model without sharing raw data between multiple ships, followed by optimization techniques to determine the optimal sailing speed that minimizes fuel consumption. Each client and the server used a basic deep neural network with three hidden layers as the DL model. According to the results, the suggested approach could guarantee data privacy while reducing fuel usage by 2.5%–7.5% when compared to other models. Despite this, the research had some limitations, such as using artificial data rather than real datasets.

Another example of FL for fuel consumption prediction was carried out by the authors in study [21], where they used it to predict engine efficiency in ship systems. ANN, which is good for both linear and non-linear function predictions was fed fuel consumption data from two ships and weather condition information to predict engine efficiency. Results from FL and centralized models were compared, FL had slightly lower accuracy but significantly improved the privacy and communication overhead experienced by the centralized model.

FL has also been employed to enhance cyber resilience in maritime transportation systems. Authors in [132] proposed a CNN-MLP-based FL framework for intrusion detection, achieving 88.1% accuracy. DisBezant, a Byzantine-robust FL system, which maintained 90% accuracy even with 30% malicious nodes was introduced in study [133]. Han et al. [134] proposed common layer mean detection (CLMD), a method for detecting and preventing poisoning attacks in FL, effectively maintaining model accuracy even with 25% malicious clients. These studies highlight FL's potential to secure maritime systems against cyber threats while preserving data privacy.

Authors in [135] applied FL for three different predictive maintenance tasks in ship systems. The tasks included using regression-based degradation prediction of naval propulsion gas turbines, classification-based monitoring and prediction of ship primary engine condition, and time-series regression to predict ship fuel consumption. Fourier convolutional neural networks (FCNN) were utilized as the underlying DL model for the regression and classification tasks and

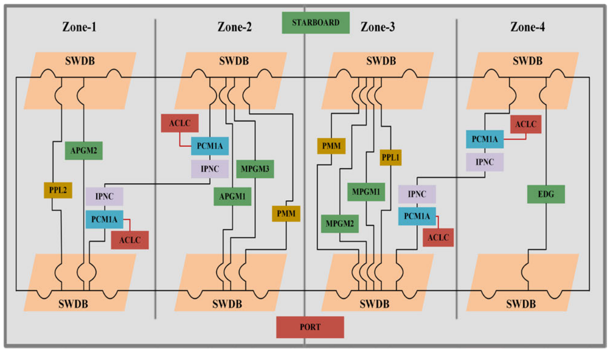

FIGURE 22. Four-zone SPS model.

an RNN with LSTM cells was used for the time-series regression task. Four different FL aggregation algorithms, FedAvg, FedSGD, FedProx and FedAvgM, were tried, and MAE values obtained from each FL algorithm for each task were compared. FedAvg and FedProx algorithms performed equally well on task one. FedAvg and FedAvgM performed better than the other aggregation algorithms for task two and FedProx performed better than the other FL algorithms for the third and final task.

In the domain of collision avoidance and anomaly detection, FL has been applied to enhance safety in maritime operations. Authors in [136] developed a cooperative collision avoidance system using FL and MEC, achieving over 92% accuracy in collision detection. This work was further extended, demonstrating almost 100% collision avoidance in simulated scenarios [137]. For anomaly detection, Graser et al. [138] introduced M^3 Fed, an FL-based framework that detected 12,156 anomaly events with 98% accuracy while reducing data transmission by 98%. These applications underscore FL's role in improving maritime safety and operational efficiency.

Another notable application of FL is in predictive maintenance and battery health estimation. FedChain [139], an FL framework enabled by blockchain, was proposed for battery state of health estimation in marine vessels. While FedChain ensured tamper-proof data and model updates, it showed no significant improvement over local or centralized training. Furthermore, authors in [4], applied FL to detect cyber-attacks in SPS, effectively identifying false data injection (FDI) and controller hijacking (HIJ) attacks using LSTM models. These studies demonstrate FL's versatility in addressing diverse maritime challenges.

FL has also been explored for vessel location forecasting and ship detection. FedNautilus [140], an FL-based framework for vessel location forecasting, was capable of achieving a final displacement error (FDE) of 1.7 km while reducing communication costs by 84%. Duong et al. [141] applied FL for ship detection from multi-source satellite images, achieving mAP50 scores of 0.85 with FedProx and FedAvg. These studies highlight FL's potential to improve navigation and monitoring systems in maritime environments.

A summary of the literature on FL in ship systems is presented in Table 4.

