Artificial Intelligence-enabled Recommendation System for Electric Vehicles

by

Zeinab Teimoori

A Thesis
Submitted to the Lakehead University in
Partial Fulfillment of the Requirement for the
Degree of Doctor of Philosophy (Ph.D.)
in
Electrical and Computer Engineering

Lakehead University
Thunder Bay, Ontario, Canada

July 2024

Examining Committee Membership

The following served on the Examining Committee for this thesis.

Supervisor: **Dr. Abdulsalam Yassine**,

Department of Software Engineering, Lakehead University

Examiners: **Dr. Waleed Ejaz**,

Department of Electrical Engineering, Lakehead University

Dr. Farhan Abdul Ghaffar,

Department of Electrical Engineering, Lakehead University

Dr. Irfan S. Al-Anbagi,

Faculty of Engineering and Applied Science, University of Regina

Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

The drastic growth in the conventional transportation system raises serious air pollution concerns. Eco-friendly vehicles, in contrast, have been introduced as an alternative to alleviate such environmental issues. To support the Canadian government's goal of achieving 100% sales of zero-emission vehicles by 2035, there is an increasing need for advancements in charging infrastructure and the performance of Electric Vehicles (EVs). These improvements aim to address range anxiety which is the primary concern of EV consumers who fear running out of electricity during a journey and being unable to find a charging point. However, so far, the main investment focus has been on the installation of Fixed Charging Stations (FCSs) which requires significant budget contributions and proper charging station placements. Therefore, to achieve higher EV popularity, this work aims to elevate user satisfaction and alleviate Range Anxiety by developing an intelligent system to manage EV charging demands, accurately estimating State of Charge (SoC) levels, and offering user-centric suitable service recommendations. Nevertheless, the scarcity of EVs historical data for Artificial Intelligence (AI)-based predictions poses a significant difficulty. To mitigate the aforementioned concern, we present a model based on Deep Transfer Learning (DTL) between domain-variant data sets, to reduce the need for the existence of a vast amount of EV data, including driving characteristics and patterns.

Furthermore, the accurate proposed DTL-based energy consumption estimation mechanism allows us to introduce an optimized Federated Learning (FL)-based recommendation system. Our intelligent system identifies nearby charging sources while preserving user privacy, which is a crucial aspect of the Internet of Things (IoT) framework security. Since the focus of this system is to increase the recommendation performance, we go beyond FCSs by integrating recently developed flexible Mobile Charging Stations (MCSs) to enhance the functionality of our system for EV consumers. This system prioritizes user satisfaction by balancing the desired charging outcomes with minimal inconvenience and expenses among all types of available charging services. Hence, it alleviates range anxiety and enhances

the overall user experience within the EV ecosystem. We further investigate the inherently dynamic functioning environment of MCSs, which is influenced by inconstant user preferences, energy demands, and charging service availability, to ensure cost efficiency and fairness. Therefore, in this thesis, we develop an optimization FL-based mechanism that enables decentralized learning with minimal data transfer to maximize the potential profit of MCSs while optimizing their daily operational efficiency.

Acknowledgements

With deep appreciation for those who have significantly contributed to my academic journey, I express my sincere thanks:

I wholeheartedly value the consistent support and motivational guidance, as well as the invaluable insights and scholarly enlightenment provided by my supervisor, **Dr. Abdulsalam Yassine**. It has truly been an honor to conduct my research under his supervision.

I want to express my deep gratitude to my beloved family for the unwavering support, nurturing care, encouragement, and understanding provided by **my husband and parents** throughout my academic journey. Their belief in my abilities has been a constant source of strength during this scholarly pursuit.

Dedication

To my beloved husband, mother, father, and brother.

Table of Contents

Declaration iii

Abstract iv

Acknowledgements vi

Dedication vii

List of Figures xii

List of Tables xvii

List of Acronyms xviii

List of Symbols xx

1 Introduction 1

1.1 Motivations 5

1.2 Objectives 8

1.3 Methodology 9

1.4 Contributions 15

1.5 Thesis Organization 18

1.6 List of Publications 19

1.6.1 Journal Papers 19
1.6.2 Conference Papers 20

2 Background and Related Work 21

2.1 Introduction to Chapter 2 21
2.2 Thesis Background 22
2.2.1 Role of Internet of Things in Electric Vehicles 22
2.2.2 Deep Transfer Learning 24
2.2.3 Mobile Charging Stations 25
2.2.4 Data Security in Electric Vehicles IoT Network 27
2.2.4.1 Federated Learning 28
2.2.4.2 Blockchain 30
2.3 Related Work 32
2.3.1 Electric Vehicle Behavioral Analysis 32
2.3.2 Electric Vehicle Charging Source Selection 37
2.3.2.1 Fixed Charging Stations 37
2.3.2.2 Mobile Charging Stations 42
2.3.3 Mobile Charging Station Performance Optimization 43
2.4 Chapter 2 Summary 46

3 Deep Transfer Learning for Detecting Electric Vehicles Highly Correlated Energy Consumption Parameters 48

3.1 Introduction to Chapter 3 48
3.2 System Model and Problem Formulation 49
3.2.1 Data Normalization 51

3.2.2 Training Source and Target Models 51
3.2.3 Facilitating Domain Adaptation and Transfer Learning 55
3.2.4 Implementation of the BiLSTM-DTL Algorithm 57
3.3 Model Evaluation and Results Analysis 57
3.3.1 Datasets 57
3.3.2 Results and Analysis 62
3.3.3 Experimental Setup 63
3.3.4 Hyperparameters Fine-Tuning 64
3.3.5 Performance Evaluation 66
3.4 Chapter 3 Summary 77

4 Smart Vehicles Recommendation System for Artificial Intelligence-enabled Communication 79

4.1 Introduction to Chapter 4 79
4.2 System Model and Problem Formulation 80
4.2.1 Intelligent User-centric Recommendation 82
4.2.2 Secure Data Sharing with Federated Learning 89
4.2.3 Implementation of the Secure Intelligent Recommendation Algorithm 91
4.3 Model Evaluation and Results Analysis 95
4.3.1 Datasets 95
4.3.2 Results and Analysis 95
4.3.3 Experimental Setup 97
4.3.4 Performance Evaluation 97
4.4 Chapter 4 Summary 105

5 Empowering Consumer Electric Vehicle Mobile Charging Services with Secure Profit Optimization **106**

5.1 Introduction to Chapter 5 106

5.2 System Model and Problem Formulation 107

5.2.1 Implementation of the Secure Profit Optimization Algorithm 113

5.3 Model Evaluation and Results Analysis 116

5.3.1 Datasets 116

5.3.2 Experimental Setup 117

5.3.3 Performance Evaluation 117

5.4 Chapter 5 Summary 126

6 Blockchain and Federated Learning for Electric Vehicle Charging Station Recommendation **127**

6.1 Introduction to Chapter 6 127

6.2 System Model and Problem Formulation 128

6.2.1 Implementation of the fogChain Algorithm 131

6.3 Model Evaluation and Results Analysis 132

6.3.1 Datasets 132

6.3.2 Performance Evaluation 133

6.4 Chapter 6 Summary 135

7 Conclusions and Future Research **136**

7.1 Conclusions 136

7.2 Future Research Directions 138

References **140**

List of Figures

1.1 Historical and projected costs of mid-sized Nissan Leaf EVs compared to traditional Honda Civic vehicles in Canada. 2

1.2 Flowchart of the objectives, methods, and publications. 14

2.1 General aspects of IoT-based EV energy management system. 23

2.2 In the DTL mechanism, learning a new task relies on the previous learning tasks. Freezing the layers of the pre-trained model is to prevent them from being updated during training. Then additional layers on top of the pre-trained network are added for the specific task. 24

2.3 Different categories of types and technologies for mobile charging stations. 27

2.4 Security Problem Statement: An unsafe example scenario of a conventional recommender model, sharing all consumer electronic entities' (EV, FCS, and MCS) sensitive and private information to the centralized module. 28

2.5 An example of a general federated learning framework for secure data exchange between different entities. 29

2.6 The PoS protocol is an alternative solution for a less wasteful validation algorithm. 32

3.1 Model framework. The Deep Recurrent Neural Network (BiLSTM) Transfer Learning technique is implemented to estimate EV energy consumption based on learned and trained parameters from electric bus energy consumption. Feature Domain Adaptation and correlation between the source (electric bus) and target (EV) data is used to optimize the model performance with generated discrepancy losses. 50

3.2 The illustration of remaining battery charge (in %) of one e-bus in a one-day trip, and one EV in an eight-minute trip, in relation to the vehicle speed. 62

3.3 The impact of driving location on an EV battery discharging level. Routes are taken from the different roads of the real-world target dataset. Urban routes (with higher speed limitations and stronger wind pressure) require more electricity from EV batteries. 63

3.4 Hyperparameters fine-tuning evaluation with GridSearch cross-validation. . 65

3.5 Illustration comparing the performance of our model with two distinct groups of existing approaches. 69

3.6 Energy consumption prediction performance and residual for the source electric bus dataset model. 70

3.7 Energy consumption prediction performance and residual for the target EV dataset model. 71

3.8 Important factors on energy consumption for EVs. The level of factors changed after transferring prior parameters weight knowledge from the electric bus model. 73

3.9 SHapely Additive exPlanations. SHAP values explain how much each feature contributes to the output of the model's prediction. Positive values show positive effects on the model's performance. 74

3.10 Heat-map depicting the correlation of features between the source (electric bus) and target (EV) domains, with the x-axis representing the source domain and the y-axis representing the target domain. 75

3.11 Comparing the training metrics in our model before (blue) and after (green) applying the transfer learning technique. 76

3.12 Performance evaluation of the proposed model on the supplementary EV dataset. The line graph illustrates the decreasing loss values after applying TL on the right y-axis compared to the left y-axis range values over 20 training epochs. 77

4.1 Consumer electronics recommendation model framework with secure federated learning-based decentralized fog-edge network communication, considering both fixed and mobile charging points for an EV with charging demand. 81

4.2 A diagram that shows the order of actions in the suggested recommendation model, where requests come from EVs to get energy from nearby charging spots, which can be either fixed or mobile. 94

4.3 Distribution of labeled Electric entities in a selected region of Ann Arbor city, illustrating their spatial arrangement and density. 96

4.4 Availability Indicator values (ρ for FCS, and ρ' for MCS) to an EV with the charging request. The size and color of the points (which have been enlarged for finer illustration), show the range of the sources' availability. . 98

4.5 Gained maximum utility values for every 6 EV consumer electronics from the MCSs and FCSs to get to their requested SoC level (dashed red line) from their current SoC. 100

4.6 Total gained utility (SoC%) of EV consumer #3, comparing the simple distance_based charging source selection, and our optimized recommendation. 101

4.7 The likelihood of suggesting a charging source in (a): when the nearest charging source is mandated for recommendation due to the pressing electricity demand for EVs, and in (b): when an EV seeks the most available and cost-effective charging source for efficient charging. 103

4.8 Comparative computation times in seconds in Centralized vs. Federated Learning with Differences in second across 6 numbers of EVs. The graph highlights the impact of computation efficiency and the corresponding differences between the two recommendation approaches. 104

5.1 Sequence diagram showing the actions in the MCS optimization process. It includes registration, EVs sending requests, and the algorithm directing MCSs to either recharge at FCSs or service EVs, with Fog Nodes enabling communication. 114

5.2 Depiction of the relationship between the booking times for charging requests from 6 EVs within the service zone of MCS #4 and the potential profit generated based on a charging price of $2.5 during **normal traffic conditions**. The figure also shows the corresponding traveling distances for MCS #4 to deliver charging services to these EVs, illustrating how both booking times and travel distances influence the MCS's profitability. 119

5.3 Representation of the interaction between the booking times for charging requests from 6 EVs within the service zone of MCS #4 and the potential profit generated at a charging price of $2.8 during **peak hours**. This figure includes the travel distances for MCS #4 to reach each EV, highlighting the impact of higher demand periods on both profit and operational logistics. . 120

5.4 Visualization of the relationship between the booking times for charging requests from 6 EVs within the service zone of MCS #4 and the potential profit generated at a charging price of $2.0 during **off-peak hours**. The figure also details the traveling distances for MCS #4 to provide charging services, emphasizing how reduced demand and travel requirements affect the MCS's overall profitability during less busy times. 121

5.5 The operational scheduling scenario for MCS#1 selecting 2 nearby EVs for service delivery. By providing energy to EV#1 followed by EV#4, the MCS can earn $90 during peak hours. Subsequently, the MCS must decide where to recharge itself, selecting from 3 nearby FCSs based on their queue times and charging prices. The color-coded arrows indicate the available options, extending from the nearest to the most distant, arranged from left to right. 122

5.6 Distribution of labeled Electric entities in a selected region of Ann Arbor city, illustrating their spatial arrangement and density. 123

5.7 Optimized profit for each MCS by analyzing energy transactions with EV and FCSs at various locations. The subplots show profit, cost, and total profit (net profit) for each MCS when choosing from seven different FCSs. FCSs 1, 5, and 6 offer free charging, but they may be far and crowded, potentially leading to time wasted traveling there. The line graph in each subplot represents the distance between the MCS and each FCS, highlighting the spatial considerations influencing costs and profits. 124

5.8 Total distance, time, and money saved by EVs using nearest MCSs instead of traveling to nearest FCSs, highlighting the benefits of MCSs in the ITS. 125

6.1 New transaction generation by a new fog node. 129

6.2 Proposed model architecture. The VFL-based fogChain framework is used to establish a decentralized secure communication between parties. 130

6.3 The secure recommender system execution time with different numbers of EVs and FCSs. 133

6.4 New block mining execution time by scaling the fogChain from two fog nodes to ten. 134

List of Tables

2.1 Comparison of EV driving and charging behavior analysis. 36

2.2 Comparison of FCS recommendation mechanisms for EVs. 39

2.3 Comparison of secure FCSs recommendation mechanisms for EVs. 41

2.4 Comparison of existing literature reviews covering MCSs integration into the recommendation system, and our work. 42

2.5 Comparing existing literature reviews in MCSs performance optimization stating their strength and limitations. 45

3.1 Samples of the source (electric bus) and target (EV) datasets. 60

3.2 Source Dataset Description. 61

3.3 Target Dataset #1 Description. 61

3.4 Hyperparameters Search Range 65

3.5 The proposed model's performance comparison. 67

4.1 Fixed Charging Stations Availability Values 98

4.2 Mobile Charging Stations Availability Values 98

5.1 Consumer Electronics dataset samples. 116

List of Acronyms

ACK	– Acknowledgement.
AI	– Artificial Intelligence.
AP	– Access Point.
BiLSTM	– Bidirectional LSTM.
CS	– Charging Station.
CNN	– Convolutional Neural Network.
CIoT	– Consumer Internet of Things.
DTL	– Deep Transfer Learning.
DPoS	– Delegated Proof of Stake.
EV	– Electric Vehicle.
EHH	– Exponential Harris Hawks.
FL	– Federated Learning.
FCL	– Fully Connected Layer.
FCS	– Fixed Charging Station.
GPS	– Global Positioning System.
HFL	– Horizontal Federated Learning.
HEV	– Hybrid Electric Vehicle.
IoT	– Internet of Things.
IoV	– Internet of Vehicles.
ICE	– Internal Combustion Engine.
ITS	– Intelligent Transportation System.
IPM	– Interior Permanent Magnet.
LAN	– Local Area Network.
LASSO	– Least Absolute Shrinkage and Selection Operator.
LSTM	– Long Short-Term Memory.
MDA	– Multiple Domain Adaptation.
MMD	– Maximum Mean Discrepancy.
MRPE	– Mean Relative Percentage Error.
MSE	– Mean Squared Error.
MCS	– Mobile Charging Station.
MDP	– Markov Decision Process.
PBK	– Public Key.
PK	– Private Key.

