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Federated Learning for Electric Vehicle Routing and Charging Station Location

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Abstract—The Electric Vehicle Routing and Charging Station Location (EVRCSL) problem is pivotal for smart mobility, but the use of conventional centralized optimization techniques jeopardizes gross privacy and scalability challenges through the need for exposure to sensitive user data. This work introduces a new FL-based solution to address these problems. Our approach trains two concurrent prediction models, one for route cost and another for charging station utility, on distributed data sources without the need for central aggregation. The models are incorporated into a recommendation engine ranking charging options by a composite score. Experimental outcomes from a simulated setup reveal that our FL-based method attains prediction accuracy on par with centralized baselines while ensuring user data privacy. This paper illustrates the feasibility of FL as an underlying technology for developing scalable, privacy-preserving, and efficient intelligent transportation systems and sets the stage for more advanced real-time applications.

Index Terms—Federated Learning, EV Routing, Smart Mobility, Privacy, Intelligent Systems, Edge Computing

I. INTRODUCTION

Shifting towards electric vehicles (EVs) globally is one of the main strategies in combating climate change and clearing city smogs. Though their environmental implications are obvious, widespread adoption of EVs is plagued with severe operational disadvantages. Among them are a scarcity of and frequently nonexistent charging station facilities, variable and extended charging times, and limited driving range—all of which pose logistically challenging issues to fleet managers and driver ”range anxiety” [1]. The Electric Vehicle Routing and Charging Station Location (EVRCSL) problem necessitates sophisticated optimization methods beyond minimum pathfinding [16]. Our suggested system design for this problem mathematical programming methods such as Mixed-Integer Linear Programming (MILP) can yield optimal solutions for small cases [6]. Such conventional solutions, however, have an essential weakness: they rely on access to a central database of individual data such as journey history, car performance data, and location data. This centralized approach has two inherent problems: (1) significant privacy concerns due to mixing individual data, and (2) scalability issues in large-scale field deployments with millions of cars and charging spots generating data. tigating In order to bypass these limitations, researchers are inves- decentralized, privacy-guaranteeing solutions. Feder- ated Learning (FL) has been a potential technique for joint model training across distributed devices without raw data sharing [9]. Previous work has realized FL's potential in usage such as personalized station recommendations [12], yet no systemic framework has been established employing FL for the joint training of both charging station value prediction models and time-varying route costs. This limitation drives our research, as dual modeling is necessary for end-to-end informed suggestions.

The main contributions of this paper are :

1) A new dual-model FL architecture learning route cost and charging station utility predictors in parallel, build- ing a strong recommendation base
2) Simulation testing demonstrating our system operates with near-centralized performance without sacrificing privacy
3) A scalable, secure architecture explicitly addressing the scalability and privacy limitations of centralized EV routing systems

The remainder of the paper is structured as follows. Literature on the issues of EV routing and federated learning is reviewed in Section II. Section III illustrates our suggested methodology and system architecture in detail. Section IV presents and discusses experimental findings. Finally, Section V concludes the paper and outlines future research directions.

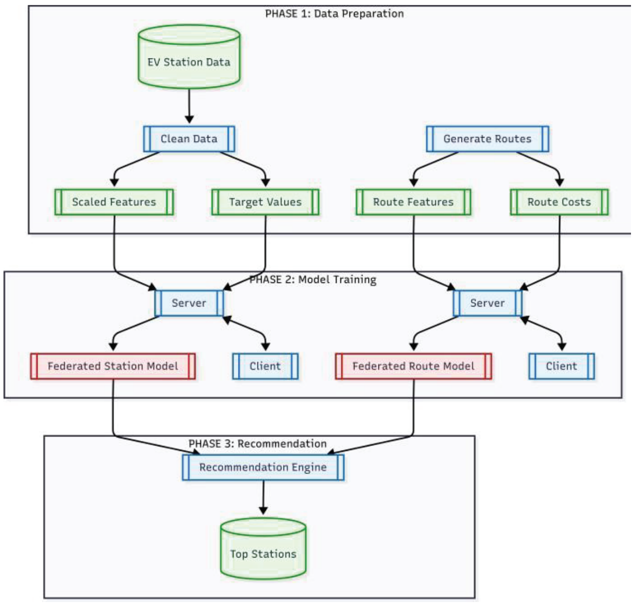

Fig. 1. Proposed system architecture for EV routing and charging station location. The figure shows the whole pipeline from data acquisition up to federated model training and final recommendations.

