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REGULAR ARTICLE

A Privacy-Preserving Energy Management Strategy for Hybrid Storage Systems with Federated Learning Algorithm

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Electric vehicle batteries need to be functional for as long as possible. This is achieved by means of Hybrid electric storage systems (HESS), which control, to a great extent, the power profiles of the charging as well as the discharging that directly impact the battery health. Hybrid Electric Storage System (HESS) integration extends battery life and optimizes energy management. In this paper, we introduce a novel energy management strategy (EMS) based on Federated Learning (FL) to address such challenges as unpredictable power demands can accelerate battery degradation. FL allows collaborative learning over multiple EVs, guarantees data privacy to facilitate accurate power demand prediction, and dynamic energy optimization. In the proposed FL based EMS, local data of individual EVs is fused and utilized to train prediction models which are aggregated into a global model. This approach is decentralized and utilizes the IoT ecosystem to improve the system-wide performance and scalability. The proposed approach is demonstrated in MATLAB simulations to reduce battery peak discharge power, minimize power variations, and increase energy efficiency. These results show the system's capacity for increasing battery life, optimizing operational efficiency, and redefining energy management in real world EV deployment.

Keywords: Energy management, Electric vehicle, Control strategy, Federated learning.

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1. INTRODUCTION

The global transition to a sustainable and greener means of transportation has created the cornerstone of Electric vehicles (EVs). The adoption rates of EVs are increasing, and technology relating to EVs is also improving, so now attention is turning to improving the efficiency and longevity of components of key importance, including the energy storage system [1]. Since one of the critical and costly components of EVs, their batteries, directly impact the performance, cost effectiveness and environmental impact of the vehicles [2]. Therefore, good management of battery usage is necessary to ensure long term sustainability.

A promising solution to overcome the drawbacks of standalone battery systems is hybrid electric storage systems (HESS). In addition, HESS can overcome the impact of sudden power fluctuations during EV operation by incorporating batteries along with super-capacitors (SCs) [3]. Yet, it remains a challenge to control the power profiles of charging and discharging within HESS. If not properly managed, variability in power demands due to dynamic driving conditions and energy usage patterns can greatly affect the health of battery [4]. Hence, a robust energy management strategy (EMS) is necessary to improve HESS performance and extend battery lifetime

New technology developments of data driven methodologies have provided the ability for development of intelligent EMS solutions [5]. Power demands have been predicted and energy efficiently allocated with the help of machine learning and optimization algorithms [6]. Convolutional Neural Networks (CNN), Genetic Algorithms (GA) as well as Seagull Optimization Algorithms (SOA) etc. have prospects for advancing energy management in HESS. While these are centralized approaches, however, they tend to suffer from scalability, computational efficiency, and data privacy issues [7]. However, preserving privacy of EV usage data to maintain system wide optimization is a significant challenge.

Federated Learning (FL) is a pioneering technique to resolving these problems [8]. FL realizes decentralized learning as individual devices train and train their models locally and only share model updates with a central server. It guarantees data privacy and makes use of the collective knowledge of a distributed network [9]. Integrating FL into the EMS framework for HESS opens the ability to predict power demand with greater accuracy,

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optimize energy distribution, and make the entire system more adaptive to different conditions. Moreover, as the decentralized nature of FL allows for integrations and high scalability, FL is best suited for the need of large-scale EV networks [10].

The problem statements considered for this study are:

- Existing strategies fail to achieve minimal battery peak discharge power and power variations, which consequently translates to less efficient energy usage and shortened battery life.
- Traditional centralized methods do not have the ability to efficiently handle large scale deployments as the number of EVs grows.
- User privacy is often sacrificed at the expense of using data driven optimization techniques, which is a roadblock to universal adoption.

This work aims to develop a privacy preserving, scalable energy management strategy for Hybrid Energy Storage Systems (HESS) used in EVs without uncertain system behaviors, while maximizing the system performance. To address these gaps, this study proposes a Federated Learning (FL) based Energy Management System (EMS). However, unlike traditional centralized methods, FL based EMS guarantees the protection of data during optimization processes, making the proposed method qualified for real world applications. Results show that the proposed approach can mitigate battery peak discharge power, reduce power variations, and improve overall energy efficiency, hence providing a universal solution for the limitations of state-of-the-art EMS strategies for HESS in EVs. The remainder of this article is organized as follows: Section 2 describes the system proposed in this study. In Section 3, the proposed algorithm and its principles are presented. MATLAB simulations are presented in Section 4 to demonstrate the results. In the end, the paper ends with conclusions, with directions for future research.