PoW	– Proof of Work.
PoS	– Proof of Stake.
P2P	– Peer-to-Peer.
QoE	– Quality of Experience.
RF	– Random Forest.
RMSE	– Root Mean Squared Error.
RNN	– Recurrent Neural Network.
SG	– Smart Grid.
SMC	– Secure Multi-party Computation.
SLSQ	– Sequential Least Square Quadratic.
SoC	– State of Charging.
SVM	– Support Vector Machine.
SMAPE	– Symmetric Mean Absolute Percentage Error.
SA	– Service Area.
SP	– Service Provider.
TL	– Transfer Learning.
TX	– Transaction.
UAV	– Unmanned Aerial Vehicle.
UGV	– Unmanned Ground Vehicle.
VED	– Vehicle Energy Dataset.
VFL	– Vertical Federated Learning.
V2V	– Vehicle-to-Vehicle.
V2G	– Vehicle-to-Grid.
WTA	– Waiting Time Accuracy.
X2V	– Anything-to-Vehicle.

List of Symbols

f_t – BiLSTM forget gate at time t.

i_t – BiLSTM input series at time t.

o_t – BiLSTM output at time t.

$Sig()$ – BiLSTM network sigmoid activation function.

h_t – BiLSTM network hidden layer at time t.

c_t – BiLSTM cell state at time t.

W_h – BiLSTM network weights at hidden layer h.

b_h – BiLSTM network biases at hidden layer h.

$\mathcal{H}$ – Hilbert space.

N_{sc} – Source domain feature size.

M_{tg} – Target domain feature size.

F – Correlated feature size.

$\phi(.)$ – Hilbert embedding kernel function.

μ – Data mean value.

σ – Data standard deviation.

$\hat{x}$ – Standard error.

$\mathcal{N}$ – Source dataset size.

$\mathcal{M}$ – Target dataset size.

$\hat{EC}$ – Estimated energy consumption.

$\mathcal{L}$ – Model loss function.

$\widehat{MMD}^2$ – Maximum mean discrepancy function.

cs_j – A FCS in the service area.

ms_k – A MCS in the service area.

Λ – Distance between participants.

SoC_{sit} – An EV desired battery level

$\vec{\rho}$ – A charging source availability indicator.

n – The number of empty spots at cs_j.

n'	–	The number of idle batteries at ms_k.
q	–	The number of EVs waiting to get charged at cs_j.
q'	–	The number of EVs waiting to get charged at ms_k.
$\vec{t}$	–	Charging sessions remaining time at cs_j.
$\vec{t'}$	–	Charging sessions remaining time at ms_k.
$\vec{\delta}$	–	Batteries remaining capacity at a ms_k.
Φ	–	Charging service fee.
S	–	Total number of the charging spots at a cs_j.
B	–	Total number of the installed batteries at a ms_k.
o_s	–	An occupied spot at cs_j.
a_b	–	An actively charging battery at ms_k.
$\mathcal{R}$	–	A Very large positive number.
Υ	–	Weights to balance the utility function.
v_i	–	An EV with a charging request.
$U(v_i)$	–	EV with a request utility function.
τ_{dis}	–	Distance threshold.
τ_{SoC}	–	Minimum SoC level threshold.
$\mathcal{D}_{d\in D}$	–	Local datasets for data holders in FL.
θ	–	Local trained models for entities in FL.
θ^*	–	Local updated trained models for entities in FL.
w	–	Global model's contribution weights in FL.
ϑ	–	Global model's control hyperparameter in FL.
ζ	–	Availability indicator thresholds for a FCS.
κ	–	Availability indicator thresholds for a MCS.
R	–	Earth's radius = 6,371km.
h	–	Haversine formula variable.
r_i	–	Energy request sent from an EV v_i.
D	–	Set of data owners.
$\mathcal{D}_d$	–	Local dataset of Participant d.
$\{x_i, y_i\}_{i=1}^{\mathcal{D}_D}$	–	Pairs of input-output sets.
λ	–	Regularization parameter.
$g(.)$	–	Regularization function.
[[HM]]	–	Additive homomorphic encryption function.

$[[\frac{\partial \mathcal{L}}{\partial w}]]$	– Gradients function.
$\mathcal{C}$	– Set of fogs.
$\mathcal{C}_{miner}$	– A miner fog node.
t_{pool}	– Block-mining process initiation waiting time.
b_{ready}	– Ready-to-be-mined block.
b_{new}	– Newly mined block.
$\mathcal{T}$	– Number of transactions in a block.
τ_{period}	– fogs update period.

Chapter 1

Introduction

The transition from gasoline-powered vehicles to Electric Vehicles (EVs) is a major shift in the automotive industry. This shift aims to reduce environmental impacts and enhance energy efficiency. However, several critical challenges impede this transition. These include cost and development, range anxiety, limited driving ranges, and inadequate charging infrastructure. Addressing these challenges is essential to encourage widespread EV adoption and realize their benefits, such as reduced greenhouse gas emissions and less reliance on fossil fuels.

The cost of EVs is a critical factor influencing consumer adoption. While EV prices have decreased over the years, they are still generally higher than those of traditional Internal Combustion Engine (ICE) vehicles. The higher upfront cost can be attributed to several factors, namely, (a) battery costs, (b) manufacturing costs, and (c) economies of scale. Many governments offer subsidies, tax credits, and other incentives to lower the effective cost of EVs for consumers. However, in addition to the cost barriers, there are several economic and developmental challenges that need to be addressed for the successful integration of EVs into the mainstream market. Developing a robust charging infrastructure requires substantial investment. For instance, Canada is investing $1.2 billion to build 84,500 chargers by 2029 to support the growing number of EVs [1]. Figure 1.1 illustrates the projected Honda Civic Sedan, and Nissan Leaf vehicle prices from EF2018's Reference

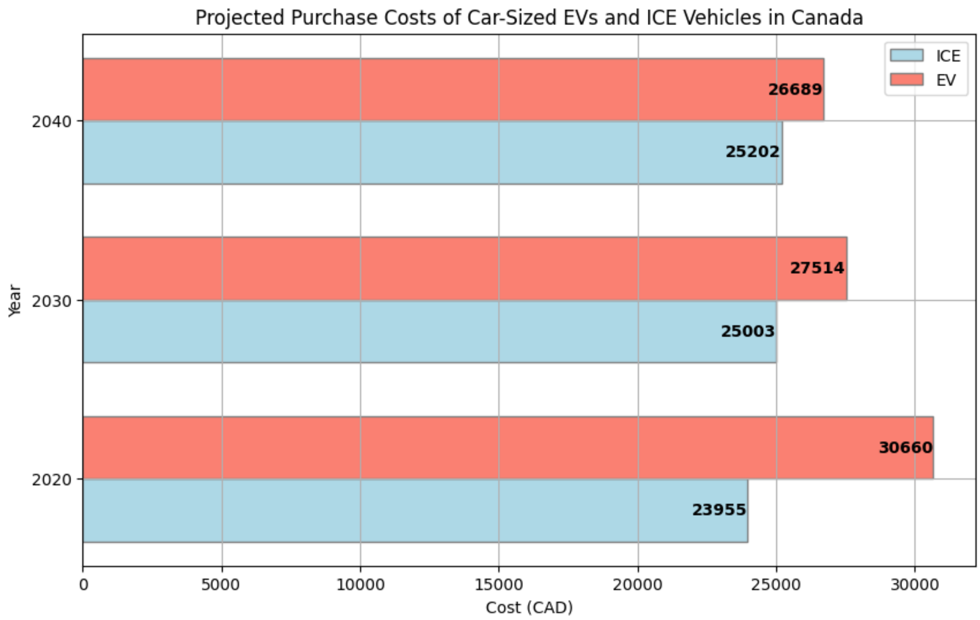


Figure 1.1: Historical and projected costs of mid-sized Nissan Leaf EVs compared to traditional Honda Civic vehicles in Canada.

Case collected from the National Energy Board (NEB) of Canada [2] for the years 2020, 2030, and 2040. The graph reveals that while ICE car prices are generally lower than those of EVs, the cost of ICE vehicles slightly increases over time, whereas the price of EVs decreases.

Regardless, range anxiety, the fear of running out of battery power during a journey, remains a major concern for potential EV buyers. While current EV companies' navigation systems suggest chargers along the route, they could benefit from more advanced algorithms that consider user driving habits, real-time traffic, and alternative charging options, including third-party stations. This issue has deteriorated because of the lack of Charging Station (CS) infrastructure compared to the growing number of EVs, especially in remote areas. The long time required for a full charge further complicates this problem. Prolonged wait times and a lack of available charging spots, especially during peak hours, make the situation worse. By ensuring that EV users have access to reliable and optimized charging recommendations, the proposed system directly addresses range anxiety and improves the overall EV user experience. These challenges highlight the need for an intelligent charging source recommendation system to improve the EV experience by enhancing charging accessibility and efficiency.

Current research on EV aspects such as charging service recommendation, charging scheduling, CS selection, and route optimization often falls short because they lack comprehensive models. These models should accurately consider the behavioral patterns of EV users, including travel times, energy requirements, battery capacity, and charging intervals. Additionally, existing deep learning models need large and diverse datasets, which are often unavailable. This leads to inadequate solutions that fail to address the real-world complexities of EV energy consumption.

Developing accurate energy consumption estimators is a significant technical challenge. These estimators need to predict EV power needs based on various correlated factors. This involves capturing the dynamic nature of EV driving behaviors. Another challenge is integrating these insights into a system that can effectively optimize charging schedules and station selection. Ensuring data privacy and security is also crucial, and consequently, collecting and analyzing sensitive user data, such as location and charging habits, poses significant risks.

Addressing the above-mentioned challenges is essential for several reasons. First, accurate energy consumption models and optimized charging solutions can reduce range anxiety, making EVs more appealing to potential buyers. For instance, by using the proposed system to accurately predict energy consumption and recommend optimal charging sources, users can confidently plan their journeys, knowing they will not run out of battery unexpectedly. Second, promoting EV adoption can significantly reduce greenhouse gas emissions and fossil fuel dependency, contributing to a cleaner and more sustainable environment. Finally, developing intelligent energy management and charging source recommendation systems and secure data handling mechanisms will push the boundaries of current technological capabilities and enable innovation in the automotive and energy sectors.

Therefore, in this thesis, we propose several solutions to these challenges. First, Deep

Transfer Learning (DTL) can improve the accuracy of energy consumption estimations by leveraging knowledge from related domains. This reduces the need for extensive datasets and computational power, enabling more precise and efficient predictions. Second, integrating Mobile Charging Stations (MCSs) into the existing infrastructure offers a flexible and cost-effective alternative to Fixed Charging Stations (FCSs). MCSs can be deployed quickly in response to demand, reducing the stress on the existing fixed infrastructure and providing a solution to the lack of charging stations in underserved areas. MCSs can address temporary needs and enhance the overall Quality of Experience (QoE) for EV owners, especially in underserved areas.

Third, the Internet of Things (IoT) ecosystem transforms EVs into intelligent entities capable of near-real-time communication with the grid and other infrastructure components. Fog computing supports this by processing data locally, reducing latency, and improving system responsiveness. Fourth, Federated Learning (FL) offers a collaborative approach to machine learning where raw data remains decentralized, enhancing privacy and security. This is particularly important in IoT applications, ensuring that sensitive data is protected while still enabling accurate and personalized charging recommendations.

Finally, integrating blockchain technology into the EV recommendation system further enhances data security and integrity. Blockchain provides a tamper-proof and transparent method for verifying transactions and ensuring the authenticity of data exchanges. This mitigates risks associated with data breaches and unauthorized access. By ensuring that charging data is secure and trustworthy, users can rely on the system to provide accurate and timely recommendations, further enhancing their confidence and reducing range anxiety. Together, these solutions aim to address the key challenges in EV adoption, improve user experience, and promote sustainable transportation solutions.

To sum up, widespread EV adoption links to overcoming significant technical and infrastructural challenges. Addressing range anxiety, optimizing energy consumption, enhancing charging infrastructure, and ensuring data privacy are critical. By leveraging advanced technologies such as DTL, MCSs, fog computing, FL, and blockchain, we can develop a robust and intelligent energy management and recommendation system. This system will not only improve the EV experience by providing reliable and secure charging solutions but also contribute to environmental sustainability by encouraging the use of cleaner energy sources and reducing greenhouse gas emissions. This thesis aims to provide comprehensive solutions to these challenges. It will contribute to the advancement of the EV industry and the realization of its environmental benefits. Furthermore, this chapter details the motivations, objectives, and contributions of this thesis.

1.1 Motivations

One side of an efficient energy management and recommendation system is dedicated to minimizing EV owners' range anxiety, and it is one rising challenge related to EVs' widespread public adoption. Minimizing this potential concern, which is impacted by efficient optimization of factors including charging scheduling, charging source selection, range estimation, CSs placement, and route selection, is a promising answer to support comprehensive switching over EVs[3, 4]. The first two optimization factors (charging scheduling and charging source selection) are considered important ones since they directly impact users' QoE [5, 6]. Charging scheduling focus is to schedule a suitable charging time period for EVs while charging source selection aims to recommend an optimal charging source for an EV when it requests charging. These two challenges are similar to some extent as we can classify charging scheduling and charging source selection into temporal scheduling and spatial scheduling, respectively [7]. The key objective of charging scheduling is to mitigate the impact of EVs' energy demands on the grid while maintaining user satisfaction. In contrast, the charging source selection aims to minimize the overall charging time consisting of driving time, queuing time, and charging time at a station [8]. Therefore, it is critical to recommend EVs with an ideal charging source to improve user QoE by minimizing overall charging time. Moreover, the charging source selection affects more or less other issues. For instance, it affects EVs routing optimization, and CSs placement [5].

Considering the range anxiety issue, which according to a study affects almost around 50 percent of EV owners [9], a reliable recommendation system must identify the parameters with the highest impact on EV charging consumption and scheduling. It is not efficient to present spatial charging scheduling algorithms without precisely analyzing EV behavioral patterns and estimating energy consumption [10]. Constructing an optimized energy consumption estimator model can be achieved by detecting the correlation between EV driving behaviors and energy consumption and capturing the extent of the influence of these factors on charging scheduling performance. To initial the behavioral analysis, the model needs to establish some necessary characteristics that can better help us understand the travel pattern and charging pattern, such as the travel times of EVs during a given day, the required energy for travel of EVs (kWh/km), the percentage of remaining battery capacity before charging, the duration between two adjacent charging events, the starting time period of the day when EVs receive electricity from the grid, and so on [11, 12]. However, the absence of a dedicated model tailored for precise estimation of EV energy consumption arises from the inadequacy of available real-world EV datasets or the constraints imposed by sparse and limited datasets. This deficiency in relevant data hinders the development of a reliable model capable of accurately predicting EV energy consumption.

Another problem that we will consider investigating a proper solution for, is finding an alternative approach to identify energy resources rather than FCSs. The inadequacy of the low growth rate of FCSs with respect to EVs should be addressed before deploying large-scale EVs on the road. On the other hand, such a significant surge of EVs can result in power grid overloading and quality degradation [13]. Therefore, a systematic strategy is required to prevent potential EV buyers from ending up fully discharged on the road with no FCSs around them or in a long queue to get charged in order to widen the customer adoption of EVs. The utility grid and EV owners can benefit from a substitute available option for energy transferring among electricity prosumers to mainly provide a feasible EV fueling method that will be beneficial for the utility grid and EV owners [14]. When an EV needs power refilling, the fastest way to find energy sources to recharge is to search for any surrounding available electricity provider, and not only FCSs. Consider an EV with low battery status in a rural area where no FCS is placed for miles. However, an intelligent charging source recommendation system that integrates MCSs can employ a user-centric approach in EV charging to maximize user satisfaction while minimizing associated costs. In this case, a win-win situation will be created for both the EV and the MCS operator, which willingly participates in order to increase its income by selling some amount of its available battery energy.

Thus, these intelligent charging source recommendation models need centralized control units that can collect and process the required data with data exchange mechanisms to extract more comprehensive and related features of EVs, FCSs, MCSs, power distribution networks, and road networks [15]. However, with ever-increasing data security and user privacy protection regulations, sharing such private data (identity of drivers, location, charging status, etc.) can raise privacy concerns [16]. If malicious users get access to this valuable data, they can use such information to extract patterns of EV owners' lifestyles and behavior preferences, such as commute habits [17]. These centralized units can suffer from a single-point-of-failure and cause service downtime, which will degrade the QoE for time-sensitive models and can not offer scalability and acceptable latency. Due to transmission delay, limited bandwidth, and unstable connections, traditional centralized unit solutions are not practically applicable for an efficient near-real-time system [18].