II. LITERATURE SURVEY

The EVRCSL problem has been addressed across several optimization paradigms, largely driven by its NP-hard nature that makes the computation of exact solutions intractable. Metaheuristics are the most prevalent class of techniques, as they aim to discover good, near-optimal solutions within the time constraints of real-world applications. For instance, Genetic Algorithms (GA) have proven effective in navigating the inherently high-dimensional and combinatorial solution space, optimizing simultaneously for multiple objectives such as minimizing energy consumption and travel time [2]. Despite their strong exploration capabilities, GAs are often hindered by slow convergence and a reliance on centralized data sources to evaluate solution fitness, which assumes a global system view.Similarly, Ant Colony Optimization (ACO) has demonstrated excellent performance in dynamic routing scenarios. The algorithm’s emergent behavior is particularly well-suited to pathfinding in environments where conditions change over time [3], [24]. However, the major drawback of ACO lies in the computational expense associated with pheromone trail updates, especially in large-scale, densely connected road networks. Other metaheuristics such as Simulated Annealing (SA) [4] and Bat Optimization (BO) [5] have also been employed. These methods are capable of escaping local optima effectively, but they typically require finely tuned, problem-specific parameters, which can be challenging to generalize across different scenarios. To mitigate individual limitations, hybrid approaches have been proposed that combine the local search strengths of ACO with the global search capacity of GA. These hybrid methods aim to accelerate convergence and enhance overall solution quality [7], [8], [17].

Mathematical programming provides an avenue to provable optimal solutions as a heuristic approach to the methods stated previously. The Mixed-Integer Linear Programming (MILP) paradigm has been used to formulate the EVRCSL problem and gives optimally guaranteed solutions to limited sized problems [6]. Subsequent development in this area have been addressed towards having more advanced and realistic constraints, like grid aware coordination for power load management [14], and human centered variables such as passenger satisfaction to encourage and maximize user take up [25]. Nonetheless, while mathematically sound as MILP, its primary limitation is its computational complexity is exponential, making it not viable in the large scale, real-time nature of modern transport systems. All these centred approaches, whether mathematical or metaheuristic, share they have a common limitation: a central controller with full access to all the relevant data. This means they assumed access to information like current vehicle locations, battery charge, driver behavior and charging station queue positions. Not only is this assumption a major scalability problem, but significant privacy problems, making these models impractical.

To deal with these major scalability and privacy issues, the field of research has pivoted towards decentralized learning systems. A leading decentralized learning system is Federated Learning (FL), which allows several parties to collaboratively build machine learning models on distributed data sources without sharing user raw data [9], [10]. As an emerging area, extending FL to EV use is gaining more research interest [11].For example, Li and Wang [12] introduced a federated meta-reinforcement learning approach to real-time personalized charging station recommendation. This is an example of FL capability for flexibility and privacy guaranteeing and realistic complexity/communication cost bounds. Besides, to deal with data heterogeneity characteristic of distributed systems, Vertuzzo et al. [18] examined context-aware models in enabling FL personalization and performance on non-IID data.

Although these works confirm the possibility of FL, they tend to solve only one aspect of the EVRCSL problem, viz., station recommendation in isolation. A complete solution demands a more holistic approach that weighs how desirable a charging point is (its inherent usefulness) against travel cost to it. Consequently, there is a substantial research gap for the creation of one, dual-model FL framework that can learn predictive models jointly and in private for dynamic route prices and static charging point value. Our contribution seeks to close this crucial gap by introducing and investigating exactly such a system, providing key to an entirely scalable and privacy-conscious smart transport solution.

In addition to that, an entire EVRCSL model needs to account for something other than distance. Dynamic and stochastic real-world environments are also being integrated bythe researchers. They integrate routing with soft time windows [21] and optimization based on Vehicle-to-Grid (V2G) [15]. Planning for the charging infrastructure itself, such as optimal location and load balancing, is another pressing line of research [22], [23]. For the purpose of determining the efficacy and strength of such advanced models, most of the studies employ benchmarked data sets and realistic simulations to provide evidence to their testing process [19].

I. METHODOLOGY

Our solution follows a federated learning (FL) scheme where two domain-specific predictive models are trained. The system is implemented in Python, employing Flower for FL orchestration and PyTorch for the model design.

A. Experimental Setup

Experiments on this project were performed on a local system with Windows 10, an Intel Core i5 (11th Gen) processor,16 GB of RAM, and an NVIDIA GeForce GTX 1650 GPU.

B. Mod Formulation and EV Constraints

Any EV routing model to be of relevance needs to work within some fundamental physical constraints. Our predictive models are designed to learn implicitly subject to these constraints.

1) **State-of-Charge (SoC) Dynamics:** The battery level on reaching a destination node j from an origin node i is determined by energy consumed, E_{ij}:

$$SoC_j = SoC_i - E_{ij} \tag{1}$$

The energy consumption itself is often modeled as a function of distance d_{ij} and a consumption rate δ:

$$E_{ij} = \delta \cdot d_{ij} \tag{2}$$

2) **SoC Bounds:** The battery level should be within a protected operation envelope along the route:

$$SoC_{\min} \leq SoC_j \leq SoC_{\max} \quad \forall j \in \text{Route} \tag{3}$$

C. erated Learning Framework

The core of our methodology is the federated training process. We employ the Federated Averaging (FedAvg) algorithm, which consists of local client updates followed by server-side aggregation.