VIII. FEDERATED EMS FOR A FOUR-ZONE SPS

In this section, a case study of using the FL approach to implement the EMS of a four-zone SPS is presented. The test system in this study is a notional maritime SPS with a 12 kV dedium voltage DC (MVDC) zonal model, where all the components in the system are divided into four separate zones. There are a total of five generating units, of which three are main power generator modules (MPGM), each with a maximum power rating of 34.48 MW and two auxiliary power generator modules (APGM), each rated at 4.48 MW. The system load consists of two propulsion motor modules (PMM) and service load modules distributed among the four zones of the SPS model. An illustration of the SPS model is provided in Figure 22. The pulsed power loads (PPL1 and PPL2) and the electrostatic discharge gun (EDG) are kept inactive since controlling such high ramp rate loads is beyond the scope of this work.

The key objective of the EMS of this SPS is to ensure that the generators provide sufficient power to meet the system load demand, made up of the propulsion and service loads. In order to meet this objective, the EMS has to ensure that each generator has optimal power output and power sharing among each other. The cost function for the main and auxiliary generators can be expressed by (6) and (7), respectively [42].

$$c_i(P_i) = (87.52 - 1.87\, P_i + 0.06\, P_i^2 - 0.0007\, P_i^3)P_i \tag{6}$$

$$c_i(P_i) = (82.62 - 6.942\, P_i + 0.663\, P_i^2)P_i \tag{7}$$

The generators share power with each other to meet the entire load demand of the system, making it a distributed optimization problem for the EMS. The total cost function and the optimization problem for each controller can be expressed as:

$$\begin{aligned} &\min_{P_i, P_{ji}} \left(c_i(P_i) + \sum_{j\in N_i} f_i(P_{ji}) \right) \\ &\text{subject to} \quad \sum_{j\in N_i} P_{ji} + P_i = P_{L,i} \\ &P_i^{\min} \leq P_i \leq P_i^{\max} \end{aligned} \tag{8}$$

Here P_i, P_{ji}, and $P_{L,i}$ are the output power of the generator, the power transferred from generator j to generator i, and the load demand for each generator, respectively.

The gated recurrent unit (GRU) is a type of RNN designed to handle sequential data. The basic idea behind GRU is to use gating mechanisms to selectively update the hidden state of the network at each time step. This is done by controlling the flow of information in and out of the network via the reset gate and the update gate. The reset gate determines how much of the previous hidden state should be forgotten, while the update gate determines how much of the new input should be used to update the hidden state. In other words, the reset gate can discard irrelevant past information and the update gate controls the balance between keeping past information and incorporating new information. This improves the network's ability to remember important details for longer periods, making it suitable for carrying out EM in this SPS, where it has to predict the output power of generators in a sequential manner. The output of the GRU is calculated on the basis of the updated hidden state [145].

The equations used to calculate the update gate output (z_t), reset gate output (r_t), candidate hidden state ($\tilde{h}$) and hidden state (h_t), using sigmoid (σ) and the tanh activation functions, and GRU model parameters such as update gate weights (W_z) and biases (b_z), reset gate weights (W_r) and biases (b_r) and hidden state weights (W_h) and biases (b_h) are as follows:

$$z_t = \sigma(W_z.[h_{t-1}, x_t] + b_z) \tag{9}$$

$$r_t = \sigma(W_r.[h_{t-1}, x_t] + b_r) \tag{10}$$

$$\tilde{h_t} = \tanh(W_h.[r_{t-1}.h_{t-1}, x_t] + b_h) \tag{11}$$

$$h_t = (1 - z_t).h_{t-1} + z_t.\tilde{h_t} \tag{12}$$

The LSTM, another variant of RNNs, employs three gating mechanisms–forget gate (f_t), input gate (i_t), and output gate (o_t)–alongside a cell state (C_t) to manage sequential dependencies. These gates, governed by (σ) and (tanh) functions, regulate information retention, integration, and propagation:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{13}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{14}$$

$$\widetilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{15}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C}_t \tag{16}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{17}$$

$$h_t = o_t \odot \tanh(C_t) \tag{18}$$

Here, C_{t-1} is the previous cell state, $\odot$is element-wise multiplication, W_f, W_i, W_C, W_o are learnable weight matrices and b_f, b_i, b_C, b_o are learnable bias terms. (C_t) preserves long-term dependencies through additive updates, while the hidden state (h_t) captures short-term context. This architecture enables LSTMs to mitigate vanishing gradient issues, making them effective for sequential tasks like power prediction in SPS [146].

