Secure Energy Management for Ship Power Systems using Federated Learning

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***Abstract*—This paper presents a Federated Learning (FL) based Energy Management System (EMS) for Ship Power Systems (SPS). The proposed method addresses the challenges of maintaining a stable power supply while ensuring data privacy, a critical concern in shipboard environments. The FL framework enables collaborative training of Gated Recurrent Unit (GRU) models across multiple generators without sharing sensitive local data. The use of FL, along with mitigating some of the security concerns associated with centralized Machine Learning (ML) configurations, also reduces the computational requirements making the overall framework more scalable. The system was trained using load data from a Medium Voltage DC (MVDC) SPS. The results demonstrate accurate power output prediction and effective load management, indicating the potential of the proposed approach to enhance energy efficiency and reliability in ship systems.**

***Index Terms*—Federated Learning, Energy Management, Ship Power System, Gated Recurrent Unit.**

I. Introduction

Electric Ship Power Systems (SPS) rely on electric power generators, energy storage systems such as battery banks, and renewable energy sources such as photovoltaic panels for power and propulsion. This combination significantly reduces the dependency on fossil fuels and 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]. 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].

To meet the challenging operating conditions of the SPS, an effective Energy Management System (EMS) is crucial. The primary goal of an EMS is to ensure an adequate supply of energy at minimal cost. The EMS 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. It 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]. An EMS is 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.

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. Unlike traditional programming, where explicit instructions are required, ML algorithms learn from past data and can improve their performance over time through experience and learning from new data with minimal human intervention. Several studies have used ML and DL to improve the operation of EMSs. The authors in [4] developed a Random Forest Regression (RFR) model to predict the fuel consumption of the ship using the speed of the sail, the weight of the cargo, the weather and the sea conditions. An Artificial Neural Network (ANN) model was used to improve energy efficiency by optimizing and predicting fuel consumption in ship systems in [5]. In study [6], an intelligent EMS based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) was implemented to optimize the power distribution in a hybrid SPS consisting of fuel cells and batteries, with the aim of improving energy efficiency. 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 State of Charge (SoC). However, only simulation-based results were provided, and the study lacks validation through

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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 [7]. 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. In addition, Reinforcement Learning (RL) techniques such as Deep Reinforcement Learning (DRL) have been employed for optimal control of DC SPS in [8], demonstrating improved load current sharing, better DC bus voltage regulation and fast charging of energy storage units.

Although conventional ML and DL models with centralized training have shown promise in EMS, they face challenges when applied to dynamic and distributed systems, such as SPS. These challenges include data privacy concerns, high computational complexity, and reduced response times. Cyber-physical security and data privacy are key concerns in modern ship systems, particularly naval vessels where the controllers that are responsible for system monitoring and automated control are prime targets for cyberattacks [9]. Federated Learning (FL) has emerged as a solution to these problems, enabling collaborative training of ML models in distributed environments without sharing sensitive data. FL has been applied in ship systems in some scenarios. For example, an FL approach was used for collaborative fault diagnosis among shipping agents, improving training efficiency [10]. The authors in [11] developed an FL framework to predict ship fuel consumption and optimize sailing speed while addressing data privacy issues. FL has also been utilized to predict engine efficiency using fuel consumption data and weather information, improving privacy and reducing communication overhead [12]. FL has been employed to predict the primary power of the ship's engine using various ML models, showing a precision comparable to centralized methods while maintaining data privacy [13]. Angelopoulos et al. [14] applied FL for predictive maintenance tasks in ship systems, including predicting degradation, monitoring engine condition, and predicting fuel consumption.

A. *Contribution and Structure of the Paper*

The main contributions of this research include:

- Introduction of an FL framework for energy management of SPS while ensuring data privacy and security by enabling collaborative model training without sharing sensitive local data.
- The proposed framework utilizes Gated Recurrent Units (GRUs) to predict and optimize the power output of individual generators in a distributed manner. GRUs are chosen for their ability to handle sequential data efficiently, making them well-suited for dynamic and time-varying load profiles in SPS.
- The FL-based EMS is validated using verified load data from an MVDC SPS, demonstrating its ability to accurately predict generator power outputs and effectively manage system load demand.

The rest of the paper is organized as follows. Section II discusses the methodology of the proposed EMS framework, including the SPS model, GRU architecture, and FL implementation. Section III presents the experimental setup, results, and key findings from the FL-based EMS. Finally, Section IV concludes the paper, highlighting some future research directions.