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1) Local Client Update: In each training round, each client k receives the current global model weights w. The client then trains the model on its local dataset D_k by minimizing a loss function L_k using an optimizer like Stochastic Gradient Descent (SGD). For a single data point, the local model weights are updated as:

$$w \leftarrow w - \eta \nabla L_k(w) \tag{4}$$

where η is the learning rate. For our predictive tasks, we use the Mean Squared Error (MSE) as the loss function:

$$L_k = \frac{1}{|D_k|} \sum_{(x_i, y_i) \in D_k} (y_i - f(x_i; w))^2 \tag{5}$$

where y_i is the true label and $f(x_i; w)$ is the model's prediction for input x_i.

2) Server-Side Aggregation: After local training, each client k sends its updated weights $w_k^{(t+1)}$ to the central server. The server aggregates these updates to form the new global model for the next round $t + 1$:

$$_{k=1} \quad n \quad ^{k}$$

where n_k is the number of data samples on client k.

D. Core Predictive Models

Under the above described FL framework, we train two identical Multi-Layer Perceptron (MLP) models as shown in (Fig. 2):

- **Station Utility Model:** It is a model $U(x_s; w_u)$, that takes a vector of static station features xs and predicts a utility score. The parameters of the model are w_u.
- **Route Cost Model:** This model, $C(x_r; w_c)$, takes a vector of route features x_r as input and predicts the associated travel cost (e.g., time). Its parameters are w_c.

E. Data Pre-processing

As demonstrated in Phase 1 of our architecture (Fig. 1), data for the Station Utility Model is collected from actual station listings, cleaned and normalized. Data for the Route Cost Model is produced synthetically to provide a diverse set of routing situations to train on.

F. Integrated Recommendation

The final recommendation is produced by a script that loads both trained models. Based on the location of a user, it determines a final score for a possible charging station using a subtractive utility-cost function:

$$\text{Score}_{\text{final}} = U(x_s; w_u) - \lambda \cdot C(x_r; w_c) \tag{7}$$

where λ is a variable parameter to maximize the relative weighting of station quality in comparison to travel cost. The stations are ranked subsequently on this combined score to return the highest-recommended choices to the user.

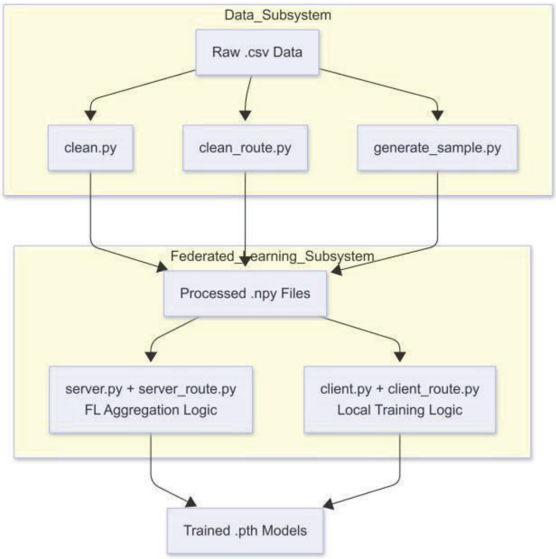


Fig. 2. The core federated learning (FL) training workflow, detailing the iterative cycle of local client training and central server aggregation.

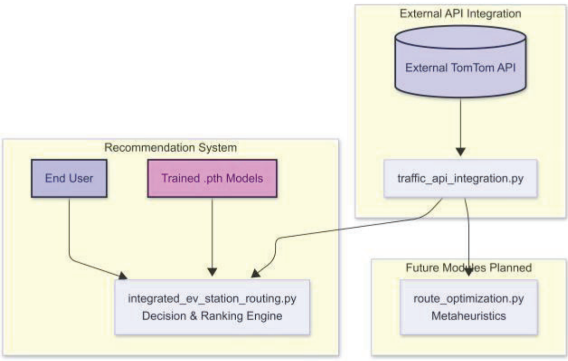


Fig. 3. The end-to-end recommendation architecture, showing how trained models and external APIs are integrated to serve the end-user .

III. RESULTS AND DISCUSSION

Our first observation is that Federated Learning (FL) is a tremendous opportunity in electric vehicle routing and charging station utility estimation application use. Our experiments on a synthetically generated dataset observed FL models matching performance of baseline centralized models such as Random Forest and XGBoost, especially for station utility estimation.