2. PROPOSED SYSTEM DESIGN

Figure 1 shows the configuration of the Energy Management System (EMS) for the IoT–enhanced Hybrid Electric Storage System (HESS). Vehicle 1 is the vehicle under consideration as the primary power source of the HESS. If two vehicles, vehicles 1 and 2, are driving in the sequence, where vehicle 2 is in front of vehicle 1, and vehicle 2 shares all the relevant operational information using vehicle-to-vehicle (V2V) communication technology, and vehicle A additionally has embedded sensors like accelerometer, gyroscope, radar, etc. along with advanced communication systems.

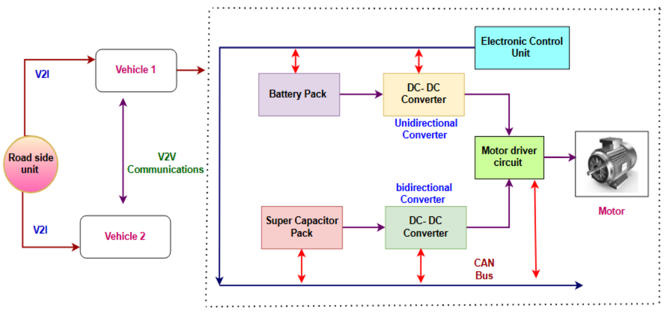

Fig. 1 – Schematic layout of the proposed system

The sensors allow the vehicle to observe critical parameters as acceleration, spacing, and speed. Moreover, the system utilizes roadside infrastructure and a vehicle to infrastructure (V2I) communication to derive and process environmental information. Periodically, this data is sent to the cloud, e.g., a centralized traffic monitoring center, to be used for real time traffic analysis. Finally, the processed results are communicated to the vehicles where they are utilized to provide actionable insights to reduce driving inefficiency and increase safety.

This system is based on electronic Control Units (ECUs) embedded in the vehicles. They can make complex computations and real time control decisions. The store, analyze, and act beachhead where data from sensors and sources outside the fog is stored, analyzed, and acted upon. The predictive algorithms employed by the EMS are used to estimate the power consumption of the system. Using a Federated Learning (FL) – based methodology, power consumption prediction is performed in this research in a decentralized, yet collaborative, distributed paradigm with privacy preserved. Aggregated vehicle updates iteratively refine the system's neural net models to better and more efficiently manage energy. In dynamic traffic environments, the proposed approach shows much better performance than the existing algorithms in terms of design complexity, scalability, and privacy and operation reliability for HESS in electric vehicles.

3. PROPOSED ALGORITHM

Federated Learning (FL) framework is expected to predict the power demands of a network of EVs. In a contrast to centralized systems, FL allows individual vehicles to train their local models using their own data and send only the model updates to the centre server. Unlike in the centralized approach, this decentralized formulation ensures the scalability of the algorithm to large networks of EVs while preserving the data privacy.

FL uses vehicle sensors and IoT based communication systems to provide real time velocity, acceleration, battery usage and energy consumption patterns from the EMS. Local training of its predictive models is done over these data points. Finally, the models are aggregated at a central server and a global model is built to be transmitted back to the vehicles to improve the power demand prediction accuracy. As shown in table 1, the FL framework is implemented with the configurations.

Table 1 – Proposed framework configuration

S. No	Parameter	Value
1	Batch Size	32
2	Learning Rate	0.001
3	Communication Rounds	50
4	Architecture	1 hidden layer, 128 neurons

Centralized approaches to managing energy in the existing centralized system has an inability to satisfy the privacy issue and does not scale well. Additionally, they cannot cope with the time varying traffic and driving conditions, resulting in inefficient power allocation. On the other hand, the FL based EMS better predicts the power demand and is thus able to meet the sudden power surges with the super capacitor (SC). It lowers the peak discharging load on the battery, thereby mitigating its wear and expanding its lifespan.

$$g_{g(x)} = \frac{1}{k}\sum g_k(x) \tag{1}$$

Here, K is number of participating vehicles. $g_k(x)$ represents the local gradient for vehicle k. $g_g(x)$ is the global gradient used to update the shared model.

3.1 Optimization of Federated Learning Moels

To improve the performance of the FL based EMS, an optimization phase is added to refine the neural network's weight parameters. During this phase it harness advanced optimization techniques that balance the exploration and exploitation in the model parameters space.

$$FF = min\left(\frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|\right) \tag{2}$$

Here, FF is the fitness function. N is number of data points. y_i and $\hat{y}_i$ are the actual and predicted power demands. The proposed EMS integrates the optimization process within the FL framework to overcome problems that traditional methods suffer from, mainly scalability, privacy, and energy efficiency, and demonstrate impressive performance. Federated Learning-based EMS proposed in this work is an advancement in the setting of energy management for EVs. A proposed solution is offered that is scalable, secure, and efficient at managing the hybrid energy storage systems in the dynamic environments based upon its decentralized architecture and robust optimization techniques combined with the hybrid heuristic solution.