II. Methodology

A. *Energy Management System (EMS)*

The main objective of an EMS is to ensure an adequate supply of energy at a 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 are met. 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 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. In islanded MG systems, such as SPS, energy management is critical to maintaining a steady supply of power to the load, reducing emissions and fuel consumption, accommodating pulsed power loads and maintaining the desired state of charge for energy storage devices [15].

The energy management layer falls in the tertiary control layer for ship MG systems. Ship MGs have a hierarchical control structure in which the control structure is divided into different levels or hierarchies of control. This architecture helps to coordinate different types of components within an SPS based on their functionality and operating timescale. There is the primary control level, which comprises the device layer control and focuses on individual component control. It operates on the fastest timescale from microseconds to milliseconds. Then there is the secondary control which carries out power management and operates on a slower timescale in the range between milliseconds to seconds. Finally, there is the tertiary control layer, which is responsible for energy management and operates on the slowest timescale, seconds to minutes [2].

In shipboard MG systems, an EMS is essential due to unique operational challenges like isolation from external power grids and the necessity for high reliability. The workflow of an EMS usually involves obtaining data from the system, feeding the data into the energy management optimization algorithm and then finally producing operational set points which are to be implemented by the real-time control system. It 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. The EMS has to ensure that it can meet the computational limitations of the physical system while maintaining the desired performance standards [15]. 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 emissions from these systems. An effective EMS can significantly decrease fuel consumption and emissions by optimizing the operation of generators and integrating energy storage systems [16]. The functioning and working principle of the EMS implemented in this work for a notional four-zone SPS based on FL and GRUs is explained in detail in section II-E.

B. Ship Power System (SPS) model

The EMS in this research is developed for a notional navy SPS. The SPS is a 12 kV Medium 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 1. 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.

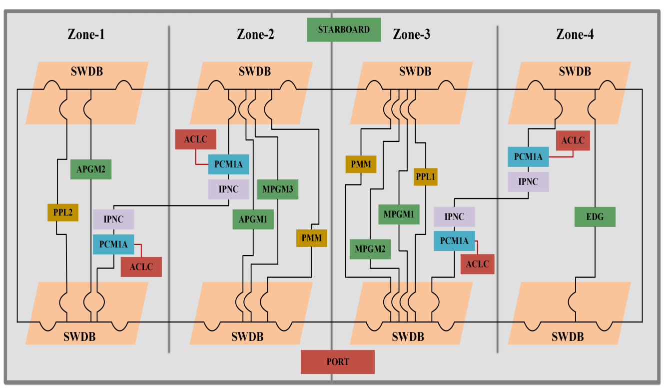

Fig. 1. Four-zone SPS model

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 (1) and (2) respectively [17].

$$c_i(P_i) = (87.52 - 1.87P_i + 0.06P_i^2 - 0.0007P_i^3)P_i \qquad (1)$$

$$c_i(P_i) = (82.62 - 6.942P_i + 0.663P_i^2)P_i \qquad (2)$$

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:

$$\min_{P_i, P_{ji}} \left(c_i(P_i) + \sum_{j \in N_i} f_i(P_{ji}) \right) \qquad (3)$$

$$\text{subject to} \quad \sum_{j \in N_i} P_{ji} + P_i = P_{L,i}$$
$$P_i^{\min} \leq P_i \leq P_i^{\max}$$

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.

C. Gated Recurrent Unit (GRU)

The GRU is a type of RNN designed to handle sequential data. It is an improved version of the LSTM; unlike LSTMs, GRUs do not have a cell state but only a hidden state, making the architecture simpler and faster to train. 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 energy management 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 [18].