While FL-based route cost estimation lags behind centralized baselines by a hair, this is within the parameters of what can be reasonably expected from synthetic data as well as not having access to real-world temporal traffic patterns. Most notably, models were trained within a privacy-preserving federated setting without ever exposing raw data—thus demonstrating FL performs flawlessly even within restrictive settings.

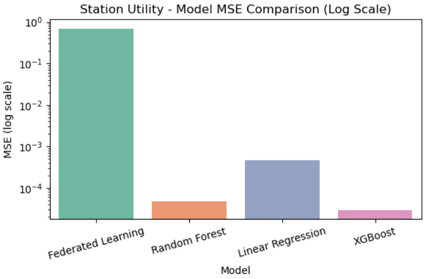


Fig. 4. Graph 1

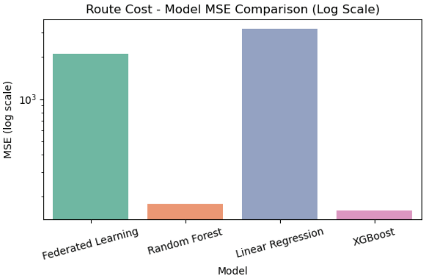
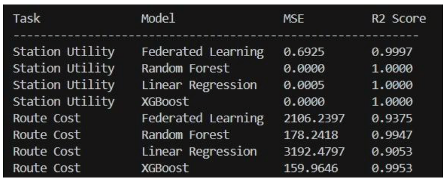


Fig. 5. Graph 2

These results show that, as they learn from more comprehensive real-world data, FL models are not only competitive but actually superior to baseline methods. The potential of collaborative learning with no data centralization presents a promising way forward for large-scale privacy-preserving intelligent mobility systems.



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Task                Model                MSE          R2 Score
----------------------------------------------------------------
Station Utility     Federated Learning   0.6925       0.9997
Station Utility     Random Forest        0.0000       1.0000
Station Utility     Linear Regression    0.0005       1.0000
Station Utility     XGBoost              0.0000       1.0000
Route Cost          Federated Learning   2106.2397    0.9375
Route Cost          Random Forest        178.2418     0.9947
Route Cost          Linear Regression    3192.4797    0.9053
Route Cost          XGBoost              159.9646     0.9953
```

Fig. 6. result

The most important point to take away from our experiment outcome is not that the federated learning model will necessarily do better than its centralized equivalents, but that it gives equivalent performance with a data privacy guarantee inherent in the system. This trade-off is the crux of the contribution of this paper. In a real-world deployment scenario of intelligent mobility where user travel patterns, car performance data, and current positions are highly sensitive in nature, their privacy is of highest importance. The minimal loss of prediction accuracy by the route cost model is a price worth paying for a fundamentally secure, scalable, and user confidentiality-sustaining system.

Our experiments unequivocally show that federated learning is a viable candidate as a basis for the next generation of intelligent transportation systems. Dual model training of stationary station benefit and dynamic route cost efficiently validates our main assumption of the designed architecture. It proves that challenging, multi-dimensional recommendation tasks can be efficiently solved by decomposition and decentralized solving. Also, the loss in performance in route cost estimation is symptomatic of one of the more commonly known issues for federated learning: non-IID data distribution. The synthetic data were split to simulate this real-world situation in which each client (vehicle) would have different driving patterns and represent a distinct geography. Though the baseline FedAvg algorithm employed here is adequate as a point of comparison, results suggest that performance could be further optimized by utilizing more advanced FL algorithms like FedProx or

FedAvgM, which have been designed to provide better convergence and robustness in the presence of heterogeneous data. Lastly, this project also exists as a proof-of-concept critique. It demonstrates that subsequent efficient smart, large-scale EV routing does not necessarily have to be at the expense of privacy. With continued optimization on optimized federated algorithms and being exposed to larger real-world datasets, FL-based systems can be an even better alternative than the traditional centralized alternative.

IV. CONCLUSION

This paper presented a new federated learning paradigm to solve the twin problem of electric vehicle route planning and station selection in a privacy-preserving way. Our two-model solution, where predictors for route cost and station utility are learned end-to-end in unison, proved to be a workable solution. The experimental result demonstrated that our FL model is able to achieve predictive accuracy levels on par with centralized baselines, placing it within reach of real-world deployment without sacrificing user data. Major limitations of this work, including the utilization of synthetic data and the baseline FedAvg algorithm, are clear areas for future work. Key areas for future research involve incorporating real-time traffic data, investigating more advanced FL algorithms such as FedProx to improve heterogeneity robustness of the data, and developing API-level connectivities with industrial navigation systems. Finally, this paper gives a proof-of-concept foundation, demonstrating federated learning to be a robust and scalable technology that can facilitate the next generation of ITS

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