DNNs process inputs in a single pass with no internal memory of previous inputs, and they are good at tasks where each input is independent of the others or non-sequential data. Recurrent connections in RNNs allow information to persist across time steps, enabling them to model dependencies in sequences, making them suitable for tasks like time-series prediction, language modeling, and speech recognition [147]. Standard RNNs, however, struggle with long-term dependencies due to vanishing/exploding gradients; RNNs with GRU and LSTM cells can better retain and control information over long sequences for sequential data [148]. Since the power and load data for the given SPS in this case study are sequential in nature, RNN models with

TABLE 4. Summary of federated learning applications in ship systems.

Reference	Application	FL Algorithm	Drawbacks
[129]	Fault Diagnosis	AdaPFL	Simulated data; scalability limitations
[131]	Fuel Efficiency	FedAvg	Synthetic data evaluation
[21]	Fuel Efficiency	FedAvg	Limited to 2 agents
[132]	Intrusion Detection	FedBatch	Assumes uniform data distribution
[133]	Byzantine Robustness	DisBezant	No real dataset validation
[134]	Poisoning Prevention	CLMD	Lacks maritime data
[135]	Predictive Maintenance	FedAvg, FedProx, FedSGD	Energy consumption not addressed
[136]	Collision Avoidance	FedAvg	High computational requirements
[137]	Collision Avoidance	FedAvg	Simulated data used
[138]	Anomaly Detection	Prototype-based	No ground truth data
[139]	Battery Health	FedChain	No improvement over centralized ML
[140]	Cyber-Attack Detection	FedAvg	Limited client count
[141]	Vessel Location	FedProx	High client-drift
[142]	Ship Detection	FedAvg, FedProx, FedOpt	Privacy-performance tradeoff
[143]	Load Prediction	Federated XGBoost	Implementation barriers
[144]	Fuel Prediction	FedAvg	Common objective assumption
[145]	Maritime Comm.	Part-FL (PFL)	Poorly correlated data issues

LSTM and GRU cells have been used instead of a simple fully connected DNN or a standard RNN.

The general representation of the proposed FL-based EMS for the SPS is illustrated in Figure 23. Here, the hierarchical control structure of the SPS is also illustrated with the FL-based EMS being carried out at the tertiary level of control. In the EM layer, each generator is controlled by its individual controller, which uses RNN models with LSTM or GRU cells. Each of these five controllers is an agent in the FL system, and they predict the output power of the respective generator they are controlling. For this implementation, the total dataset has been equally divided among each client in the network and all five clients participate in each round of training. Each round of the FL process begins with the server sending the current global model to all five agents in the SPS. After this, the agents simultaneously train the global model in a distributed manner using their local data, comprising the system load profile and respective output power for the generator they are controlling. Once local training is completed for each agent, the updated local model parameters from each agent are sent to the server. The server then uses the FedAvg aggregation algorithm and compiles a new global model from these local model updates. In this way, the EM optimization using FL continues until the specified number of communication rounds is completed.

To verify the accuracy of the proposed EMS, experiments were carried out with a load profile that has 4200 seconds of data obtained from the SPS operation shown in Figure 24. The FL-based EMS is trained on the first 2940 seconds of the data, and the remaining 1260 seconds of the data are used for testing purposes, i.e., a 70-30 split of the data is done. Each DL model used the Adam Optimizer to minimize the loss function during training and the rectified linear unit (ReLU) activation function to introduce non-linearity to capture the complex ship load profiles. A batch size of 2048 and a learning rate of 0.001 were chosen for each DL model. The mean squared error (MSE), where the difference of the actual power output y_i and predicted power output $\hat{y}_i$ is squared as shown in (19), was chosen as the loss function. This is because MSE is more sensitive to outliers and prevents large errors due to the squaring operation. Comparison is also made with the centralized learning (CL) paradigm, where a single network is used to predict the output power for all five generators. The FL system has five networks for the five clients, where each was trained for 10 epochs each round for a total of 20 FL rounds, resulting in a total of 1000 training epochs. To ensure fair comparison, the centralized system was also trained for a total of 1000 epochs using the same RNN models with GRU and LSTM cells, with all the other hyperparameters being the same. Both FL and CL systems were trained and tested on the same hardware, consisting of an Intel Core i7 processor and 16 GB of RAM. A summary of all the model parameters chosen for both FL and CL systems is represented in Table 5.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{19}$$