Based on the above, some novel algorithms are needed to solve challenges related to an optimized, reliable, accurate, and secure EV charging source recommendation system. These identified issues can directly impact the performance of the EV industry if not addressed duly. Therefore, in the following section, we will present our approach and solutions to overcome the aforementioned critical issues related to developing an intelligent EV recommendation system.

1.2 Objectives

The overarching goal of this thesis is to solve issues in intelligent charging source recommendation systems for EVs that will promote the reduction of EV owners' range anxiety. To achieve that, we pursue the following objectives:

Objective 1: Solve the data deficiency issue of the accurate energy consumption estimation algorithm.

- Define a detailed analysis of EV behavior to detect correlated parameters with the highest impact on the EVs' energy consumption.
- Design a Recurrent Neural Network (RNN)-based DTL algorithm to mitigate the issue of poor generalization to unseen and future input data.
- Design a refined domain adaptation mechanism to prevent the transfer of non-related feature parameters between distinct domains.

Objective 2: Enhance the QoE and well-being of EV users during charging.

- Design an accurate charging source recommendation algorithm incorporating MCS.
- Design a user-centric approach to optimize EV charging considering user satisfaction and cost minimization.

Objective 3: Improve MCS operators' QoE and performance.

- Design an algorithm to optimize MCSs' daily operation costs.

Objective 4: Improve user data security for EV charging source recommendation algorithm.

- Design a secure mechanism leveraging collaborative FL to protect user data privacy.

[19].

- Develop a secure system utilizing blockchain around distributed fog nodes, ensuring that only authorized aggregators can access the shared parameters.

All of the above-mentioned objectives are interconnected by the shared goal of designing an intelligent recommendation system for EVs that addresses data deficiencies in energy consumption estimation, improving user experience and operational efficiency, and ensuring data security. Each objective offers specific improvements: accurate energy consumption predictions through RNN-based algorithms, enhanced user satisfaction with charging recommendations, cost-effective MCS operations, and secure data sharing via FL and blockchain. These enhancements collectively aim to improve the overall efficiency, user experience, and security of EV systems.

1.3 Methodology

Objective 1:

This thesis approaches addressing EV users' range anxiety issues from a different perspective. Accurate energy consumption and State of Charge (SoC) estimation are vital for reducing range anxiety in EVs by providing reliable predictions of remaining driving range and battery status. This predictability allows drivers to plan routes and charging stops effectively, builds confidence in the vehicle's capabilities, optimizes charging schedules, and maintains battery health. To this end, we design an algorithm based on an energy-aware driving pattern analysis of EVs leveraging a DTL-enabled approach to evaluate different energy consumption levels. Investigating and performing an in-depth EV driving behavioral analysis to obtain energy consumption patterns and consequently detect the effective weighted factors is the primary component of optimally planning a CS selection mechanism [19].

This analysis focuses on identifying the highly correlated parameters from the prepared datasets to estimate EV charging consumption, properly schedule EV charging plans, and find the most relevant charging points according to EV requirements. By considering the accuracy and high-correlation nature of the analysis, leveraging the DTL technique is a promising solution to strengthen the learning approach by transferring a trained model on one task to a second related task to minimize the requirements of large-scale datasets and high computational power devices [20]. Furthermore, To prevent the transfer of non-related feature parameters between distinct domains, a domain adaptation technique is incorporated within the DTL framework, ensuring that only relevant features are transferred, thereby enhancing the accuracy and relevance of the model.

In addition to the DTL algorithm, this thesis incorporates a BiLSTM-based approach to further enhance the accuracy and generalization of EV energy consumption and SoC estimation. The BiLSTM algorithm processes data bidirectionally, capturing both past and future contexts, which is crucial for understanding complex temporal dependencies in EV energy consumption patterns. By considering information from both directions, the BiLSTM can identify intricate correlations and trends that single-directional models might miss. This bidirectional processing, combined with the inherent ability of LSTMs to manage long-term dependencies and mitigate vanishing gradient issues, ensures that the model can effectively learn from extensive sequences of data. Consequently, the BiLSTM-based methodology improves the robustness and reliability of predictions, addressing the challenge of poor generalization to unseen and future input data.

Objective 2:

Regrettably, the FCS infrastructure and availability have not kept pace with the growth of the EV industry. We design a charging source recommendation algorithm by integrating MCS infrastructure into the recommendation system, filling the gap left by insufficient and costly Fixed/Stationary CSs, especially in remote areas. These MCSs are generally equipped with wheels and are movable which provides flexibility and convenience to lessen the cost of FCS installations [21]. They are excellent replacements for certain circumstances or temporary needs, in order to improve the overall EV ownership QoE, mainly for urban EV owners who are being affected by the lack of charging accessibility.

To integrate this alternative portable energy unit into the EV charging infrastructure effectively, our intelligent recommendation algorithm encompasses both types of energy units (fixed and mobile) [22]. This algorithm primarily prioritizes the well-being of EV owners by suggesting the most appropriate energy source based on the heuristic greedy optimization function that makes local optimal choices with the hope of finding a global optimum and aims to enhance the amount of electricity an EV can acquire from a given charging service. Consequently, our proposed user-centric algorithm tailors the recommendations to the specific preferences of the EV owner, such as traveling time, waiting time, and energy unit price.

Objective 3:

The environment in which the recommendations operate is dynamic. Factors such as user preferences, energy demand, and availability of charging services can change rapidly. We design a heuristic greedy optimization method that makes local optimal choices with the hope of finding a global optimum and can adapt to these changes and optimize cost efficiency and fairness among MCS operators. To increase how much money a MCS makes each day, the driver or operator's choice to accept a charging request becomes a stochastic optimization problem where there are random variables in the measurements provided. It depends on whether they think they will get a better offer soon or not. It also depends on where the MCS will end up after delivering energy, in a busy area with a higher number of requests or in a quieter place with fewer EVs needing a charge. Moreover, deciding where to park when not in use and idle also needs to be addressed for a MCS, which further involves considering whether to move to a different location after completing an energy-transferring task from the MCS to an EV battery [23, 24]. This integrated method adds an extra feature of the energy delivery recommendation optimization by minimizing MCSs' self-charging costs during their idle time and ensuring the operation cost fairness between the MCSs and FCSs. In other words, it aims to maximize the potential profit of these stations while optimizing their daily operational efficiency.

Objective 4:

To effectively tackle the challenges related to user data privacy, we incorporate a new form of distributed machine learning, FL. The primary purpose of FL is to enable a new paradigm of industrial informatics where collaborative learning of a shared model occurs on IoT devices (e.g. EVs, mobiles, etc.) without sharing private data. In other words, raw data are protected from leaving distributed datasets to jointly train a machine learning model. Therefore, by applying such an innovative approach to our EV charging source recommendation system, we can minimize private data leakage concerns among EV owners.

As we use FL, all stages of behavioral analysis and model training take place within each data holder's space, and no private information is shared with others. FL was first categorized into different domains based on the data partitioning and common training data samples between data owners (parties). For our proposed secure intelligent recommender model aiming to optimally charge EVs and select the best charging source for them, Vertical Federated Learning (VFL) is used, in which different data holders (FCSs, MCSs, EVs, and electricity providers) own different sets of attributes but share the same samples of training entities [25]. It is the master point(s) responsibility to obtain and join the locally trained model parameters and then send back the computed output to identified parties to make the scheduling and recommendation. If we replace the conventional training model with a VFL technique for this example, the master point(s) only needs to gather locally calculated parameters from each side, update the global values, and send the results back to each one of them[26].

The VFL model will operate efficiently as long as the master point(s) is available and can respond with the minimum communication delay. Instead of building a centralized master point(s) aggregator [16], a lightweight decentralized fog-based architecture can alleviate the issues regarding single-point-of-failure or long communication delays for a near-real-time energy management system. Furthermore, fog infrastructure is easier to set up in new areas as the number of cloud service providers and industrial applications is rising steadily, resulting in relieving some concerns about communication infrastructure scalability and location management [27]. In our model, a fog architecture is used to provide low end-to-end latency by bringing cloud computing services closer to the source of information, which is a more suitable system for future industrial mobility [28]. This architecture allows our model to address scalability as the number of EVs increases and the requests for energy allocation increases, by utilizing decentralized fogs which can be installed almost in any area covered by an Internet connection. However, As EVs might be moving while sending their requests, they must be connected to an authorized trusted fog residing in the area. These fogs are responsible for parameter exchanging and model updating among participating parties. Therefore, their truthfulness must be verified by our energy management system. To this end, we propose a protection layer using blockchain technology which can also increase the reliability of the system [29]. Integrating blockchain to transparently evaluate the truthfulness of available master point(s) is one solution provided in this thesis to design a tamper-proof network of trusted fogs for our proposed model.

Figure 1.2 summarizes the thesis objectives, methods, and resulting publications.

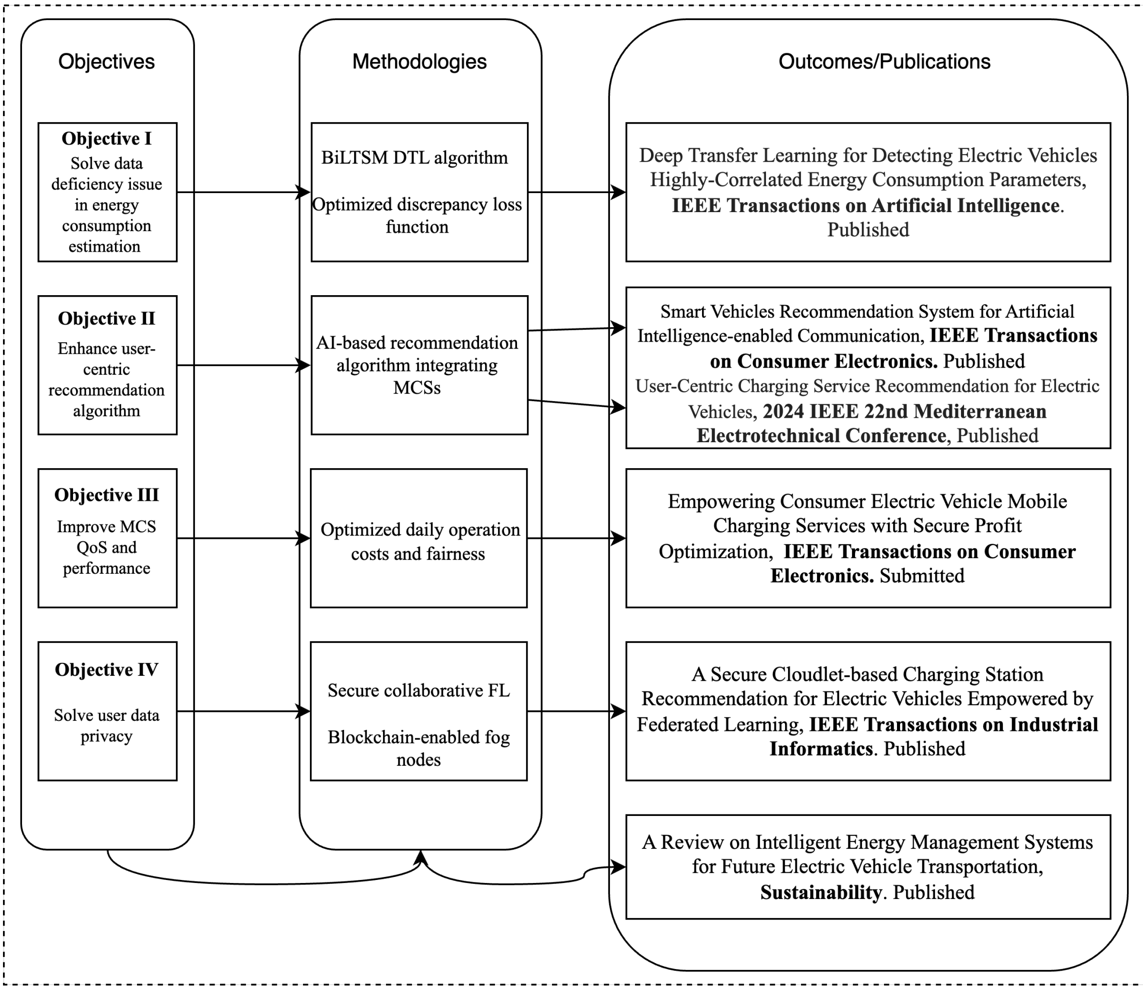


Figure 1.2: Flowchart of the objectives, methods, and publications.

1.4 Contributions

The main contributions of this thesis based on each objective are summarized in this section.

Objective 1:

(a) We develop an AI-powered energy consumption detector designed for EVs. Leveraging time-series deep learning techniques to capture the dynamic data of vehicles more precisely, we aim to enhance the accuracy of our proposed detector. While most of the existing studies focused on analyzing a restricted set of vehicle characteristics, our approach's significance is to perform a detailed analysis on two real-world datasets with wide-ranging internal/external elements to detect parameters with the highest impact on energy consumption.

(b) To address the challenge of learning over-fitting in the constrained EV target dataset, our approach involves the design of a deep transfer learning model. This innovative solution entails the transfer of knowledge acquired from a large-scale dataset of electric buses (source) to the EVs (target) dataset. Remarkably, this marks the first instance of leveraging AI to transfer learned knowledge between these distinct domains. The significance of this methodology lies in its ability to mitigate the issue of poor generalization to previously unseen and future input data. Furthermore, it establishes a pathway for facilitating knowledge transfer across the domains of electric buses and electric vehicles, thereby enhancing adaptability and robust performance.

(c) We employ a refined domain adaptation mechanism by identifying highly correlated energy consumption parameters between source and target datasets, optimizing compatibility through non-parametric distance probability measurements. This enhancement using an optimized discrepancy loss function, prevents the transfer of non-related feature parameters between distinct domains, prioritizing the precision of the adaptation process. In addition, we conduct an extensive and comprehensive simulation and evaluation of the proposed scheme's performance. This evaluation, bench-marked against various existing frameworks, demonstrates the practicality and effectiveness of our approach in real-world scenarios. The results underscore the scheme's superior performance compared to established methodologies.

Objective 2:

(a) In this thesis, we introduce a recommendation system that goes beyond traditional fixed charging stations. By including the mobility and flexibility of MCSs, the proposed system offers a comprehensive solution to the challenges faced by urban EV owners, providing a more adaptable and convenient charging infrastructure. This addresses the challenges associated with the lack of charging accessibility in urban areas and offers diverse services to enhance the QoE for Intelligent Transportation Systems (ITS).

(b) The user-centric approach in EV charging aims to maximize user satisfaction while minimizing associated costs. Therefore, we formulate an optimization function within the recommendation system that prioritizes user satisfaction. It contributes to the well-being of EV consumers by addressing an optimization problem that considers the desired charging level and minimizes costs related to waiting time, charging service fees, and travel distance. By balancing the desired charging outcomes with minimal inconvenience and expenses, this contribution aims to alleviate range anxiety and enhance the overall user experience within the EV ecosystem.

Objective 3:

(a) We introduce an on-demand mobile charging service system that aims primarily at minimizing daily operational costs incurred during self-charging, while simultaneously optimizing total profits to the highest degree possible.

(b) Define a stochastic optimization approach for accepting charging requests. This function helps operators decide whether to accept charging requests based on the probability of receiving better offers and the potential future demand in different locations. It also optimizes idle parking strategies, determining if and when the MCS should relocate to areas with higher expected demand after completing a charging task.