4. RESULTS AND DISCUSSION

The simulation results are presented and the efficiency of the proposed method is evaluated in this section. The intent of this methodology is to mitigate power fluctuation and decrease the maximum discharge power of batteries using a hybrid approach. With these goals, the proposed technique does an effective job. The results on the velocity prediction for different time horizon (2 sec, 5 sec and 10 sec) before the actual velocity are shown in this figure. Each subplot provides an individual view of the predictive performance, covering a total duration of 300 seconds.

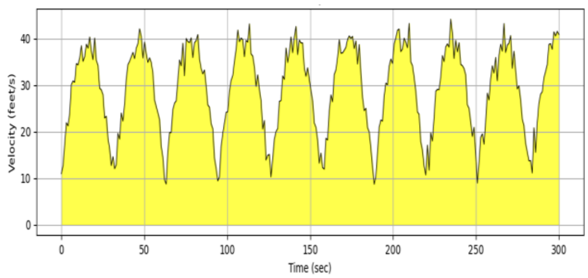

Fig. 2 – Real value velocity distribution (2s ahead)

The short-term prediction capability is shown by Figure 2. It indicates the predicted velocity, which matches reasonably well with the actual velocity curve. The result indicates that the model behaves well for the near future and captures both the trends and fine details of the true velocity. For applications requiring immediate real time responses such accuracy is perfect.

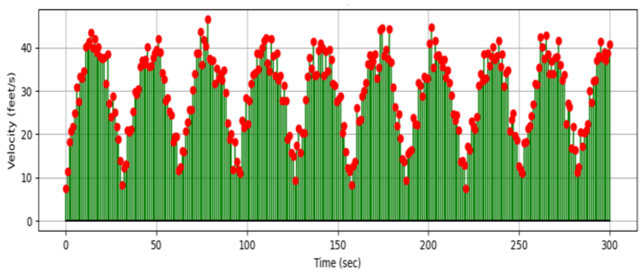

Fig. 3 – Real value velocity distribution (5s ahead)

Figure 3 shows medium term forecasting. The green bars represent the actual velocity here, the red dots the predicted velocity. Though the model adheres to the general trend of velocity fluctuations there is some divergence, with the model results not matching the actual levels. This shows a modest decrease of accuracy with an increase in the prediction horizon, which reflects the increase in the uncertainty in predicting further out into the future.

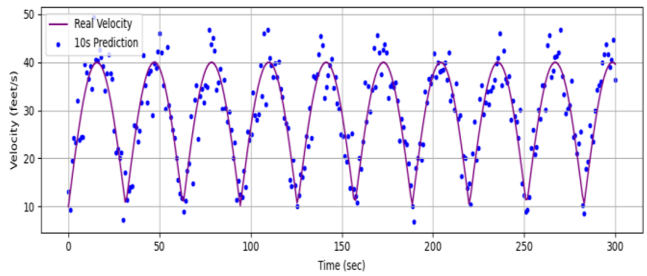

Fig. 4 – Real value velocity distribution (10s ahead)

The challenge of long-term forecasting is shown in Figure 4. Solid line is the predicted velocity, and dots are actual velocity. The model is successful in capturing the sense of the data, but not the finer sense of the data, resulting in large errors. The difficulty of predicting on longer time horizons is also illustrated by this reduced accuracy.

This Figure (5-7) presents three subplots that compare the actual velocity to predicted velocity over time for different prediction horizons: Twenty seconds, ten seconds, and five seconds. Subplots show how the predictive performance changes in terms of the horizon.

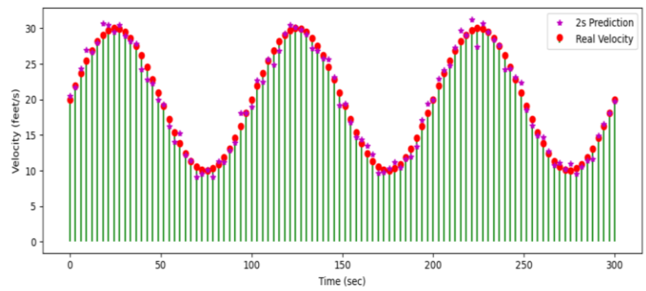

Fig. 5 – Predicted means velocity distribution (2s ahead)

The short-term velocity prediction is shown in Figure 5. Dots and stars represent the predicted value, and the green vertical line represents the actual velocity. We can see that the predicted values are closely following the actual velocity, both in terms of the trend, as well as in the magnitude. The 2 second ahead predictions suggest that the model has high accuracy of prediction over the short time interval, hence demonstrating minimal error.