The proposed FL-based EMS demonstrated better performance across both GRU and LSTM models compared to the centralized system. In the FL system with GRU models, the total predicted power output of the SPS, calculated by

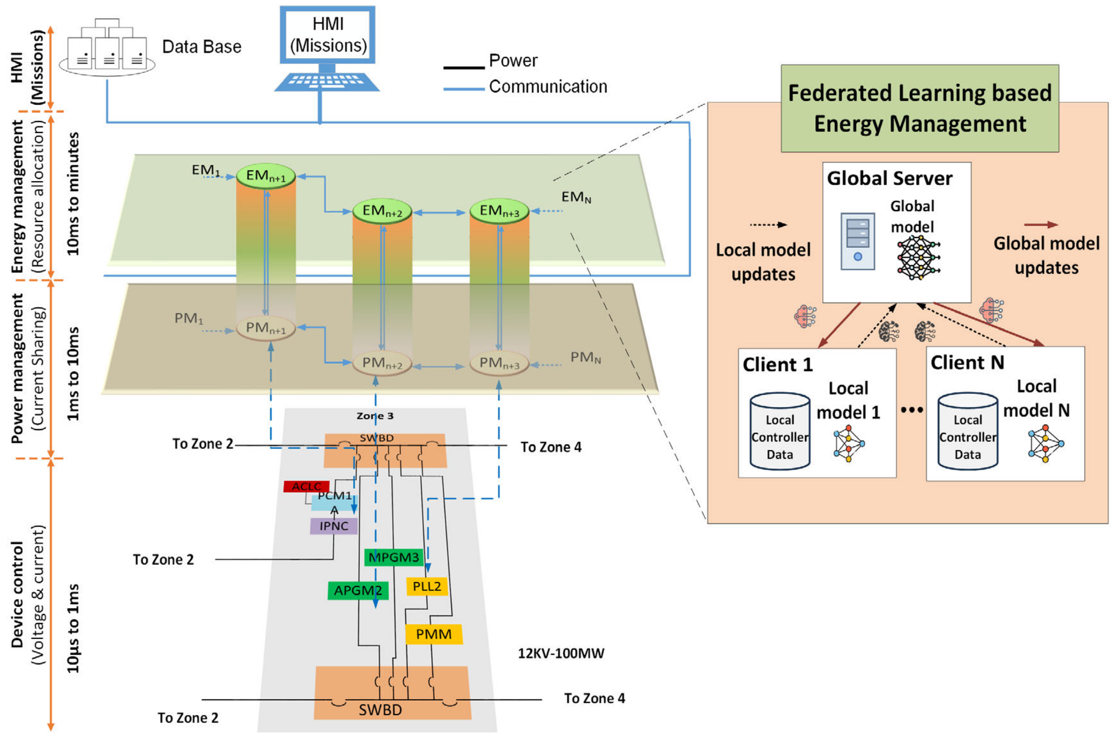

FIGURE 23. FL-based EMS for the SPS.

TABLE 5. Model parameters for FL and CL.

Parameter	FL	CL
Activation function	ReLU	ReLU
Optimizer	Adam	Adam
Learning rate	0.001	0.001
Batch size	2048	2048
FL communication rounds	20	N/A
Number of FL clients	5	N/A
FL client training epochs	10	N/A
CL total training epochs	N/A	1000

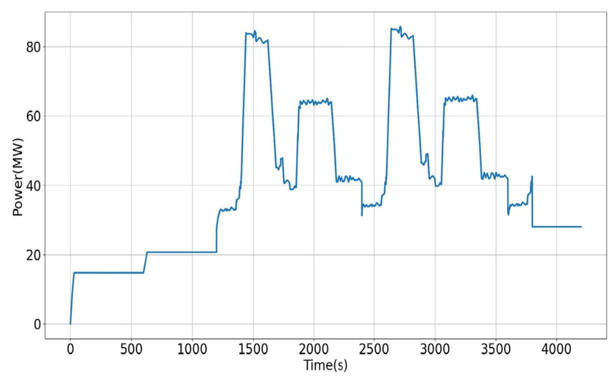

FIGURE 24. Load profile used in the setup.