Objective 4:

(a) Within the security perspective, this thesis introduces a robust recommendation system that combines the efficiency and security of fog computing within the IoT network. This approach not only improves the responsiveness of the recommendation system but also ensures the privacy and security of sensitive user data through the utilization of Federated Learning (FL). We propose a VFL algorithm to train a recommender system for EVs to find the most relevant charging sources according to their requirements. This algorithm allows EVs and charging sources to collaborate in a learning system based on the distinctive attributes residing on each side. The significance of this system lies in the fact that only the learning parameters are shared between the parties to update the locally trained models inside each party without revealing any private information.

(b) We design a secure mechanism surrounding the fog nodes to allow only authorized aggregators to have access to the shared parameters. This mechanism preserves privacy by ensuring that every fog node must first register into a distributed blockchain network to become verified by others. The importance of this new architecture is that it prevents malicious users from entering into the fog network for data theft or data tampering attacks.

1.5 Thesis Organization

The remainder of this thesis is organized as follows:

Chapter 2: Background and Related Work. The chapter begins with an overview of the research background, providing context and foundational knowledge necessary for understanding the subsequent sections. It then presents a detailed review of the related works and previous studies, which is classified into three major parts depending on the objectives that our thesis follows. It covers an overview of EV behavioral analysis, charging source recommendation and selection models, and MCSs scheduling. Additionally, the security perspective is reviewed in each category, considering the implementation of FL and blockchain technologies.

Chapter 3: Deep Transfer Learning for Detecting Electric Vehicles Highly Correlated Energy Consumption Parameters. This chapter investigates DTL to identify critical parameters influencing EV energy consumption. It outlines the methodology for applying DTL and domain adaptation to enhance prediction accuracy by transferring relevant features. The chapter also highlights the use of BiLSTM to improve generalization to new data, resulting in more reliable energy consumption estimates and optimized EV energy management.

Chapter 4: Smart Vehicles Recommendation System for Artificial Intelligence enabled Communication. This chapter focuses on developing a recommendation system for smart vehicles, utilizing AI to enhance charging source selection accuracy. It details the integration of AI techniques to provide personalized recommendations for vehicle users. The chapter highlights the use of both FCSs and MCSs to improve the accuracy and efficiency of recommendations, thereby enhancing user experience and overall effectiveness in the smart vehicle ecosystem.

Chapter 5: Empowering Consumer Electric Vehicle Mobile Charging Services with Secure Profit Optimization. This chapter addresses the optimization of mobile charging services for EVs to maximize profitability. It explores strategies for efficient decision-making to enhance daily revenue, incorporating optimization to handle uncertainties in charging requests and future demand.

Chapter 6: Blockchain and Federated Learning for Electric Vehicle Charging Source Recommendation. Presents a blockchain-based recommender system utilizing FL to suggest proper charging sources for EVs demanding battery power. This proposed mechanism mainly focuses on keeping entities' data safe and unrevealed by only sharing locally trained parameters among trusted nodes within the transportation network and energy distribution network.

Chapter 7: Conclusion and Future Research. This section provides a comprehensive summary of the research conducted in this thesis, highlighting key findings and contributions. It also outlines potential future research directions, such as further enhancements in EV energy consumption prediction models, advancements in MCS optimization algorithms, and the integration of emerging technologies like advanced blockchain frameworks and more robust federated learning techniques to enhance security and efficiency in EV systems.

Finally, references are included.

1.6 List of Publications

1.6.1 Journal Papers

1. Z. Teimoori, A. Yassine, and M. S. Hossain. "A Secure Fog-based Charging Station Recommendation for Electric Vehicles Empowered by Federated Learning.", IEEE Transactions on Industrial Informatics, vol. 18, no. 9, pp. 6464-6473, Sept. 2022.

2. Z. Teimoori and A. Yassine. “A Review on Intelligent Energy Management Systems for Future Electric Vehicle Transportation.”, Sustainability, vol. 14, no. 21, pp. 14100, Oct. 2022.

3. Z. Teimoori, A. Yassine, and M. S. Hossain. “Smart Vehicles Recommendation System for Artificial Intelligence-enabled Secure Communication.”, IEEE Transactions on Consumer Electronics, vol. 70, no. 1, pp. 3914-3925, Feb. 2024.

4. Z. Teimoori, A. Yassine, and C. Lu. “Deep Transfer Learning for Detecting Electric Vehicles Highly-Correlated Energy Consumption Parameters.”, IEEE Transactions on Artificial Intelligence, doi: 10.1109/TAI.2024.3358796.

5. Z. Teimoori, A. Yassine, and M. S. Hossain. “Empowering Consumer Electric Vehicle Mobile Charging Services with Secure Profit Optimization.”, IEEE Transactions on Consumer Electronics, [Under Second Revision].

1.6.2 Conference Papers

1. Z. Teimoori and A. Yassine. “User-centric Charging Service Recommendation for Electric Vehicles”, The 22nd IEEE Mediterranean Electrotechnical Conference (MELECON), Jun. 2024.

2. Z. Teimoori and A. Yassine. “Electric Vehicles Energy Management and Charging Source Recommendation System”, The National Research Council of Canada (NRC) Celebration of the Success of Women in STEM Symposium: Women, sustainability, and climate solutions, Feb. 2024.

Chapter 2

Background and Related Work

2.1 Introduction to Chapter 2

This chapter outlines the essential terminologies and foundational concepts of IoT in EVs in Section 2.2.1, emphasizing AI-driven energy management techniques like DTL and MCSs in Sections 2.2.2, and 2.2.3. It also reviews the security risks associated with IoT networks and discusses security solutions such as FL and blockchain, specifically in the context of EV networks in Section 2.2.4. Furthermore, we continue with a comprehensive exploration of the latest studies available by thoroughly organizing them based on their discussed subjects and the proposed solutions they offer. This chapter serves as a thorough examination of the current landscape of research within the domain of Intelligent Transportation Systems. We begin our investigation with a concentrated effort on examining the driving and charging behaviors demonstrated by EVs in Section 2.3.1. Various methodologies and models were explored to precisely estimate energy consumption and SoC battery levels of EVs, with the aim of establishing a more streamlined platform for EV navigation and alleviating concerns regarding range anxiety. Subsequently, our discussion expands to encompass an in-depth investigation into various methodologies aimed at recommending suitable charging services to EVs, all aimed at enhancing the overall QoE for EV owners. Moreover, security considerations and concerns are reviewed in each section to highlight their importance. Within Section 2.3.2, we study and explore several methods available in detail, for suggesting energy service providers, catering to both stationary and mobile charging services that are located close to the geographical coverage and energy demands of EVs. Then in Section 2.3.3, we undertake a review of the previous literature about the optimization of mobile charging station profitability. Here, we delve deep into an extensive array of studies that focused on strategically deploying these stations along optimal routes and aligning them with the unique and specific energy demands encountered.

2.2 Thesis Background

The background section of this thesis provides the foundational context necessary to understand the scope and significance of the research. By presenting a thorough overview of the relevant background, this section aims to equip the reader with the essential knowledge needed to appreciate the relevance and implications of the research findings.

2.2.1 Role of Internet of Things in Electric Vehicles

The rapid development of the EV industry has shown the ability to reduce some of the serious environmental issues in the transport sector, such as air pollutant emissions, energy consumption, and the availability of fossil fuels [30]. Eco-friendly EV industrial technology is believed to have a significant impact on addressing these environmental problems [31]. Therefore, the use of EVs should be encouraged by promoting the advantages over conventional vehicles, including zero emissions, a cleaner environment, lower fuel cost, comfort, and better driving experience, etc., to protect environmental sustainability.

However, many consumers have not adopted EVs appropriately due to a few barriers in the way of the success of EVs which need to be eliminated, such as lower cruising ranges, the inadequate number of charging locations, and lack of proper fast charging systems [11]. In some areas, the low ratio of CS infrastructure to the number of EVs is one of the main concerns that decreases the popularity of EVs among the public. In other areas, the spread of the CSs is not satisfactory for making EVs a good alternative for long-

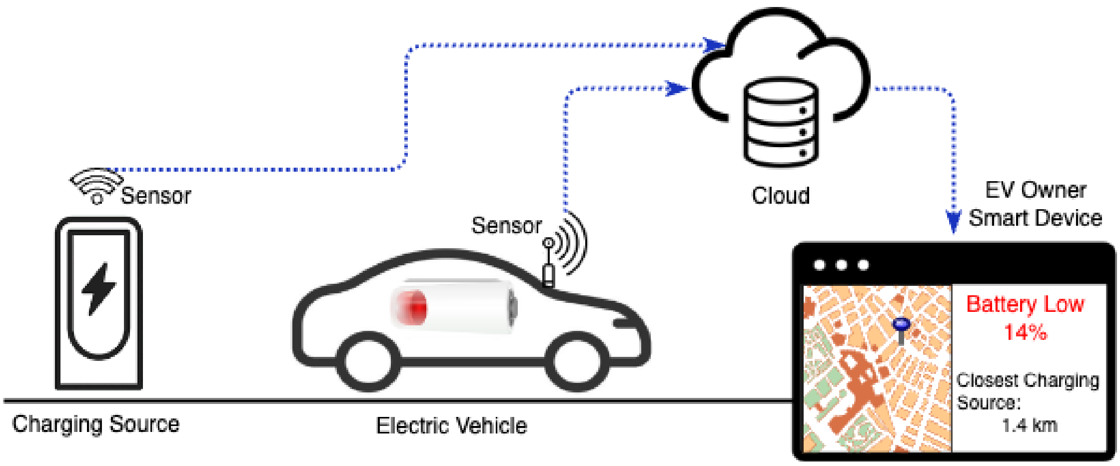


Figure 2.1: General aspects of IoT-based EV energy management system.

distance journeys. Since an EV requires more time to become fully charged [32], unavailable charging spots may stay unavailable for some periods and cause long waiting times for vehicles, especially in peak hours, resulting in a lack of supply for EVs [30]. Therefore, in order to motivate EV buyers and encourage the willingness to switch from gasoline-based vehicles to the new industrial era of EVs, designing an intelligent energy management system is necessary to improve the quality of the EV experience. Figure 2.1 illustrates the fundamental components and interactions within an IoT-based energy management system for EVs. This general setup highlights the integration of IoT technology in managing and optimizing EV performance and QoE.

EVs are advanced technologies that depend on extensive data to perform at their best. They monitor various performance metrics such as speed, acceleration, and mileage. They also manage battery usage and charging, send fault alerts, and utilize predictive maintenance systems to prevent issues. An accurate energy management scheme for EVs requires designing a data-driven model based on information exchange among different parties (EVs, charging sources, cloud infrastructure, and power grids) to efficiently handle EVs' energy demands and adequately manage their electricity utilization [27, 5]. Implementing IoT in EVs allows companies to gain valuable insights that can significantly enhance and personalize the customer experience. By leveraging data collected from IoT devices, companies can improve vehicle performance, anticipate maintenance needs, and offer tailored services to increase overall EV customer satisfaction.

Research in IoT for EVs focuses primarily on two areas. The first is developing fast communication platforms to facilitate efficient data exchange. The second is creating precise software to optimally manage electricity usage and recommend the best charging sources. This work concentrates on the latter direction, which requires a precise energy consumption estimator.

2.2.2 Deep Transfer Learning

DTL is used to improve the accuracy of behavioral analysis, in which the obtained knowledge from one setting is transferred and exploited in another setting [33]. Existing deep learning models need large and diverse datasets to detect rare events, and they perform re-training of already-trained data that requires a vast amount of computational power [34, 35]. DTL, on the other hand, can accomplish precise learning by reducing the amount and quality of required information in addition to offering a way to build models on previously obtained knowledge and not initiating the whole learning procedure from scratch [36, 37].

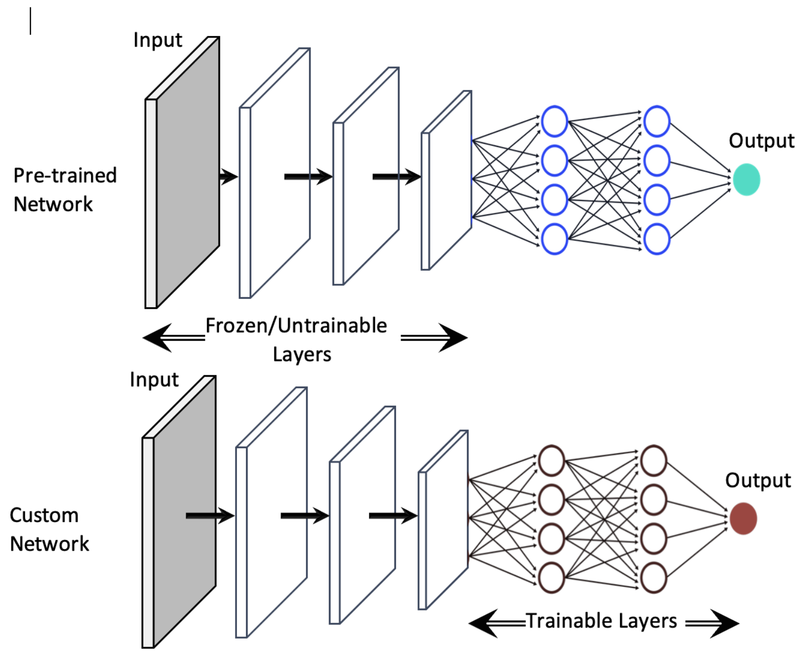


Figure 2.2: In the DTL mechanism, learning a new task relies on the previous learning tasks. Freezing the layers of the pre-trained model is to prevent them from being updated during training. Then additional layers on top of the pre-trained network are added for the specific task.

Transfer learning is a popular approach where pre-trained models developed for a task are re-purposed and utilized as a starting point for a model on a related second task to speed up training and improve learning performance [38]. If the first task's learned features are general and suitable to both the base and target tasks, then transfer learning allows rapid progress and improvements in learning the target task. Figure 2.2 is a simple illustration of the overall transfer learning process. When we adapt the pre-trained model to the target (after loading the source model with all its layers), we opt to freeze initial (general) layers and fine-tune more specific layers to preserve the efficacy of fragile co-adaptation. Freezing the layers of the pre-trained model is to prevent them from being updated during training. This is where the deep adaptation happens by disabling gradient tracking.

Transfer learning involves initially training a model on a source domain, trying to learn the source task that holds a vast amount of labeled data. Subsequently, the knowledge acquired during this pre-training phase is applied to a target domain, trying to learn the target task with only limited labeled data. The general steps in a transfer learning process are as follows:

1. Pre-training a large-scale source domain dataset, which typically is computationally expensive and can be a time-consuming process.
2. Trained weights, parameters, and features are extracted from the early layers of the source model using the extractor function.
3. Pre-trained, and domain compatibility is examined with an optimized implemented loss function.
4. Task-specific final layers are adjusted to the target model.

2.2.3 Mobile Charging Stations

A portable energy unit, commonly referred to as a MCS represents an innovative form of EV charging infrastructure equipped with one or more charging ports. A MCS grants

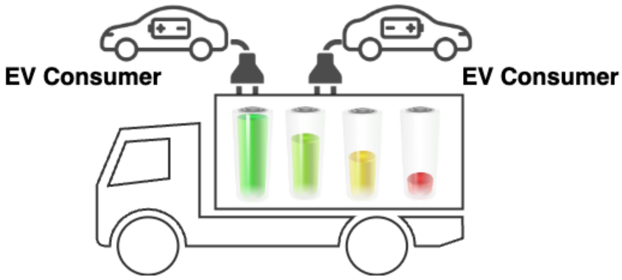
EV owners the flexibility to access EV charging services at times and locations that suit their preferences [39]. The concept stems from the notion of giving a new lease of life to a battery that retains a moderately good or healthy state, allowing it to serve beyond its original role in an EV. This re-imagining could manifest in various forms, such as a versatile high-speed charging station or a mobile charging robot, ensuring the battery's extended and useful existence. MCSs are mobilized in reaction to two distinct types of requests, those originating from overwhelmed FCSs, and requests initiated by EVs.

Based on existing literature, three variants of mobile charging services are identified, which encompass vehicle-to-vehicle energy transfer systems, truck/van-based mobile charging stations, and portable charging solutions [40].