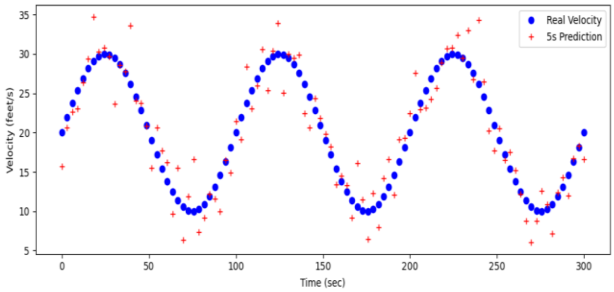

Fig. 6 – Predicted means velocity distribution (5s ahead)

Medium term predictions are shown in Figure 6. The actual velocity is given by the dots, and the predictions are represented by the plus symbols. Although the velocity predictions tend to predict the general pattern of the measured velocities, deviations exist in the peaks and troughs. We observe a moderate decrease in accuracy as the prediction horizon is increased and the uncertainty grows still better than the 2 seconds prediction.

Figure 7 shows the performance as the long-term prediction. The diamonds and stars give the predicted values, with the yellow vertical lines representing the actual velocity. The predictions fit into the wider trend of the actual velocity but the variation and error in capturing finer details is huge. The larger discrepancies indicate that the model is not very good at predicting long out into the future.

The figure ultimately shows that the prediction accuracy diminish as the time horizon increases. For short term predictions, the model performs really well and for medium and long term predictions it performs really badly. Such is the trend for predictive models; as prediction horizon increases, so does uncertainty and variability.

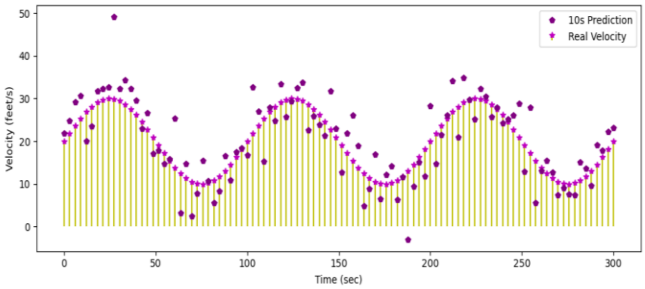

Fig. 7 – Predicted means velocity distribution (10s ahead)

5. CONCLUSION

This article proposes a federated learning-based Energy Management Strategy (EMS) for Hybrid Electric Storage Systems (HESS), which represents a new paradigm for augmenting electric vehicle (EV) battery lifetime and enhancing system efficiency. The system optimizes energy distribution and improves scalability, and privacy, relying on decentralized learning and IoT enabled communication. The resulting outcomes demonstrate the efficacy of the proposed strategy to reduce battery stress while promoting sustainable EV operations. This system can be refined subsequently for future research to alleviate its current limitations. Further Latency reduction could be explored by integrating Edge computing, enabling a little more local computation. In addition, real time adaptive algorithms could be integrated to support unforeseen driving conditions to enhance the system responsiveness. By extending the EMS model to incorporate different environmental parameters (e.g. temperature and terrain variation) on energy demand, a broader understanding of the patterns of energy demand can be provided.

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Стратегія управління енергією, що зберігає конфіденційність, для гібридних систем зберігання даних з алгоритмом федеративного навчання

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Акумулятори електромобілів повинні бути функціональними якомога довше. Це досягається за допомогою гібридних систем накопичення енергії (HESS), які значною мірою контролюють профілі потужності заряджання та розряджання, що безпосередньо впливають на стан акумулятора. Інтеграція гібридної системи накопичення енергії (HESS) подовжує термін служби акумулятора та оптимізує управління енергією. У цій статті ми представляємо нову стратегію управління енергією (EMS) на основі федеративного навчання (FL) для вирішення таких проблем, як непередбачувані потреби в енергії, які можуть прискорити деградацію акумулятора. FL дозволяє спільне навчання для кількох електромобілів, гарантує конфіденційність даних для забезпечення точного прогнозування потреби в енергії та динамічної оптимізації енергії. У запропонованій EMS на основі FL локальні дані окремих електромобілів об'єднуються та використовуються для навчання моделей прогнозування, які агрегуються в глобальну модель. Цей підхід є децентралізованим та використовує екосистему Інтернету речей для покращення продуктивності та масштабованості всієї системи. Запропонований підхід демонструється в симуляціях MATLAB для зменшення пікової потужності розряду акумулятора, мінімізації коливань потужності та підвищення енергоефективності. Ці результати демонструють здатність системи збільшувати термін служби акумулятора, оптимізувати операційну ефективність та переосмислювати управління енергією в реальному світі впровадження електромобілів.

Ключові слова: Управління енергією, Електромобіль, Стратегія управління, Федеративне навчання.