aggregating the predicted output power for all five generators, deviated by 235 kW on average from the original value, achieving an average percentage discrepancy of 0.55% as shown in Figure 25. Figure 26 verifies that the GRU-based EMS, utilizing FL, maintained stable synchronization with dynamic load variations, having an average mismatch of 277 kW between the predicted value of the total generated power and the system load demand, which represents a mere 0.56% deviation. For the centralized system using GRU, on the other hand, there were more deviations between the total predicted power output and the original total output power of the SPS, with an average deviation of 547 kW and an average percentage discrepancy of 1.71% during the testing period, as shown in Figure 27. Figure 28 illustrates that the centralized GRU-based EMS was able to achieve less stable synchronization with load variations in comparison to the FL setup, having an average mismatch of 565 kW between the predicted value of total generated power and system load demand, which accounts for a percentage deviation of 1.65%. The times taken to run the simulation for the FL and CL systems using GRU models, for the same number of epochs and on the same hardware, were 4683 seconds and 4687 seconds, respectively. This proves that using GRU models, FL is able to achieve higher accuracy than conventional CL while roughly taking the same computation time.

The LSTM model also demonstrated good predictive performance for both FL and CL setups. Figure 29 shows

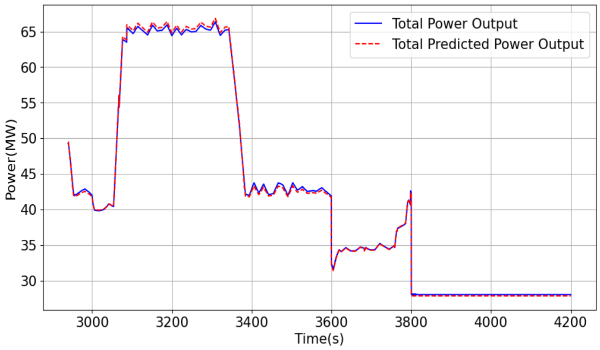

FIGURE 25. Total power output original vs. predicted for GRU in FL setup.

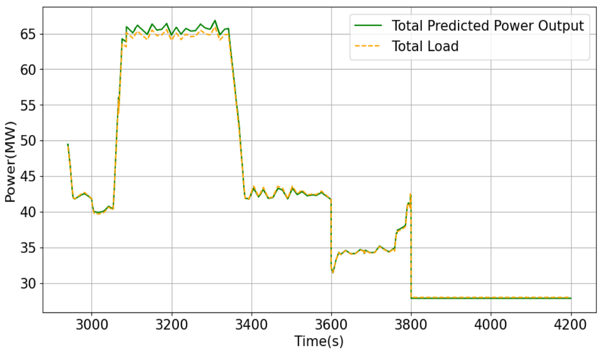

FIGURE 26. Total predicted power output and system load for GRU in FL setup.

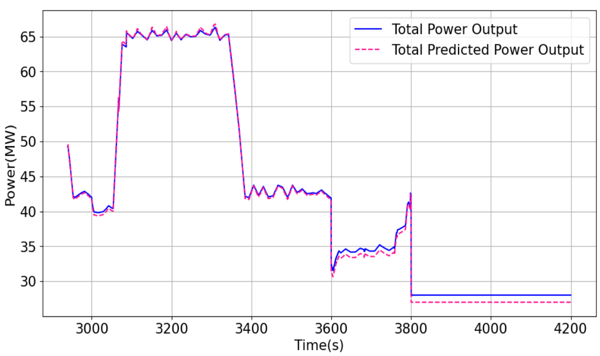

FIGURE 27. Total power output original vs. predicted for GRU in CL setup.

the total aggregated power output predicted by the LSTM model in the FL setup, which deviated from the original total power output by 286 kW on average, corresponding to an average percentage difference of 0.72%. Figure 30 underscores the LSTM-based EMS's ability to meet the system load demand successfully, maintaining an average mismatch of 248 kW or 0.72% between the total predicted power and the load demand. In the CL setup, there was a higher deviation of 310 kW on average, translating to an average percentage difference of 0.83% between the total predicted output power and the total original output power as shown in Figure 31. Similarly, the CL-based EMS with

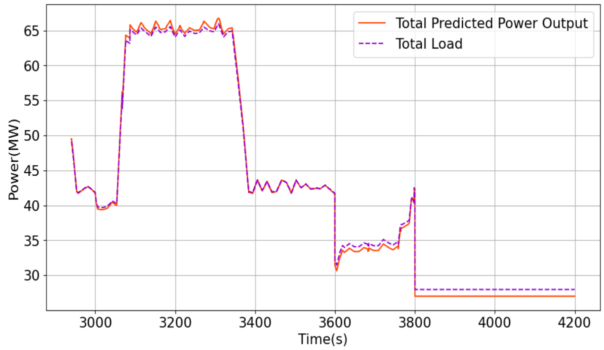

FIGURE 28. Total predicted power output and system load for GRU in CL setup.