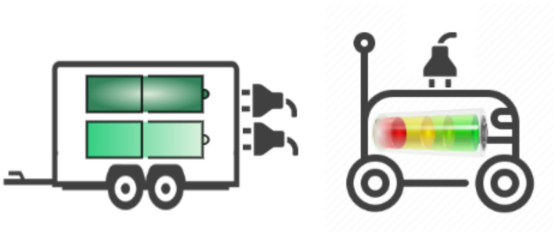
In Figure 2.3a, we can observe a truck MCS with mounted energy storage, which is designed to visit EVs at specified locations where they request, as a dependable source of roadside assistance, providing on-demand charging services. However, to prepare for future services, these truck MCS units must replenish their batteries at a designated charging depository at scheduled timelines.

Figure 2.3b displays two different portable MCS technologies. One of them involves an electricity storage unit mounted on a trailer, which can be transported by a vehicle to charge electric vehicles at specific locations. The second technology resembles a robotic unit capable of autonomous movement towards electric vehicles, or a lightweight battery storage unit equipped with wheels and ports, allowing it to be manually moved or controlled for convenient recharging.

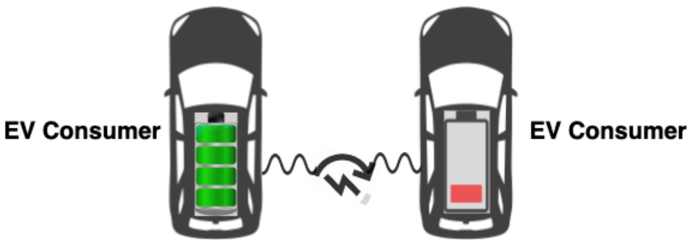
Lastly, in Figure 2.3c, a third type of MCS system (also referred to as a Peer-to-Peer (P2P) power exchange) is depicted, featuring a configuration with two EVs. One of these EVs has a substantial amount of electricity stored in its battery, while the other is on the verge of running out of charge and urgently in need of a power transfer.



(a) A truck mobile charging station example with four installed batteries showing different levels of charge.



(b) A portable mobile charging station example that can be moved by a vehicle (on the left), or an autonomous/movable light battery carried toward an EV (on the right).



(c) A Vehicle-to-Vehicle (V2V) energy transfer that is considered to be a peer mobile charging station.

Figure 2.3: Different categories of types and technologies for mobile charging stations.

2.2.4 Data Security in Electric Vehicles IoT Network

The IoT networks within the EV ecosystem are susceptible to various security risks, including data breaches and unauthorized access. These vulnerabilities can compromise user privacy, disrupt vehicle operations, and lead to significant financial and safety issues. This is why it is important to take into account the data holders' willingness to share their personal information with other entities, as there are some confidentiality concerns.

However, data owners are reluctant to share private information with the system to protect their privacy. To ensure an accurate recommendation, it is essential to facilitate the

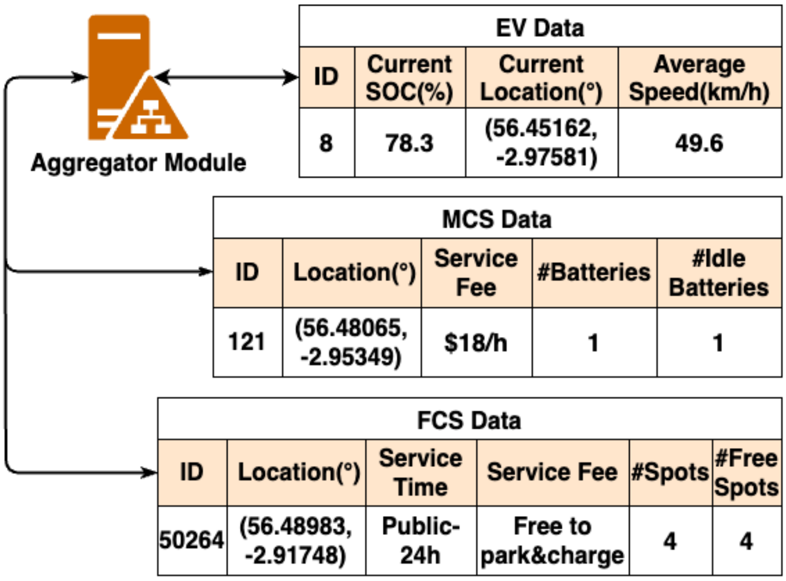


Figure 2.4: Security Problem Statement: An unsafe example scenario of a conventional recommender model, sharing all consumer electronic entities' (EV, FCS, and MCS) sensitive and private information to the centralized module.

exchange of comprehensive and relevant data related to EVs, charging sources, power distribution networks, and road networks as a whole. To deal with this issue, newly proposed systems need to apply rigorous data security algorithms to keep the users' information safe.

In order to gain a deeper comprehension of the security concern in the EV ecosystem, Figure 2.4 illustrates an insecure scenario where a traditional machine learning model makes use of three consumer electronics datasets originating from FCSs, MCSs, and EVs, each having varying features. The primary objective of the recommendation model is to choose the optimal charging source for an EV with a supply request by collecting the usable private attributes from all three participants.

2.2.4.1 Federated Learning

Originally, FL was proposed by Google Artificial Intelligence (AI) in 2016 [41]. The main idea of FL is to form distributed machine learning models based on distributed data sets across multiple devices (entities) while preventing data leakage. In other words, data owners can keep their private data yet still participate in collaborative learning strategies [42]. Figure 2.5 illustrates the basic architecture for a FL system used in the EVs energy

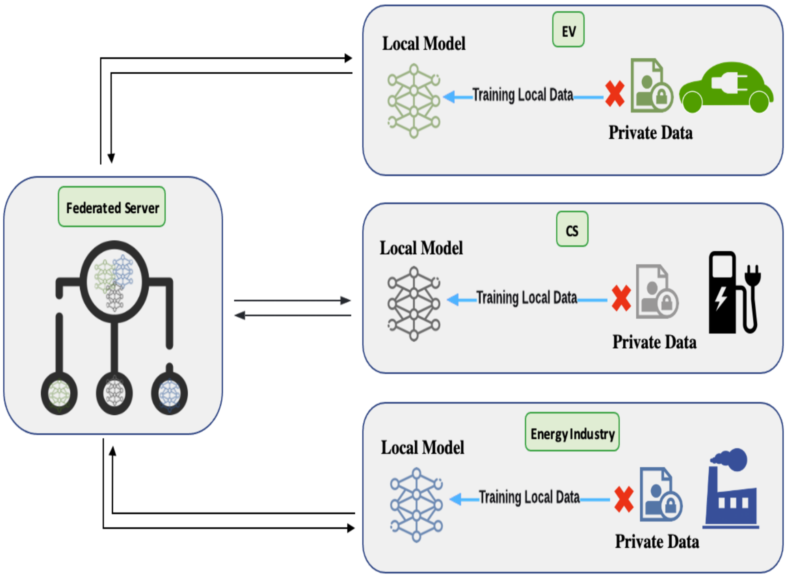


Figure 2.5: An example of a general federated learning framework for secure data exchange between different entities.

sector data exchange.

One of the essential features of FL is privacy. There are some privacy techniques used in FL that can provide meaningful privacy guarantees. Differential Privacy is one of the security models, which is also known as k-Anonymity. This method adds noise to the data to hide sensitive information from other entities to make them incapable of restoring the data [43]. Another line of work is Secure Multi-party Computation (SMC) which provides a data security framework to ensure complete zero-knowledge among parties except for input/output data. This model involves complicated computation protocols to guarantee high security with the cost of inefficiency [44]. Homomorphic Encryption is also adopted in FL to secure users' private information by exchanging training model parameters under an encryption mechanism. In this model, neither data nor the training model itself are transmitted. Homomorphic Encryption is widely used for training data on the cloud as it allows data to be encrypted and out-sourced to commercial cloud environments for processing, all while encrypted [42].

FL is classified into three categories based on the distribution characteristics of data. Horizontal Federated Learning, also known as sample-based FL, is used in cases of datasets where samples are different but they share the same feature space. For instance, two branches of an insurance company may have different users (sample ID space), but the features in the business are similar [45]. On the other hand, in scenarios with datasets sharing the same sample ID space but distinct feature space, Vertical Federated Learning or feature-based FL is applicable. For instance, an insurance company and a car-rental company datasets may likely include similar users residing in an area; therefore, the two companies' sample ID spaces may have a large intersection, however, their feature spaces differ [46]. In order to use both parties' data to process a computation, we need to build a model to collaboratively aggregate different features for similar samples. The last category defines a scenario in which datasets are distinguished in both sample ID space and feature space. Federated Transfer Learning can be applied to an example of two different companies located in geographically distributed areas with a small intercession among user groups [47].

Optimizing the large-scale communication bandwidth between entities and the aggregator server is necessary among all FL models. Also, FL models are required to provide security for the central server to protect model parameter aggregation [48].

2.2.4.2 Blockchain

Blockchain technology was first introduced in 2009 to describe the basis of developing the Bitcoin digital currency [49]. This can be another approach to reduce security threats to the private information of data owners based on Blockchain technology, which uses a complex system to record information in a digital ledger of transactions distributed and duplicated across the blockchain network. Each node (a computing system holding the distributed ledger) within the network receives a copy of the ledger hence, making it impossible to penetrate the network and forge the stored data [50].

The blockchain structure links each block to the preceding block under a cryptographic signature system; therefore, a chronological chain of blocks is generated containing transactions. Before granting permission to a node to add a new block in the chain, consensus on the validity of data must be reached among other nodes, which requires a certain effortful mechanism and particular conditions. The consensus is necessary to guarantee authenticity and to replicate other blocks, and also to avoid forking (i.e. the possibility of generating the same block by different nodes) [51].

Three main consensus protocols have been introduced to facilitate agreement among fully decentralized nodes by considering the validity of transactions. Proof of Work (PoW) performs computationally complex operations on each newly added block. Nodes compete with each other to solve these complex operations, which is a cryptographic puzzle, to be able to add a new block into the blockchain. The purpose of this puzzle is to generate a hash value with several leading zeros that is lower than a target for the hash. The lower the target, the smaller the set of valid hashes, and the harder it is to generate one. In practice, this means a hash that starts with a very long string of zeros. The PoW guarantees immutability for the blockchain as to alter a block, all subsequent blocks must be altered, which is computationally infeasible. However, due to enormous computing power, it requires vast energy consumption with low transaction throughput [50]. To address the non-scalability and energy-intensive issues of PoW, the Proof of Stake (PoS) protocol was introduced as an alternative solution. In the PoS consensus algorithm, validators lock up a stake and are randomly selected based on the staking amount of the participating validators to add a new block to the blockchain network. PoS is considered a cleaner and faster protocol than PoW since it requires lower computation power and higher transaction throughput [52]. A symbolic comparison between these two protocols is shown in Figure 2.6. The other consensus protocol is called Delegated Proof of Stake (DPoS) in which delegates vote for their favorite validators to generate new blocks in a blockchain network. As each representative has the power to vote proportional to the size of the stake in the network, this protocol is less likely to become centralized, and it is considered the democratic version of the PoS protocol. Accordingly, due to the fact that DPoS needs less number of trusted nodes to verify data in each new block of the network chain, it can handle a higher number of transactions with faster confirmation times than PoW and PoS [29].

In order to automate the execution of an agreement to receive a certain outcome among all participants, Smart Contracts are embedded into the blockchain network as simple com-

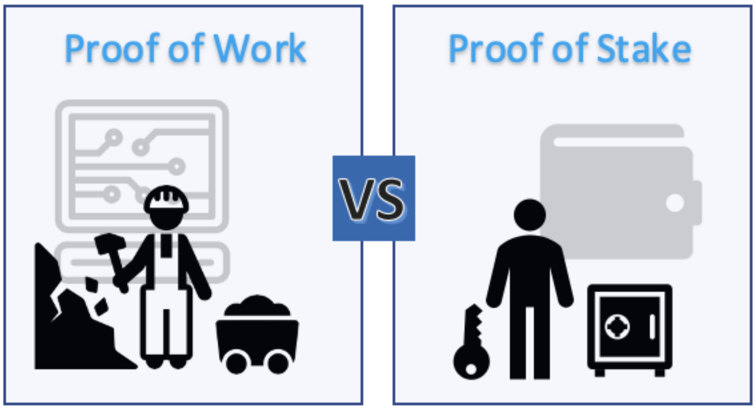


Figure 2.6: The PoS protocol is an alternative solution for a less wasteful validation algorithm.

puter programs that run when conditions are met. Smart contracts are sets of IF/WHEN-THEN rules written in codes that require an exact sequence of actions to execute predefined agreements. Once a transaction is complete, the blockchain will be updated, and consequently, the transaction will become unalterable [53].

2.3 Related Work

By examining prior studies, this section aims to identify gaps in the literature, highlight significant contributions, and establish the context for the present research.

2.3.1 Electric Vehicle Behavioral Analysis

Analyzing EV driving behavior characteristics is an essential task for future energy planning and resource allocation optimization. It is stated that the energy consumption of an EV can be determined by its driver, vehicle status, and traffic conditions.

Considering EVs in the public transportation sector (electric buses), the study proposed in [54] compared the relationship between the intensity of micro-trips for electric buses and the performance of energy consumption. The experimental results showed that the influence of the high-intense micro-trips is significantly larger than the low-intense micro-trips. In [55] a Markov Decision Process-based model was developed to investigate the electric bus network to understand its operating and charging patterns, and further verify the necessity and feasibility of a near-real-time charging scheduling. They designed a data-driven near-real-time charging scheduling system by taking factors of electric bus spatial-temporal charging distribution and time-variant electricity pricing into account and gained a dramatic reduction in the charging costs. Literature [56] studied electric bus energy consumption and battery capacity for various forms of transit services. They introduced a framework for determining the appropriate e-bus battery size with a comprehensive analysis and evaluation of real-world operational circumstances. Moreover, [57] presented a method to schedule electric buses under micro-driving behavioral analysis. The authors indicated the fact that electric buses have longer charging times and shorter cruising ranges than personal EVs. They designed a heuristic optimization model based on the genetic algorithm to estimate the scheduling by considering all bus transportation planned tasks.

Most studies of obtaining the correlation between EV energy consumption and driving characteristics focused on classifying and optimizing energy consumption from driving styles, driving behaviors, and driving cycles. Authors in [58] proposed an energy-aware driving behavior analysis to determine a near-real-time energy consumption indicator based on EV wheel cycles every three seconds. This study showed that EV acceleration and lane-change behaviors are strongly connected to energy consumption. Other driving analyses focused on analyzing the effect of the driving styles on the EV battery aging and then classifying the driving styles based on the average acceleration in three categories namely, gentle, mild, and aggressive. They showed that the traffic flow can affect the driving acceleration style and consequently, the style can have a considerable impact on the electricity consumption by vehicles [59]. In [60] a large network of real EV datasets is utilized to analyze EV charging behaviors based on some extracted features, such as the time of EV connection to the charging point, duration of the connection, and the amount of consumed electricity during the charging. The statistical probability model is then used for voltage distribution investigation and the voltage unbalance factor calculation.

Other literature in [61] studied the impact of EV charging/discharging behavior on energy load uncertainties. This study assessed the stochastic EV charging/discharging pattern with probability density function and Monte Carlo method by proposing three scenarios from a real distribution network in the UK. Their experimental results showed that EV charging has an adverse impact on power efficiency, thermal stress, and voltage drop. Similarly, authors in [62] offered insights into a flexible charging scheduling for EVs to balance the load pressure on the grid. Their studies are based on four categories of real-world charging stations, and they tried to optimize the charging time using the sequential least square quadratic (SLSQ) optimization technique. Chen *et. al.* [63] analyzed EV traveling behaviors to propose a dynamic optimization model for CSs placement and construction. They also introduced the charging scarification coefficient and queuing theory for charging demand determination.

One recent study [64] analyzed charging influential factors to develop a model of EV charging choice estimations. In this study, several factors, such as vehicle attributes, travel information, and charging point arrival activities and satisfaction were considered and as a result, two primary patterns were established to improve EV owners' attractions and charging service levels.