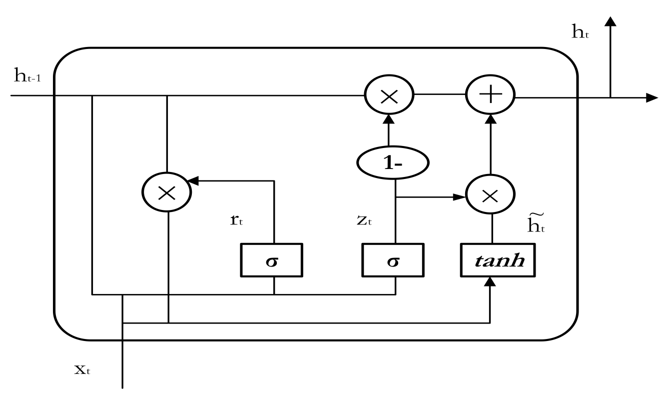

Fig. 2. GRU architecture

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:

$$z_t = \sigma(W_z.[h_{t-1}, x_t] + b_z) \tag{4}$$

$$r_t = \sigma(W_r.[h_{t-1}, x_t] + b_r) \tag{5}$$

$$\tilde{h_t} = \tanh\left(W_h.[r_{t-1}.h_{t-1}, x_t] + b_h\right) \tag{6}$$

$$h_t = (1 - z_t).h_{t-1} + z_t.\tilde{h_t} \tag{7}$$

Each generator in the SPS will be controlled by a GRU which will take the system load demand as input and intelligently predict the output power for the generator to meet the system load demand. The model architecture for this specific EM optimization problem consists of an input neuron through which the load data is fed, a GRU hidden layer made up of 64 GRU cells, followed by two more fully connected hidden layers having 64 and 32 neurons, respectively and finally, the output layer having a single neuron which gives the output power for each generator it is controlling.

D. Federated Learning (FL)

Federated learning (FL) is a technique for training ML and DL models in a distributed manner in which a global server coordinates the independent training of models by a number of 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 [19].

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 [20]. 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 some 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 [19].

E. 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 [21].
2) The parameters of the global model are sent from the server to all participating clients on the network.
3) 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.
4) The server aggregates the model updates from all clients and uses an aggregation algorithm to compile a new global model. In this implementation, the Federated Averaging (FedAvg) aggregation algorithm is used to compile the global model from the client updates.

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.

FL revolves around supervised learning, where to make predictions, input values x_i are mapped to output labels y_i. The goal is to calculate the model parameter w by minimizing the loss function $F_k(w)$ for each client, i.e., for each generator in the SPS. $F_k(w)$ is calculated using (8) 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 (9). The weight update across the global optimization can be expressed as (10), where w_{new} is the newly updated weight parameter of the global model and w_k is the model weight parameter of client k.

$$F_k(w) = \frac{1}{n_k} \sum_{i \in P_k} f_i(w) \tag{8}$$

$$f(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w) \tag{9}$$

$$w_{new} = \sum_{k=1}^{K} \frac{n_k}{n} w_k \tag{10}$$

The general representation of the proposed FL-based EMS for the SPS is illustrated in Figure 3. 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 energy management layer, each generator is controlled by its individual controller, which uses the RNN models with 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 energy management optimization using FL continues until the specified number of communication rounds are completed.

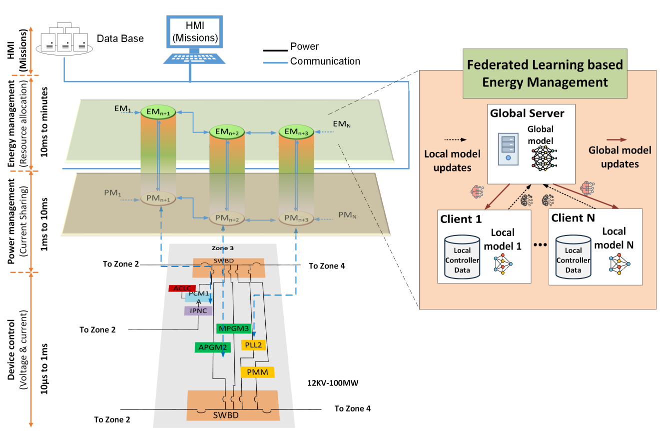

Fig. 3. FL-based EMS for the SPS

III. Results and Discussion

To verify the accuracy of the proposed EMS, experiments were carried out on two different load profiles that have 4200 seconds of data obtained from the SPS operation shown in Figure 4. The FL-based EMS is trained on the first 2940 seconds of the data, and the remaining 1260 seconds of the data is 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 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 GRU model. A total of 20 FL rounds with communication between the server and each of the five clients were carried out, and each agent trained local models for a total of 100 epochs in each of the communication rounds. A summary of all the model parameters chosen is represented in Table I. 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 (11), was chosen as the loss function. This is because MSE is more sensitive to outliers and prevents large errors due to the squaring operation.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{11}$$