LSTM model also struggled to keep up with the FL system to meet the system load demand, maintaining an average mismatch of 346 kW or 0.81% between total generated power and the load demand as illustrated in figure 32. Using LSTM models, the FL system had a simulation run time of 4224 seconds, and the CL setup took a total of 4216 seconds of run time. This once again reinforces the fact that FL is more accurate than CL while almost taking the same computational time. The results from the LSTM and GRU-based EMS for both FL and CL setups are compared in Table 6. The FL setup achieved higher prediction accuracy using both the GRU and LSTM models while roughly taking the same computation time. The LSTM architecture containing both cell and hidden states performed better on the CL setup, where a single, more complex network is required to predict output power for all five generators. Whereas the simpler GRU architecture with only a hidden state performed better in the FL setup, where five smaller networks, each with a simpler task of predicting the respective generator's power output, are used.

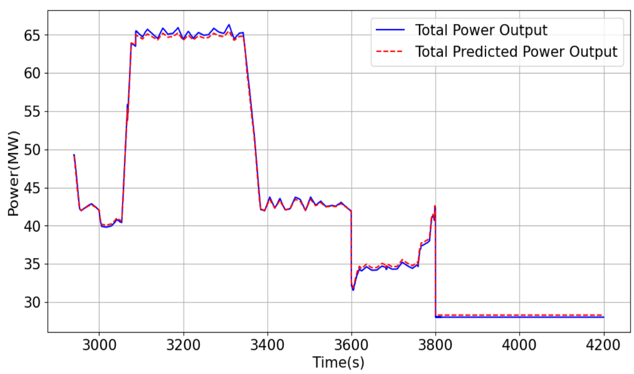

FIGURE 29. Total power output original vs. predicted for LSTM in FL setup.

IX. FUTURE RESEARCH DIRECTIONS

A. ADAPTATION TO HETEROGENEOUS DATA DISTRIBUTIONS

A common problem in FL scenarios is non-IID data across different clients. This is not uncommon in ship applications

TABLE 6. Comparison of FL against centralized DL for LSTM and GRU models.

Metric	LSTM		GRU	
	FL	CL	FL	CL
Total Power, Predicted vs. Original % Average Difference	0.72%	0.83%	0.55%	1.71%
Total Predicted Power vs System Load % Average Difference	0.72%	0.81%	0.56%	1.65%
Run time	4224 s	4216 s	4683 s	4687 s

either, as data from different ships or even data from different zones within a ship system could have different characteristics and probability distributions. A common issue with heterogeneous data distribution among clients is client drift, where client model updates are optimized more toward local objectives rather than global objectives [149]. In such scenarios, developing a single global model that can be generalized to different client data distributions becomes challenging. One way to mitigate this problem could be by adding regularization terms to client objective functions in order to constrain local updates close to the global model and reduce the deviation between local and global objectives. Improved aggregation methods, where more importance is given to client updates that are closer to the global model, through weighting mechanisms, can be another viable option to reduce the effect of client data variance and improve overall model performance. Personalized FL (PFL) is another solution to account for data heterogeneity among clients. It is a type of FL approach where model training is adapted to the different data distributions present in each client without compromising privacy [150]. This helps to reduce the difference between the client local models and the global model. PFL can be carried out through global model personalization, where the aggregated global model is personalized for each client by training it again on their local dataset. On the other hand, individual personalized models can be trained by each client, tailored to their local data distribution [151]. Other approaches, such as FedClust [152], where clients are grouped into clusters

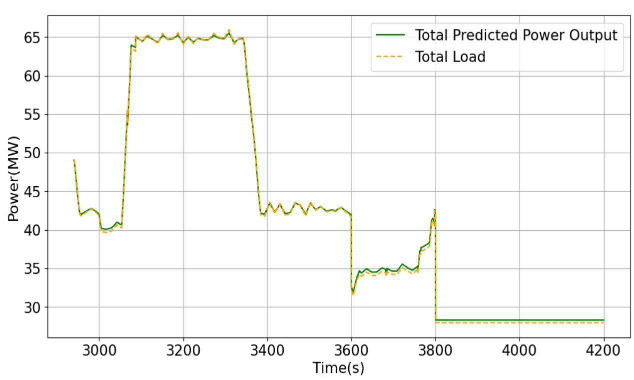

FIGURE 30. Total predicted power output against load profile for LSTM in FL setup.