Up to now, the literature on studies has aimed to devise efficient energy consumption patterns based on EV datasets. However, the scarcity of available datasets can influence the outcomes of the analysis. Alternatively, employing transfer learning can help alleviate this constraint.

In this case, one recent study measured the capacity of Li-Ion batteries used in EVs with a proposed transfer learning deep neural network model to predict the battery cycles considering three outside temperatures for a missing target dataset [65]. Another transfer learning technique [66] is applied to a multi-layer 1-dimension Convolutional Neural Network (CNN) model in order to monitor EV battery SoC levels, energy, and temperature. Their end-to-end framework collects battery cycles' current, voltage, temperature, and differential temperature only to facilitate EV battery efficient operation. Article [34] introduces an approach to transferring knowledge from ICE/Hybrid Electric Vehicle (HEV) data to EV data using a deep Bidirectional Recurrent Neural Network (BiRNN). Their approach presents a fine-grained trajectory segmentation method to develop an adaptive estimation model capable of handling various driving trajectories, enhancing model versatility. Moreover, in [67], the authors introduced a Controllable Deep Transfer Learning model to predict SoC in batteries, catering to short and long-term estimations, especially for cells with limited charging history. In their model, the controllable Multiple Domain Adaptation (MDA) technique is used between historical and target cells using two LSTM networks. It aims to improve SoC estimation accuracy and computational efficiency, demonstrating significant performance improvements over existing methods in experiments.

Table 2.1 summarizes the main contributions, benefits, and limitations of major EV charging and driving behavior analysis in previous studies.

Table 2.1: Comparison of EV driving and charging behavior analysis.

Ref. Article	Proposed Solutions	Benefits	Limitations
[54]	• Micro-trips intensity for electric buses.	• Real-world data evaluation. • Scalable to other types of EVs.	• Small number of feature analyses.
[59]	• EVs battery aging performance by driving style.	• Improving EV battery life cycle.	• Not enough feature extraction.
[58]	• EVs near-real-time energy consumption indicator.	• Proving strong correlation.	• Small number of feature analyses.
[60]	• EVs charging behavior evaluation.	• Real large dataset analysis.	• No consideration of other factors and features. • Simple probabilistic analysis.
[61]	• Monte Carlo analysis of EV charging/discharging behavior.	• Real case studies evaluation. • Applicable for other case studies.	• Simple probabilistic analytical model. • Not considering fast charging modes.
[63]	• Multistage CSs placement with EVs traveling behavioral analysis.	• Improving that optimization performance. • Real case studies.	• No discussion about charging scheduling.
[57]	• Electric bus charging scheduling with heuristic genetic algorithm optimization based on micro-driving behavioral analysis.	• Real case studies based on Beijing Public Transport data. • Introducing trip buffer time concept. • Minimizing total scheduling cost.	• Estimating only electric buses' trip times. • No discussion about traffic flow. • Not considering other charging modes.
[64]	• EVs behavioral analysis based on mixed choice models.	• Considering the heterogeneity of features. • Real case studies and survey design.	• No discussion about the model computation cost.
[55]	• Markov Decision Process for near-real-time e-bus charging schedule.	• Reducing electric bus fleet charging costs. • Near-real-time pricing-aware scheduling.	• No traffic flow impact analysis.
[65]	• Li-Ion battery cycle prediction with DTL.	• Real dataset evaluation.	• Limited number of feature selection. • No domain adaptation consideration.
[66]	• Multi-task 1D CNN DTL-based to monitor SoC.	• Facilitates EV battery efficient operation.	• Complexity of implementation. • No consideration for domain adaptation.
[67]	• EV battery cell-to-cell variations estimation with DTL.	• Generalizability improvement of the data-driven model.	• Missing large-scale data analysis.

2.3.2 Electric Vehicle Charging Source Selection

2.3.2.1 Fixed Charging Stations

A personalized charging source recommendation model requires information from separate entities such as EV status and location, user's private data, and charging source details [68]. Any previous studies focused on answering the question of how to find the best charging source that satisfies user requirements depending on the current available charging capacity and location of an EV. In this case, in the literature [69], the Exponential Harris Hawks (EHH) optimization method is used to identify the suitable FCS for EVs by prioritizing FCSs based on four stages of driving, planning, scheduling, and charging. They evaluated their proposed optimization algorithm through the highest SoC, shortest driving distance, and longest average queue time. In [3] used a hybrid decision-making algorithm based on the measurement theory from quantifiable metrics (Charging Time, Maintenance Cost, etc.). [70] investigated the charging scheduling of when to charge for EVs already been parked at FCSs, but to improve the charging QoE, they also focused on charging recommendations to optimally recommend charging spots to EVs concerning the service waiting time.

Other literature focuses on increasing the recommendation accuracy by mixing features from both EVs and FCSs platforms. The work in [10] developed an application to notify a driver to look for a FCS, find the nearest FCS, and reserve a charging slot by gathering the data from both platforms through GPS and asking the driver to enter some information into the publicly available websites. In [71] a system for electric ride-sharing was proposed to reduce the idle times while recharging. One competitive model was developed in [6] to recommend FCSs to EVs by focusing on charging demand prediction, different offers from FCSs, and users' satisfaction with their arrivals to the FCS. In 2021, one literature [72] studied the impact of a charging station scheduling and reservation approach to prioritize EVs charging demands at a FCS. Some charging scheduling algorithms were designed in [73] to achieve the load balance on the FCS side by considering different factors, such as current traffic, EV battery capacity, FCS power constraints, etc. Furthermore, a decentralized charging recommendation framework for on-the-move EVs was proposed in [74]. In this strategy, the EV's parking deadline is also considered to enhance the estimation of FCSs charging queuing and charging availability.

In addition to the private electric cars, some literature has studied different approaches to build a pricing-aware fast FCS locator for electric taxis in urban areas to increase the profit by considering the peak hours, traffic and road conditions, and high taxi-demand locations [75]. Zhang *et. al.* [76] proposed a recommendation strategy to assign e-taxis the best charging location at the best time. For the charging-time modeling, they computed factors, such as electric taxi unit time revenue, charging capacity, charging process duration, and time-of-use electricity cost. Charging location modeling, on the other hand, needed the computation of other factors including driving time, queuing time, charging capacity, and charging time.

Table 2.2 summarizes the main contributions, benefits, and limitations of major FCS recommendation models for EVs.

Table 2.2: Comparison of FCS recommendation mechanisms for EVs.

Ref. Article	Proposed Solutions	Benefits	Limitations
[5]	• Detecting potential factors affecting FCS recommendation.	• Prioritizing parameters. • Optimizing the search-based EVs constraints.	• No consideration of data security. • Evaluation over a small dataset.
[70]	• FCS reservation management and multi-objective slot allocation for EVs.	• Lower average waiting time.	• Considering assumptions and constraints for evaluations. • Only focusing on urban areas. • No consideration of data security.
[4]	• Collaborative filtering.	• Utilization of road, station, and EV conditions.	• Evaluation over a small dataset. • No consideration of data security.
[6]	• Competitive charging schedules in EVs network.	• Maximize the total revenue collected from all EVs. • Robust bidding algorithm.	• No consideration of EVs and data security. • No discussion about the algorithm execution time.
[77]	• Planning of EVs solar FCSs.	• Promote solar energy consumption and decrease energy costs. • Minimize peak-hour energy consumption. • Discussion about the feasibility and scale of the algorithm.	• No consideration of data security. • Only available for on-site installation.
[32]	• Urgency first charging scheduling policy.	• Maximize FCSs utility and benefits. • Maximize EV charging efficiency.	• Evaluation over a small dataset. • No consideration of data security.
[11]	• Multi-Phase Markov Decision Process for FCSs recommendation.	• Reduce algorithm complexity and computation delay. • Implement dynamic recommendation modeling.	• Lack of real-world dataset for evaluation. • No consideration of data security.
[75]	• Markov Decision Process for electric taxis spatial-temporal net revenue estimation.	• Near-real-time recommendation. • Utilizing real gasoline taxis GPS trajectories dataset.	• Not considering traffic information. • Neglecting FCS waiting time effect on the revenue. • No discussion about data security.
[76]	• Electric taxi charging location and time modeling.	• Computing different effective factors. • Real data set evaluation. • Improving electric taxi users' satisfaction and revenue.	• No discussion about model computation complexity. • Neglecting users' data security protection.

Although these authors have improved the performance of the recommender system, they neglected the fact that data holders are reluctant to share private information with third parties due to some privacy concerns. In [78] FL was used to predict EVs network energy demand. They proposed an energy-demand learning-based prediction from the FCSs side consideration, in which one central FCS provider collects all FCSs information and performs the learning process. Their model is based on FL therefore, no private information was shared. To improve their model performance, the learning model was based on the FCSs clustering algorithm, which could improve the accuracy of prediction and minimize the communication overhead. Authors in [79] proposed a near-real-time FL to predict autonomous vehicles' steering wheel angle prediction. They included a sliding training window to minimize communication overhead and maximize near-real-time streaming data rate. One recent research has addressed the above issues by implementing VFL in a recommender system while the data is kept with data holders and only some training parameters are shared among the platforms [80]. The problem is that the parameter aggregator node is centralized, and it can result in some communication issues and reduce the QoE for a near-real-time model.

Speaking of privacy, there is other research about securing the data from malicious attacks while being transmitted between platforms by using blockchain technology [81]. The study in [82] designed a FL blockchain-enabled model to address centralization and security issues that exist in autonomous vehicle communication. However, when using FL for large-scale applications, other arising challenges such as network and communication limitations must be considered and addressed. For example, in [83], the authors proposed a framework based on blockchain to reserve the optimal FCS, verify parties, and pay the charging price through smart contracts. However, this work lacks the evaluation results of the proposed model. Blockchain is also integrated into [84] to design a secure network of a virtual power plant to store/broadcast the power consumption prediction training models performed by a FL framework. It should be mentioned that by increasing the number of blocks, the massive memory size will reduce the model performance. The work in [52] introduced a blockchain FL architecture for on-device machine learning to reduce communication latency by optimizing the block generation rate. This work provided rewards proportional to the training sample sizes to motivate devices.

Table 2.3 summarizes the previously proposed data-privacy protection approaches of FCSs recommendation systems for EVs.

Table 2.3: Comparison of secure FCSs recommendation mechanisms for EVs.

Ref. Article	**Proposed Solutions**	**Benefits**	**Limitations**
[82]	• Blockchain-based FL for autonomous vehicles.	• High level of data protection. • Optimal block arrival rate.	• Low throughput due to network delay and forking.
[85]	• Joint decentralized federated energy learning and multi-principal one-agent contract-based method.	• Maximizing FCSs utility and profit. • Secure local predictions. • Reducing communication overhead among FCSs.	• Centralized aggregation node.
[80]	• VFL-based FCSs recommendation with Homomorphic Encryption.	• Secure cross-platform architecture.	• Centralized aggregation node. • Higher communication delay.
[83]	• Blockchain-based FCSs recommendation.	• Ensuring the privacy of user data. • Low transaction overhead.	• Lack of real-world dataset for evaluation. • No discussion about the algorithm execution time.
[86]	• FL for EVs energy prediction.	• Lightweight secure architecture to faster generate a global model. • Accurate prediction. • Incentivizing algorithm for FCSs.	• No discussion about the feasibility of the algorithm in the actual environment.
[87]	• EVs charging program based on blockchain.	• Secure charging payments. • Minimizing EVs costs. • Fully decentralized.	• Lack of scalability evaluation.
[78]	• Clustering-based FL EVs energy demand prediction.	• Secure data sharing. • Evaluating on real data set.	• Relying on a central aggregator.
[79]	• Near-real-time FL AEVs steering wheel angle prediction.	• Minimizing communication overhead. • No user private data revealing.	• No discussion of algorithm implementation on a real dataset. • Centralized aggregator.

2.3.2.2 Mobile Charging Stations

Several prior studies have proposed diverse solutions to mitigate range anxiety, reflecting the heightened interest in the realm of FCS recommendations for EVs. However, the primary objective is to meet the electricity demands of EVs without depending exclusively on forthcoming amenities. Consequently, to efficiently manage and synchronize the frequent charging needs of EVs, introducing an alternative charging service could prove highly advantageous [88].

In that instance, [24] proposed a new model to increase EVs access to the proper MCSs by optimizing the EV allocation to the scheduled MCS at the optimal location. The study in [89] also, tried to design a scheduling and routing optimization model to reduce the long waiting times and overcrowding while charging EVs in their demands. They applied a modified version of the heuristic and genetic algorithm to address the NP-hard nature of the main problem. In order to find a well-suited MCS among the list of recommended ones, literature [90] proposed an auction-based mechanism to allow the EVs to bid on the MCSs' suggested prices to maximize the fairness of the MCSs network.

Table 2.4 summarizes the previously proposed MCS integration into the recommendation system for EVs.

Table 2.4: Comparison of existing literature reviews covering MCSs integration into the recommendation system, and our work.

Problem Statement	Paper [24]	Paper [89]	Paper [90]	Paper [91]	Our Work
Mobile Charging Station Recommendation	✓	✓	✓	✓	✓
Decentralized Network	-	-	-	✓	✓
Secure Communication	-	✓	-	✓	✓
Fixed & Mobile Sources	-	-	-	-	✓

2.3.3 Mobile Charging Station Performance Optimization

Typically, literature concerning MCSs can be divided into two main groups of study: modeling and organizing [23, 92, 21], assignment and functioning [23, 24, 93, 89, 94]. The modeling and designing research category focuses on designing innovative electronic components and developing frameworks for MCS. The assignment and functioning group deals with the practical aspects of MCS operations, including the assignment of charging tasks, routing, scheduling, and day-to-day functioning. Research in this category aims to develop algorithms and strategies to manage the dynamic nature of MCS operations, optimize service delivery, and ensure cost-effectiveness. Here we conduct a more comprehensive analysis that underscores the strengths of our proposed framework in comparison to existing optimization models that fall into the assignment and functioning category.

The [92] study introduced a novel modeling approach for MCSs by replacing conventional batteries and motors with advanced components: an enhanced Interior Permanent Magnet (IPM) motor and Lithium Ferro Phosphate Battery. Their evaluation revealed that the IPM motor was selected due to its high torque capabilities and consistent performance across varying speeds. The authors from [95] suggested an enhancement to their optimization algorithm aimed at reducing operational expenses for commercial delivery fleets. Their focus was primarily on addressing the routing problem within specified time windows while also considering the utilization of mobile battery charging and swapping services. In a different study [24], researchers aimed to introduce a multi-stage framework for intelligent EV parking. They seek to optimize parking operations by managing energy allocation, sales, and demand equilibrium, while also maximizing profits for parking owners. This was achieved by integrating MCSs to enhance revenue opportunities and improve scheduling accuracy.

Another investigation [93] introduced a recommendation model tailored for EVs, taking into account MCSs to address deficiencies in charging infrastructure. The study devised an optimized EV travel path aimed at reducing both charging duration and expenses. Additionally, it explored the role of MCSs in energy demand load balancing within the smart grid. [89] in their investigation, attempted to devise a model for optimizing scheduling and routing to alleviate extended wait times and congestion during EV charging sessions. They tackled the inherent complexity of the problem by employing a customized version of heuristic and genetic algorithms. The researchers in [94] presented an innovative approach to MCS modeling for energy delivery within a designated coverage area through systematic point visits. They leveraged energy-restricted unmanned aerial vehicles (UAVs) alongside unmanned ground vehicles (UGVs) acting as MCSs. Their methodology involved formulating an optimization problem aimed at achieving steady allocation cycles across separate routes.

Additionally, in another study [23], researchers examined a novel model of MCS utilizing hydrogen fueling instead of electricity to enhance charging delivery and infrastructure, thereby mitigating range anxiety. They employed a heuristic algorithm to optimize the operation of these MCSs, exploring various service scenarios, such as several vehicles and several path-traveling algorithms. Moreover, the work by Liu et al. [91] aimed to decrease the inactivity of MCSs by advising them to EV owners wanting to cut down on charging expenses. They suggested a forecast model using FL to recommend the best places to put MCSs, learning from past travel routes. It becomes apparent that their emphasis was on predicting optimal routes for moving MCSs to minimize idleness while preserving user privacy. Despite their focus on minimizing EV costs, the consideration of FCSs, in some cases a more economical option, was overlooked.