TABLE I
Model Parameters

GRU Model	**Parameter**
Activation function	ReLU
Optimizer	Adam
Learning rate	0.001
Batch size	2048
FL	
Communication rounds	20
Number of clients	5
Client training epochs	100

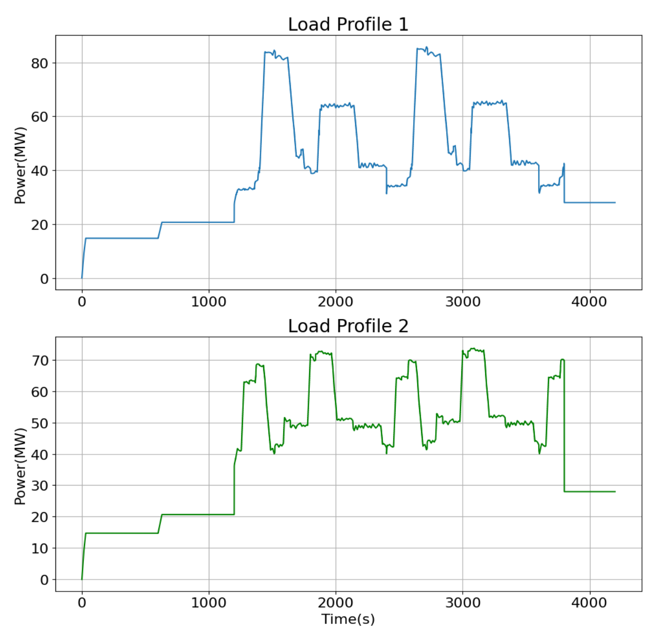

Fig. 4. Load profiles 1 and 2 used in the setup

The power output for the main generator, MPGM1 and auxiliary generator, APGM1 as predicted by their respective controllers for load profile 1, are illustrated in Figure 5 and Figure 6. The average differences between the original and predicted power output for MPGM1 and APGM1 were 82.68 kW and 11.27 kW, respectively. The average percentage differences between the original and predicted power outputs for the two generators were 0.77% and 0.53%, respectively, indicating high accuracy of prediction in comparison to the original power output values during the testing period. The original total power output and the predicted total output power of the SPS for load profile 1, as calculated by the FL-based EMS, are shown in Figure 7. The average difference between the original and predicted total power output was 261 kW, and the average percentage power difference was only 0.72%. Figure 8 illustrates the plot between the total power output of the SPS compared to the total system load during the testing period. The average difference between the total power output and the system load was 273 kW and the average percentage power difference was 0.65%, indicating the proposed EMS's ability to meet the system load demand successfully. The original total power output and the predicted total output power, along with the total system load profile for the entire duration, are illustrated in the same plot in Figure 9.