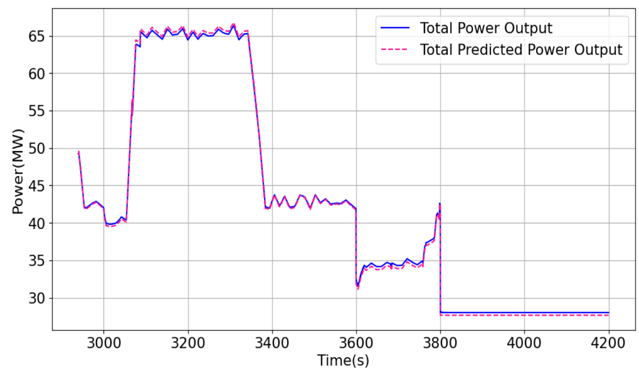

FIGURE 31. Total power output original vs. predicted for LSTM in CL setup.

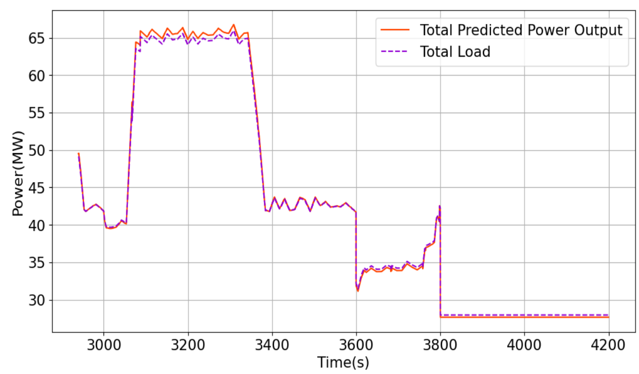

FIGURE 32. Total predicted power output against load profile for LSTM in CL setup.

based on data distribution similarity, and virtual homogeneity learning (VHL) [153], where a virtual homogeneous dataset is created to calibrate features from clients, are possible solutions that have not been applied in FL for energy systems or ship applications yet. In VHL, a separate virtual dataset that contains no private information from any of the clients is created and shared among all the clients for training, along with their own local data. Optimizing the local models on the shared virtual data helps the clients to get closer to the global objective, leading to a reduction in client drift and an improvement in overall convergence.

B. MODEL COMPRESSION TO REDUCE COMPUTATION AND COMMUNICATION REQUIREMENTS

In ship applications, computation and communication resources are limited, and this can be a bottleneck for

FL systems involving complex DL models with a large number of parameters. By integrating model compression techniques such as model pruning and quantization into the FL framework, communication overhead can be further decreased in FL. Model pruning can reduce the size and complexity of a DL model by removing less important weights and connections. This leads to benefits like smaller model size, faster inference, lower memory usage, and overall improved efficiency. Since some of the model parameters are removed during pruning, it can lead to lower accuracy; however, pruned models are usually fine-tuned or re-trained to mitigate this [154]. Quantization is used to reduce the precision of a model by using fewer bits to represent the model parameters. This involves converting the model parameters from high-precision data formats like 32-bit floating point (FP32) to lower precision formats like 8-bit integer (INT8). The quantization process leads to a reduction in model size, faster prediction times, and uses less memory and energy resources, allowing for deployment on resource-constrained devices [155]. Model pruning and quantization can be particularly useful for resource-constrained shipboard devices, as training smaller models reduces the computational requirements on the client side and leads to faster inference time and lower energy requirements. Moreover, a reduction in model size causes smaller model updates to be transferred over the communication network, leading to reduced communication overhead.

C. PHYSICS-INFORMED FL FOR SHIP APPLICATIONS

Physical ship dynamics can be incorporated into the FL training process to enhance prediction accuracy through physics-informed neural networks (PINNs). Neural networks often lack physical validity; integrating physics into the FL setup could improve ship performance forecasts under variable sea conditions. PINNs are a category of NN that integrates information about the underlying physics of the system through equations into the training process. Unlike conventional NNs, PINNs enforce physical constraints along with learning from past data, leading to more accurate predictions. PINNs can be used in scenarios that require solving complex scientific problems [156]. PINNs integrated with FL can leverage both the superior accuracy of PINNs and the privacy-preserving characteristic of FL for better model training. PINNs can incorporate physical constraints into neural networks, while FL can enable collaborative training on distributed datasets without sharing data directly. This combination is particularly useful when data is sensitive, geographically distributed, and when incorporating physical knowledge can improve model accuracy and generalization. Moreover, since PINNs utilize physical laws to guide the learning process, they can provide accurate predictions with less data in comparison to traditional ML and DL models. They can also provide better predictions than conventional NNs with noisy or incomplete data. This is particularly useful for maritime applications since the operating conditions vary a lot, and it is not possible to train the model with data representing all kinds of operating scenarios. However, training PINNs can be computationally expensive, especially when dealing with complex physical constraints.