Based on the reviewed literature, we outline the findings in Table 2.5 and highlight their strengths and areas where improvements are needed and proposed by our study.

Table 2.5: Comparing existing literature reviews in MCSs performance optimization stating their strength and limitations.

Ref. Article	Proposed Solutions	Benefits	Limitations
[95]	• VNS method for EV time-window routing.	• Synchronized MCS for recharging/swapping. • Reducing operational expenses while maintaining an optimal fleet size.	• Does not examine MCS profit optimization. • The effectiveness of their method is not compared with other routing algorithms.
[93]	• EV charging scheduling optimization with trajectory analysis.	• Range anxiety mitigation with MCSs.	• Not considering and reviewing MCS profit optimization. • Data security concern is not addressed.
[24]	• Energy balance for a smart EV parking, and profit maximization.	• Considering MCSs and increasing their accessibility. • Energy management and load balance optimization.	• Does not examine MCS profit optimization itself. • Data security concern is not addressed.
[89]	• Addressing a complex optimization problem for MCS traveling with a meta-heuristic genetic algorithm.	• MCS performance improvement.	• Not a decentralized model. • Neglecting security concerns addressing.
[94]	• Introducing UAV-UGV MCSs route planning.	• Optimized robust traveling algorithm. • Increasing the energy-delivering performance by team collaborative patrolling.	• Centralized network and unsafe for data sharing. • UAV-UGV MCSs benefit estimation is not discussed.
[23]	• An alternative Hydrogen MCSs with operation optimization.	• EV cost minimization. • Range anxiety alleviation for hydrogen EV energy demands.	• Insecure data exchange. • HMCSs profit optimization is not discussed.

2.4 Chapter 2 Summary

Building a suitable transportation infrastructure for EVs is one of the main conducive factors to enable the widespread use of EVs. While the number of EV owners is growing, coordinating the charging source foundation with the continuous improvement of the EV industry is essential. However, since improving the CS infrastructure and deploying new stations and chargers are time-consuming and high-priced, the critical concern is to address EVs charging demands without waiting for future facilities. Therefore, to better guide and coordinate the frequent charging requirement of EVs, developing intelligent charging source recommendation schemes can provide satisfaction for EV owners [96].

Taking into account different usage charging demands, researchers should implement customized charging strategies according to the purpose of travel. For personal EVs, factors including driving distance, EV charging capacity and remaining, charging cost, etc., can have an impact on the allocation of efficient CSs [97]. A practical charging source recommender should be able to address challenges for on-the-move EVs, such as where to charge and how to optimally find the charging source with the least waiting time inside the service queue to receive the required energy [5].

The comprehensive review of the latest studies within the domain of ITSs highlights several significant advancements and persistent challenges in EV management. Our investigation began with an in-depth analysis of EV driving and charging behaviors, emphasizing the importance of accurately estimating energy consumption and SoC levels. Various methodologies and models have been explored, demonstrating their effectiveness in streamlining EV navigation and alleviating range anxiety. Additionally, security considerations have been integrated into each section to underscore their critical role in maintaining the integrity and reliability of the systems.

Subsequently, the exploration extended to the selection of energy service providers, focusing on both stationary and mobile charging services. The studies reviewed have proposed numerous innovative approaches to recommending suitable charging stations, enhancing the overall user experience. By leveraging optimization algorithms and data-driven models, these approaches have shown promise in reducing charging times, minimizing queuing, and improving the efficiency of charging infrastructures. However, the implementation complexity and the need for extensive datasets remain notable challenges, necessitating further research into scalable and accessible solutions.

Finally, the review delved into the optimization of MCS performance. The studies covered various aspects, including the strategic deployment of MCSs, scheduling, and routing optimization, and the integration of advanced technologies blockchain. These efforts aim to address range anxiety and enhance the profitability of mobile charging services. Despite the progress, there is still a need for more robust models that can handle near-real-time data and adapt to dynamic conditions. By examining the comparative analysis presented in this chapter among various prior studies and their focal points, it becomes evident that this thesis strives to address the gaps observed in those preceding works.

Chapter 3

Deep Transfer Learning for Detecting Electric Vehicles Highly Correlated Energy Consumption Parameters

3.1 Introduction to Chapter 3

Energy consumption estimation for EVs is essential to address the major challenge of limited driving range by providing improvements in EV cruising range and eco-driving behavior. However, it is hard and costly to collect a comprehensive dataset from different vehicle types that can reflect the overall driving characteristics, which introduces challenges for model training. Hence, the insufficiency of EV data training samples might have an adverse impact on the accuracy of the estimation method.

In this chapter, we introduce an estimator method inspired by the DTL paradigm which is capable of achieving high prediction accuracy under vehicle dynamic working conditions despite insufficient data. We mainly aim to identify the highly correlated energy consumption parameters by transferring the knowledge from the electric bus base model to the EV target model with reduced and scarce datasets. The findings from this phase of our model will then be used to analyze EV driving behaviors in order to enhance the driving patterns to become more eco-driving behaviors.

We present details of the DTL problem formulation for energy consumption estimation, our proposed algorithm, and compare it with state-of-the-art RNN-DTL algorithms, and discuss the trade-off between model performance and efficiency.

3.2 System Model and Problem Formulation

In this section, we describe the problem of RNN embedding in the DTL mechanism with domain variant feature parameters, along with the key performance metrics for evaluating our accurate energy consumption estimation problem.

Figure 3.1 shows the primary steps followed in our model to ensure efficient information transfer at deeper network levels over feature values with stronger similarity and correlation and smaller discrepancy. The presented model's main steps are described in detail as follows.

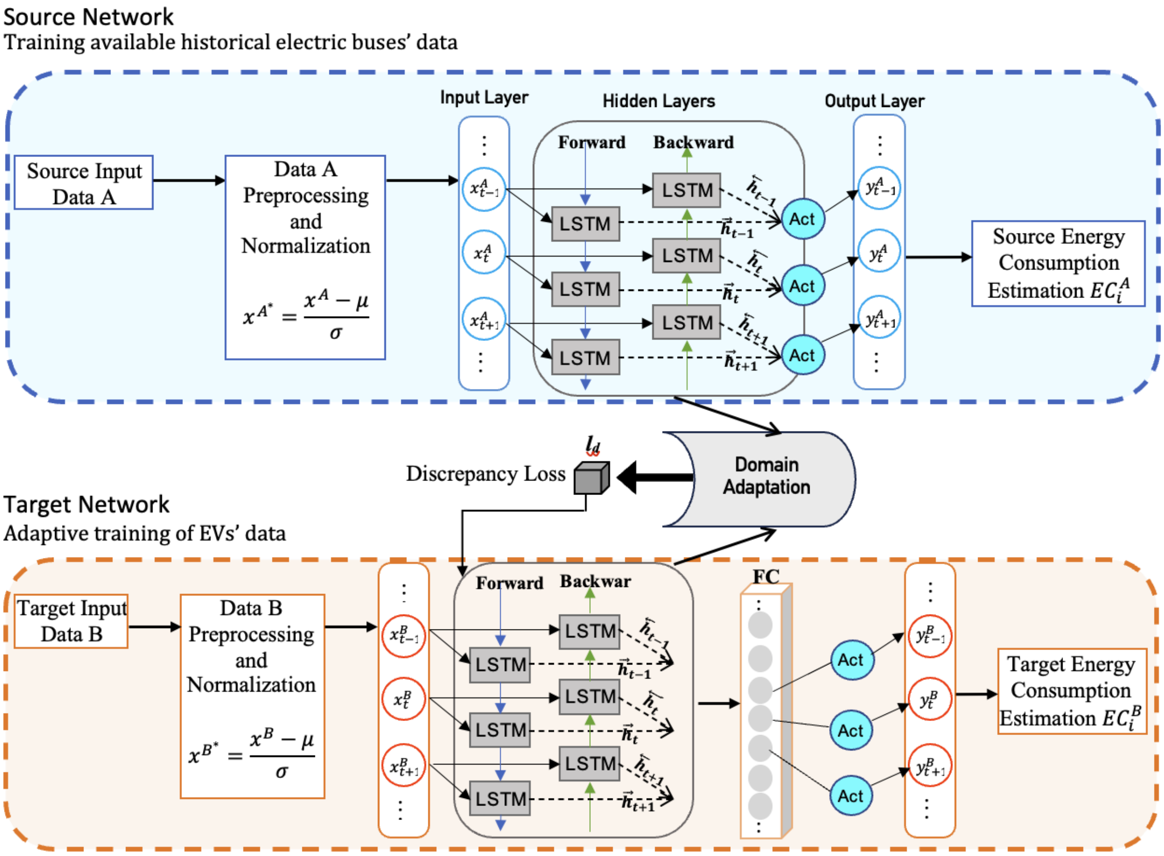


Figure 3.1: Model framework. The Deep Recurrent Neural Network (BiLSTM) Transfer Learning technique is implemented to estimate EV energy consumption based on learned and trained parameters from electric bus energy consumption. Feature Domain Adaptation and correlation between the source (electric bus) and target (EV) data is used to optimize the model performance with generated discrepancy losses.

3.2.1 Data Normalization

The captured datasets from electric buses and EVs consist of numerical values with different scales, including parameters like speed, mileage, SoC, temperature, and more. Therefore, analyzing and training these datasets requires normalizing feature values to construct standard data with common data ranges and distributions.

In the first step of building our model, we utilized Linear Scaling and Z-score normalization techniques to better transform the numeric data values with easier data comparability. Linear Scaling when values are roughly distributed over a fixed range.

$$\hat{x} = \frac{x - x_{min}}{x_{max} - x_{min}}. \tag{3.1}$$

And Z-score to indicate how far the original score value resides from the mean value.

$$\hat{x} = \frac{x - \mu}{\sigma} \qquad , and, \quad \hat{x}_{error} = \frac{x - \mu}{\frac{\sigma}{\sqrt{n}}}, \tag{3.2}$$

where x is the raw data, μ is the mean value, σ is the standard deviation. Accordingly, $\hat{x}_{error}$ indicates the standard error of the mean to also capture the error margin for future analysis by including the dataset feature's total sample size n.

3.2.2 Training Source and Target Models

The energy degradation process of EV batteries is strongly associated with the historical consumption path. EV batteries' SoC generates time-series data at various cycles that are closely linked to the preceding cycles. Therefore, we utilized the LSTM algorithm, which is an enhanced version of the RNN, with feedback connections to provide long-term memories by memorizing values from the previous series. In LSTM, each cell at time t has three gate functions (i_t input gate, f_t forget gate, and o_t output gate) to prevent training explosion/vanishing gradient, and to improve the estimation accuracy by acquiring temporal dependencies between series. The flow of data in the network, and the values of these gates are classified and limited in the range of $[0, 1]$ with a sigmoid activation function ($Sig()$). The mathematical functioning of LSTM gates and memory cells are described as follows [34]:

$$i_t = Act(W_{hi}h_{t-1} + W_{Xi}X_t + b_i), \tag{3.3}$$

$$f_t = Act(W_{hf}h_{t-1} + W_{Xf}X_t + b_f), \tag{3.4}$$

$$o_t = Act(W_{ho}h_{t-1} + W_{Xo}X_t + b_o), \tag{3.5}$$

where X_t is the input data (i.e. electric bus and EV features; longitude, latitude, temperature, etc.). W and b are weights and biases of the network parameters, and h_{t-1} is the network hidden layer at the prior cycle. By calculating i_t and f_t, the final memory cell state can be derived from equation (3.6).

$$c_t = f_t c_{t-1} + i_t tanh(W_{hc}h_{t-1} + W_{Xc}X_t + b_c). \tag{3.6}$$

Lastly, the hidden state h_t is computed from the result values of the final memory cell and output gate from equation (3.7), and passed to a Fully Connected Layer (FCL) in order to convert h_t into the anticipated output.

$$h_t = o_t tanh(c_t). \tag{3.7}$$

To capture the whole information in the input layer of vehicle data, subsequent and previous information is evenly influential for better knowledge extraction. Therefore, the BiLSTM method, which constitutes putting two LSTMs together, is implemented in the learning phase. This structure enables the network to read input data in both forward and backward directions in order to capture sequential knowledge from past series to future (left to right), equation (3.8), and also from future to past (right to the left), equation (3.9).

$$\vec{h}_t = f(\vec{h}_{t-1} - x_t), \tag{3.8}$$

$$\overleftarrow{h}_t = f(\overleftarrow{h}_{t+1} - x_t). \tag{3.9}$$

And as the last step, the final output of BiLSTM is computed by combining both forward and backward activations, equation (3.10).

$$h_t = [\vec{h}_t, \overleftarrow{h}_t]. \tag{3.10}$$

Given a normalized source electric bus input data and SoC output values D_{sc}, and target EV input data and SoC output values D_{tg}, the next step of our proposed model is to train each domain separately. Domain adaptability is one important factor to consider before applying transfer learning from the source domain,

$$D_{sc} = \{x_n^{(sc)}, y_n^{(sc)}\}, n \in \{1, 2, ..., \mathcal{N}\},$$

to the target domain,

$$D_{tg} = \{x_m^{(tg)}, y_m^{(tg)}\}, m \in \{1, 2, ..., \mathcal{M}\}.$$

Where $x_n^{(sc)}$ and $x_m^{(tg)}$ are source and target input data, respectively, $y_n^{(sc)}$ and $y_m^{(tg)}$ are available true source and target SoC values. Accordingly, the size of two domains are defined with $\mathcal{N}$ and $\mathcal{M}$, where,

$$\mathcal{N}(source) \gg \mathcal{M}(target),$$

D_{sc} and D_{tg} consist of sequential data with time-series dependencies. To this end, the BiLSTM recurrent neural network is applied to catch the temporal relativity between data more precisely.

Each domain (source and target) will apply the feature-specific training model using equation (3.10) to generate the BiLSTM hidden layer output h_{sc} and h_{tg}, respectively.

Transfer learning from the source domain of electric buses to the target domain of EVs involves leveraging the knowledge gained from electric bus operational data to improve the performance and efficiency of EV models. In this approach, a deep BiLSTM network trained on electric bus data, which includes extensive information on driving patterns, energy consumption, and charging behaviors under various conditions, is adapted to work with EV data. Consequently, transfer learning in this algorithm involves initially training a model on the source domain,

$$D_{(source)} = \{X^{(source)}, g^{(source)}(X)\},$$

trying to learn task $T^{(source)}$, that holds a vast amount of labeled data. Subsequently, the knowledge acquired during this pre-training phase is applied to the target domain,

$$D_{(target)} = \{X^{(target)}, g^{(target)}(X)\},$$

trying to learn task $T^{(target)}$,with only limited labeled data. The transfer learning process generally involves the following steps:

1. **Pre-training:** A large-scale dataset from the source domain is used to pre-train a

model. This step is often computationally expensive and time-consuming.

2. **Feature Extraction:** Trained weights $W^{(source)}$, parameters $\theta^{(source)}$, and features are extracted from the early layers of the source model using the extractor function $A(X : W, \theta)_{source}$.

3. **Compatibility Check:** The pre-trained weights $W^{(source)}$, and parameters $\theta^{(source)}$ are examined for compatibility with the target domain using an optimized discrepancy loss function $\mathcal{L}$.

4. **Adaptation:** The final layers of the model are adjusted to be task-specific for the target domain.

Equation (3.10) is then passed to the fully connected layer to estimate electricity usage of electric buses or EVs at the present moment ($E\hat{C}^{(sc)}$ and $E\hat{C}^{(tg)}$, respectively), as shown in equation (3.11):

$$\begin{aligned} E\hat{C}^{(sc)} &= W_{FCL} h_{sc} + b_{FCL}, \\ E\hat{C}^{(tg)} &= W_{FCL} h_{tg} + b_{FCL}. \end{aligned} \tag{3.11}$$

3.2.3 Facilitating Domain Adaptation and Transfer Learning

$E\hat{C}^{(sc)}$ will generate more valid estimation results as it is the outcome of a deep analysis of the large-scale electric bus dataset. However, $E\hat{C}^{(tg)}$ might be over-fitted due to insufficient EV input data since it is trained and informed with too few data sets and might fail to fit for further unseen observations. Hence, transferring the pre-trained W_{FCL} and b_{FCL} source model parameters into the target model and replacing its over-fitted parameters is the main step of this proposed study.