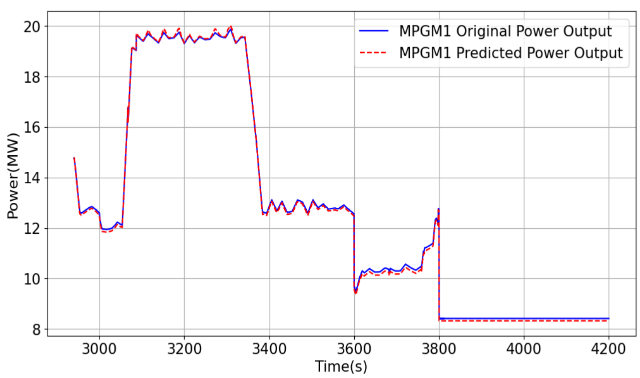

Fig. 5. Main generator predicted power output for load profile 1

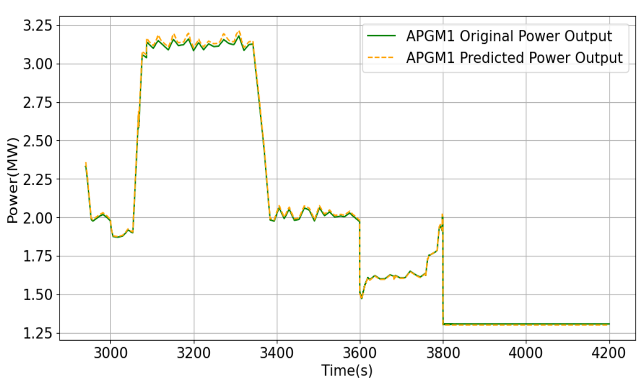

Fig. 6. Auxiliary generator predicted power output for load profile 1

In the case of the second load profile, the predicted power outputs for MPGM1 and APGM1, as generated by their controllers, are presented in Figure 10 and Figure 11. The average discrepancies between the original and predicted power outputs were 72.7 kW for MPGM1 and 15.24 kW for APGM1. The corresponding average percentage differences were 0.63% and 0.65%, respectively, underscoring the consistency and reliability of the prediction models. Figure 12 displays the original and predicted total power outputs of the SPS for the second load profile, as computed by the FL-based EMS. Here, the average difference was 237 kW, with an average percentage difference of 0.6%. Figure 13 further illustrates the relationship between the total power output of the SPS and the second

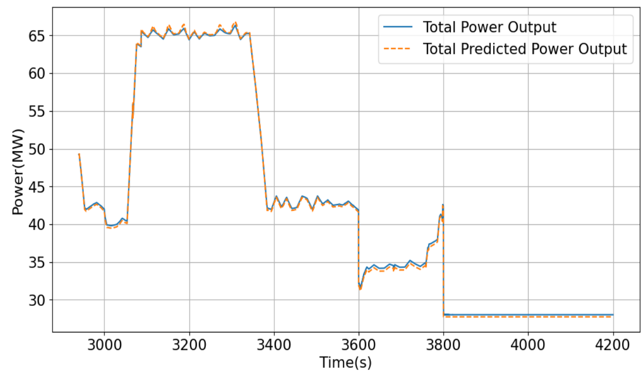

Fig. 7. Total power output original vs. predicted for load profile 1

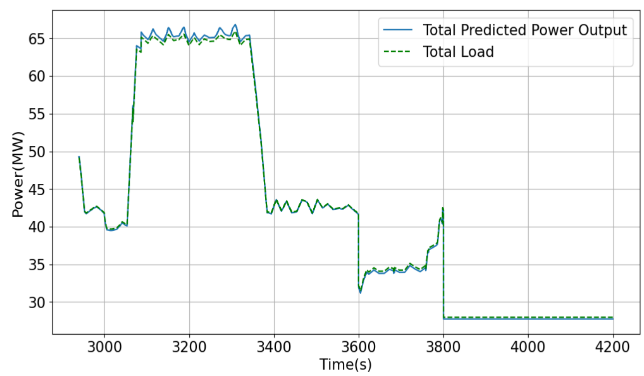

Fig. 8. Total predicted power output against load profile 1

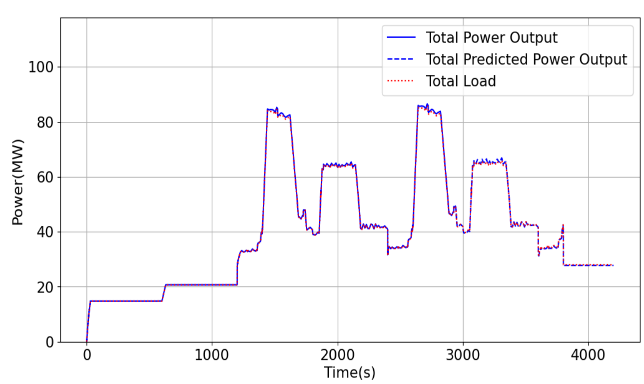

Fig. 9. Total power output against load profile 1 for entire duration

load profile during the testing period. The average difference between the total power output and the system load was 203 kW, with an average percentage difference of 0.54%. Finally, Figure 14 combines the original total power output and the predicted total power output with the total system load profile on a single plot for a comprehensive comparison.