D. REAL-TIME FL IMPLEMENTATION AND HARDWARE VALIDATION

While existing studies demonstrate FL's potential in simulations, hardware validation remains critical to address the gap between theoretical performance and real-world operation. FL systems can be implemented on real-time testbeds like controller hardware-in-the-loop (CHIL) testbeds to evaluate computational constraints, communication overhead, latency, and energy consumption of FL algorithms under actual operating conditions. Transitioning from simulation-based studies to real-time deployment can quantify FL's responsiveness to generator ramp-rate limits or pulsed loads in a hardware setup. Such validation can provide more detailed insights on trade-offs between local training and global model aggregation, particularly for resource-constrained shipboard devices. Additionally, hardware testing could identify failure modes unique to maritime environments, such as adverse weather conditions or thermal stress on controllers. Bridging the gap between simulation studies and real-time hardware testing is essential to optimize FL frameworks for ship applications, ensuring they meet the required response times and reliability standards.

X. CONCLUSION

An effective EMS is pivotal for modern maritime operations, balancing key objectives such as fuel efficiency, reducing negative environmental impacts and ensuring operational reliability. This paper presented a comprehensive review of EMS methodologies for SPS, emphasizing the integration of advanced computational techniques to address the unique challenges of dynamic, isolated marine environments. Traditional EMS strategies, including evolutionary algorithms, MPC, and fuzzy logic, were systematically analyzed, revealing their strengths in optimization and predictive accuracy but also underscoring critical limitations such as implementation complexities, scalability issues, and a few more. The exploration of ML and DL algorithms highlighted their potential in predictive analytics, load forecasting, and adaptive control. However, the conventional centralized ML and DL frameworks face inherent risks related to data privacy and communication overhead. FL has been identified as a solution, enabling decentralized, privacy-preserving model training across distributed clients or systems. By eliminating raw data exchange and leveraging collaborative learning, FL has been able to address cybersecurity concerns while maintaining high predictive accuracy in MG systems such as SPS applications, as demonstrated through several references on fuel consumption optimization, fault diagnosis, cyber-attack detection, etc. To further illustrate FL's practical efficacy in maritime applications, the case study of a four-zone MVDC SPS was explored. Utilizing LSTM and

GRU models within an FL framework, the system achieved minimal prediction discrepancies with average generator power output differences between 0.72% and 0.54% and only a difference of 0.72% and 0.56% between the total generation output and the system load for the LSTM and GRU models, respectively. Comparison was made with the CL setup, and the results confirmed higher accuracy of FL over CL for both GRU and LSTM models while taking the same computation time. These results underscore FL's potential to successfully carry out global optimization across distributed systems in dynamic environments. However, real-time experiments across diverse ship configurations and operational scenarios will be critical in validating FL's scalability and resilience. This has not been explored a lot in current literature and remains a challenge and an area of future research. Moreover, there are a few other challenges in applying FL in ship systems, such as data heterogeneity among clients, limited computational resources and communication bandwidth, increased model parameters for large systems, and more. A few of these challenges and the possible solutions have been discussed in the paper to provide future research directions in this area. The naval transportation sector is crucial for trade, tourism and military applications, and it is imperative to make it as efficient and as environmentally friendly as possible. Data-driven approaches such as FL not only promise enhanced operational efficiency and environmental compliance in ship EMS but also ensure secure and privacy-preserving data communication, which is a necessity in modern times.

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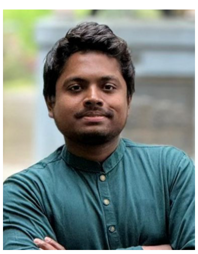

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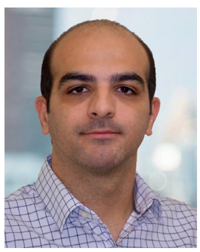

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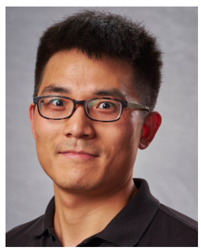

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