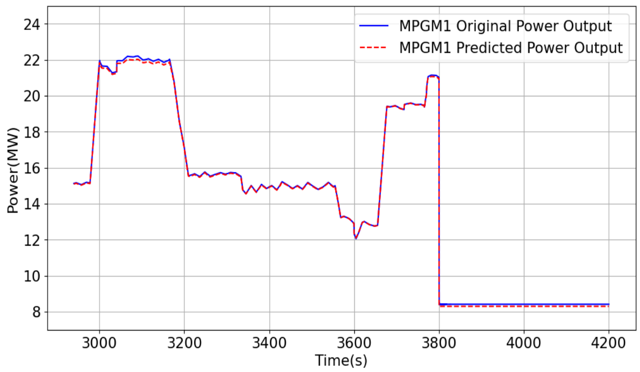

Fig. 10. Main generator predicted power output for load profile 2

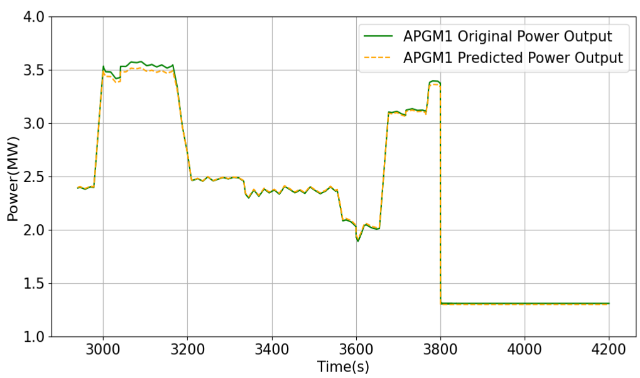

Fig. 11. Auxiliary generator predicted power output for load profile 2

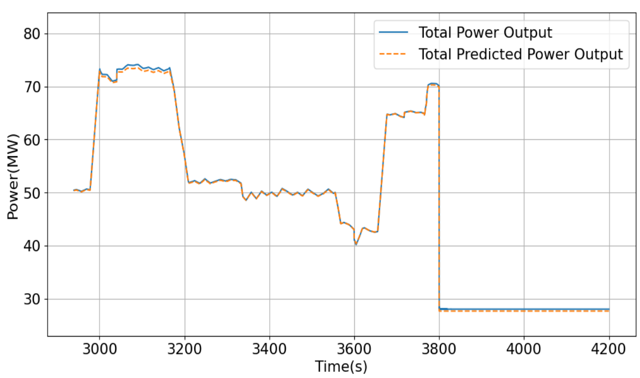

Fig. 12. Total power output original vs. predicted for load profile 2

IV. Conclusion

The paper presented an FL-based EMS for optimal power dispatch between the generators of an MVDC ship system.

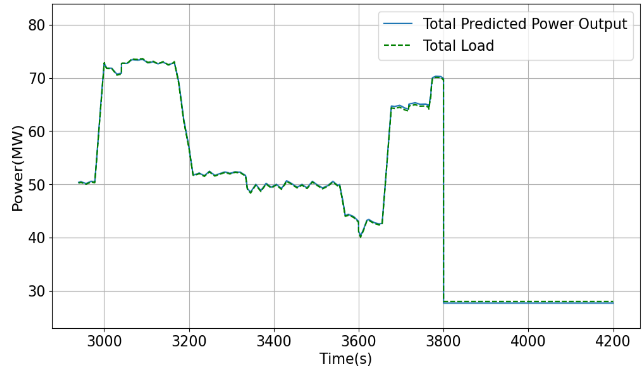

Fig. 13. Total predicted power output against load profile 2

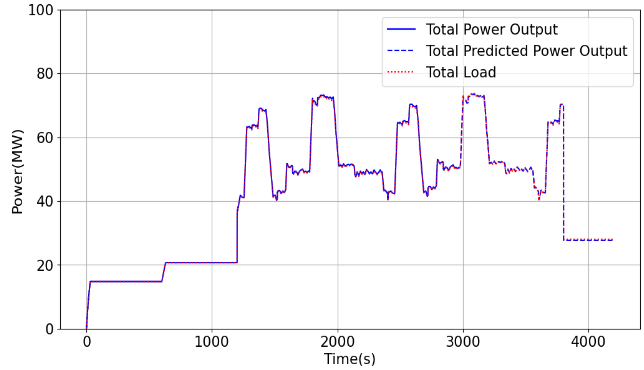

Fig. 14. Total power output against load profile 2 for entire duration

RNN models with GRU cells were used to control the power output of each generator within the FL framework. The system also improves security and privacy since sensitive data is not shared between clients and the server. Compared to traditional centralized ML configurations, the presented FL model requires lower computational resources and is more scalable. Results from the proposed model demonstrate the FL-based EMS's ability to predict each generator's output power with a high accuracy of over 99%. The EMS also managed to meet the overall system load for both load profiles fairly accurately, with an average percentage error of less than 1% in both cases. Future research directions involve exploring other federated aggregating algorithms and testing the energy management framework on more complex ship models consisting of energy storage systems.

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