Transferring the trained parameters between two different datasets with distinguished feature scopes raises a concern about selecting a proper parameter similar to the target domain. Domain Adaptation and the rationale behind it involves introducing a loss to the fine-tuned model as a means of regulating the distribution divergence within two domains. Consequently, the elements that contribute to this process include establishing a loss function for calculating the distance, and creating a training model with a modified forward pass incorporating this loss function.

To alleviate this concern, we utilized the Maximum Mean Discrepancy (MMD) mechanism, equation (3.12), to estimate feature distribution distances as a means to enable feature comparison before transferring their trained parameters.

The MMD is a classification accuracy metric to calculate the distribution dependability and similarity among groups of samples. In the proposed deep transfer learning mechanism, the similarity between transferable features should be captured to facilitate a fine-tuned and effective transfer of pre-trained learning parameters. Hence, before transferring features among domains at the deeper layers of the training network, their correlation needs to be measured to build a manageable domain-constant attribute transition.

To calculate the distance between two features' similarity, MMD compares the difference between the mean likelihood distributions of their data points, as shown in equation (3.12).

$$\begin{aligned}\widehat{MMD}^2(h_{sc}, h_{tg}) &= \left|\left| \sum_{n=1}^{N_{sc}} \frac{\phi(., h_n^{(h_{sc})})}{N_{sc}} - \sum_{m=1}^{M_{tg}} \frac{\phi(., h_m^{(h_{tg})})}{M_{tg}} \right|\right|_{\mathcal{H}}^2 \\ &= \sum_{n,m}^{N_{sc}} \frac{\phi(h_n^{(h_{sc})}, h_m^{(h_{sc})})}{N_{sc}^2} - 2\sum_{n,m}^{N_{sc},M_{tg}} \frac{\phi(h_n^{(h_{sc})}, h_m^{(h_{tg})})}{N_{sc}M_{tg}} \\ &+ \sum_{n,m}^{M_{tg}} \frac{\phi(h_n^{(h_{tg})}, h_m^{(h_{tg})})}{M_{tg}^2},\end{aligned} \tag{3.12}$$

where h_{sc} and h_{tg} are the source and target features at the deep layer to be compared with the second-norm MMD in Hilbert space $\mathcal{H}$. The size and number of comparable features are defined as N_{sc} and M_{tg} for the base and target domains, respectively. Function $\phi(.)$ is the Hilbert embedding kernel that preserves density estimations of similarity between two input features.

Accordingly, we adapted and optimized the target model's loss function ($\mathcal{L}$) to equation (3.11) to compute the error between estimated $EC^{(tg)}$ and actual $EC^{(tg)}$, while considering the discrepancy loss function to produce smaller values, which indicates a stronger correlation between feature F distributions. In this context, the parameter λ serves as a trade-off parameter utilized to balance and optimize the overall loss of the model.

$$\mathcal{L}_{tg} = \frac{1}{F\mathcal{M}} \sum_{f=1}^{F} \sum_{m=1}^{\mathcal{M}} (EC_{f,m}^{(tg)} - \hat{EC}_{f,m}^{(tg)})^2 + \lambda . \widehat{MMD}^2 (h_{sc}, h_{tg}). \tag{3.13}$$

3.2.4 Implementation of the BiLSTM-DTL Algorithm

The overall approach of our proposed model is illustrated in Algorithm 1. The assumption is that we already estimated the source (electric bus) energy consumption metrics. Lines 2 to 9 show the target training steps. From lines 10 to 16, the transfer learning phase with feature correlation considerations are displayed.

Generally, from the Algorithm 1 perspective, our proposed model's computational complexity is efficient, and it is in the order of $O(T * \mathcal{M})$, which is relative to the number of training epochs (T) and input data ($\mathcal{M}$).

3.3 Model Evaluation and Results Analysis

In this section, we present the performance evaluation of our model and analyze the outcomes of our experiments. Also, we will showcase the effectiveness of our proposed approach and provide insights into the achieved results.

3.3.1 Datasets

1) Source Dataset: The primary dataset used in this research is collected from ten electric buses with the same characteristics (weight, capacity, size, battery, and engine power),

Algorithm 1 : Highly-correlated energy consumption parameters with DTL

Given: Normalized $D_{tg} = \{x_m^{(tg)}, y_m^{(tg)}\}$, h_{sc}, $W_{FCL}^{(sc)}$, $b_{FCL}^{(sc)}$, initialized network learning parameters

Output: $\hat{EC}^{(tg)}$, $\mathcal{L}_{tg}$, $corr(f_{sc}, f_{tg})$

for $t = 1 : ephocs$ **do**
  for $m = 1 : \mathcal{M}$ **do**
    Compute forward LSTM:
    $\vec{h}_m = f(\vec{h}_{m-1} - x_m)$
    Compute backward LSTM:
    $\overleftarrow{h}_m = f(\overleftarrow{h}_{m+1} - m_t)$
    Combine $\vec{h}_m$ and $\overleftarrow{h}_m$ to get $h_m = [\vec{h}_m, \overleftarrow{h}_m]$
    Identify feature discrepancy:
    $mmd = \widehat{MMD}^2(h_{sc}, h_{tg})$
    if $mmd < threshold$ **then**
      Transfer $W_{FCL}^{(sc)}$, $b_{FCL}^{(sc)}$
      Estimate $\hat{EC}_m^{(tg)} = w_{FCL}^{(tg)} h_m + b_{FCL}^{(tg)}$
      Re-train the target model
      Re-estimate $\hat{EC}^{(tg)} = W_{FCL}^{(sc)} h_{tg} + b_{FCL}^{(sc)}$
    end if
    Calculate target loss function $\mathcal{L}_{tg_m}$
  end for
end for

including a total of 2022 trips on consecutive and separate trips in China between 2017 and 2018. Table 3.1 shows a sample example of this dataset. In this dataset, there are 54 interior and exterior features captured from the operating electric buses [98]. The sensor device data were captured every 10 seconds to report bus conditions at different vehicle statuses (charging/driving). Accordingly, e-bus energy consumption and effectiveness weights of features were computed and analyzed in the first phase of the model, then the trained parameters were used to enhance the energy estimation accuracy of the insufficient EVs (target) dataset. A brief description of the raw data in this dataset is displayed in Table 3.2.

2) Target Dataset: As part of our study, we utilized an open real-world driving dataset, Vehicle Energy Dataset (VED), consisting of the collection of fuel and power data of 383 personal vehicles [99]. More precisely, in this dataset, there are 264 ICE vehicles, 92 HEVs, 24 Plug-in HEVs, and 3 EVs providing dynamic and static data. Our research benefited from the 4,721 km mileage in 495 recorded trips from three EVs driving in Ann Arbor, Michigan in 2018. EV-related captured static/dynamic parameters include longitude, latitude, velocity, exterior air temperature, supplementary power, and battery data. Table 3.1 shows a sample example of this dataset, and a brief description of the raw data in this dataset is displayed in Table 3.3. To better analyze the performance and functionality of our proposed model, we utilized a second real-world EV dataset in our study. EV data #2 is a distinct set of EV metrics, encompassing parameters like Time, Speed, Current, Voltage, Accelerator Pedal Position, Cell Temperature, Cell Relative Humidity, Dynamo-meter Tractive Effort[N], and SoC levels, collected from the Nissan Leaf Test dataset [100]. A sample data selected from this dataset is displayed in Table 3.1, EV Data 2.

Table 3.1: Samples of the source (electric bus) and target (EV) datasets.

Electric bus Data						
Time	**Speed [km/h]**	**Mileage**	**SoC [%]**	**Temp. [°C]**	**Alt. [m]**	**Wind Speed**
20180130070522	31	649190.0	98.0	4.8	5.437	2.4
EV Data 1						
Trip #	**Timestamp [ms]**	**Latitude [°]**	**Longitude [°]**	**Speed [km/h]**	**Temp. [°C]**	**SoC [%]**
1558	5400	42.27725417	-83.76251167	54.29	5	96.3414
EV Data 2						
Time [s]	**Speed [m/h]**	**Cell Temp. [°C]**	**Voltage [V]**	**Accel. Pedal [%]**	**Current [A]**	**SoC [%]**
8.8	1.648	21.326	383.661	5.404	2.768	73.90

Table 3.2: Source Dataset Description.

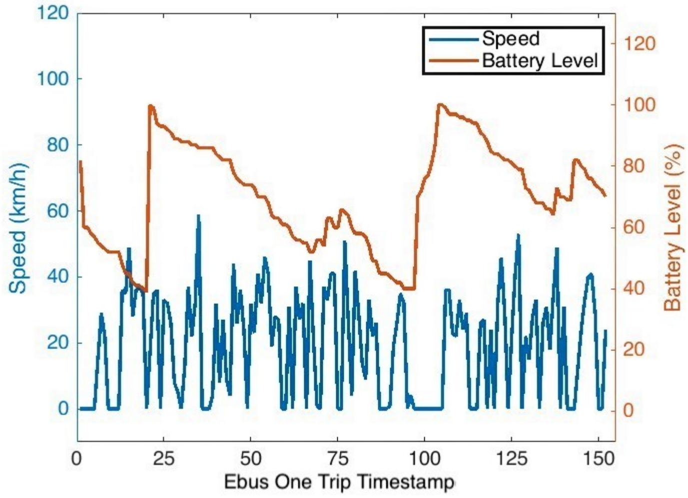
Property	**Available Values**
Number of electric buses	10
Total trip duration (h)	1,617.6
Total covered mileage (km)	36,396
Speed range (km/h)	[0, 78]
Temperature scope (°C)	[3.9, 37]
SoC range (%)	[17, 100]

Table 3.3: Target Dataset #1 Description.

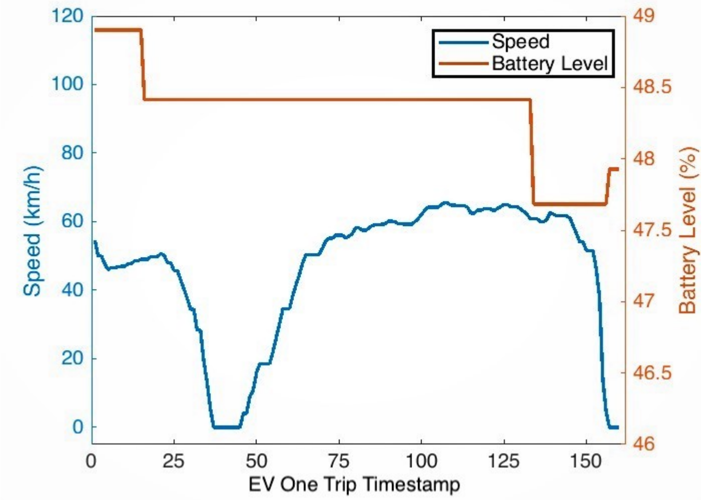
Property	**Available Values**
Number of electric passenger vehicles	3
Total trip duration (h)	542.56
Total covered mileage (km)	4,721
Speed range (km/h)	[0, 132.13]
Outside Temperature (°C)	[-15.5, 36]
Heater power range (watts)	[0, 4250]
SoC range (%)	[9.63, 100]

3.3.2 Results and Analysis

Based on the collected data from electric buses and electric passenger vehicles, a sample historical driving pattern is pictured in Figure 3.2. In both figures, the SoC degradation of vehicles' batteries (in orange color), and vehicles' speed (in blue color) are depicted for one randomly selected e-bus 3.2a and EV 3.2b over a period of driving. For the e-bus, the correlation between battery level and speed is captured over one-day of driving of approximately 170 kilometers. On the other hand, an adverse impact of speed on the battery level for an EV is reported over a nine-minute trip.



(a) Battery status for one electric bus, according to the vehicle's speed over time.



(b) Battery status for one electric vehicle, according to the vehicle's speed over time.

Figure 3.2: The illustration of remaining battery charge (in %) of one e-bus in a one-day trip, and one EV in an eight-minute trip, in relation to the vehicle speed.

The previous analysis of the impact of speed on the SoC was just one simple example to demonstrate the importance of an accurate investigation and estimation of energy consumption factors. A more complex impact demonstration instance is Figure 3.3, in which the relation between driving location, speed, and SoC is depicted. As can be seen, the battery level degradation is higher on urban roads (approximately 0.6%) as EV drivers are more likely to have higher vehicle speeds. On the other hand, EVs lose battery power more slowly while driving in downtown areas with more limited vehicle speeds.

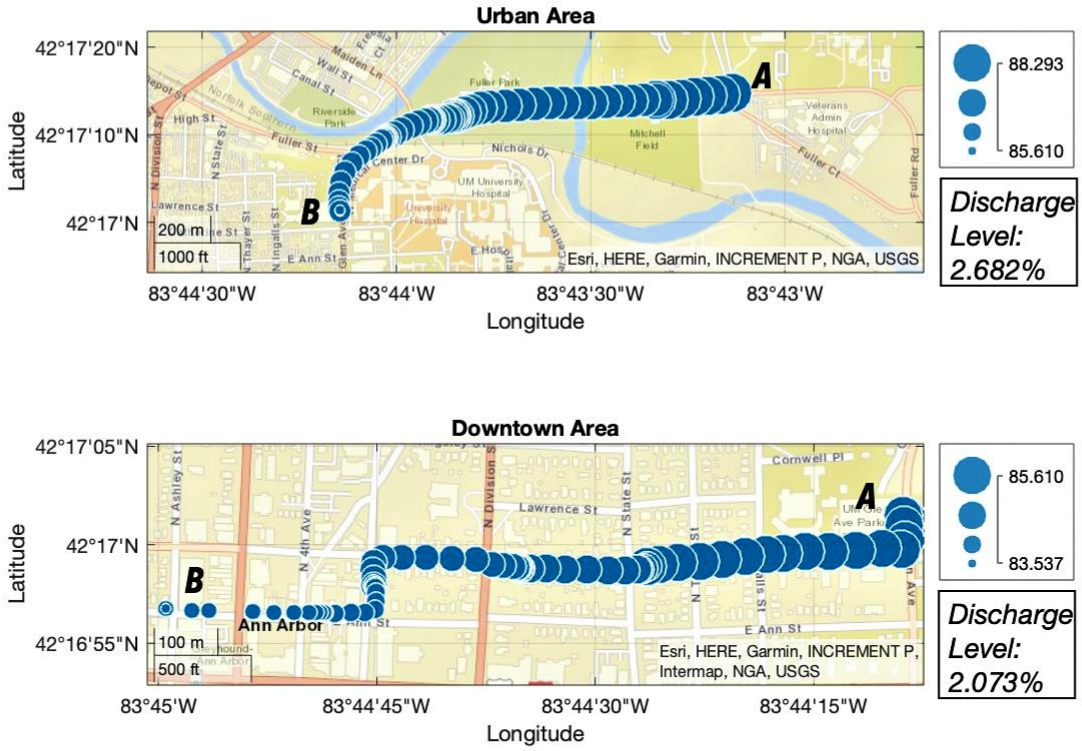


Figure 3.3: The impact of driving location on an EV battery discharging level. Routes are taken from the different roads of the real-world target dataset. Urban routes (with higher speed limitations and stronger wind pressure) require more electricity from EV batteries.

3.3.3 Experimental Setup

The implementation of this model is done by using TensorFlow and Keras libraries in Python programming language. All the experiments are conducted on a Mac Book Pro M1 GPU with 16 GB of RAM. The settings of the experiment's hyper-parameters are tuned with a sequence length of 24, batch size of 128, learning rate of 0.001, Adam Optimizer, 64 nodes in BiLSTM layer units, with the ReLU activation function.

3.3.4 Hyperparameters Fine-Tuning

There are various methods for hyperparameter tuning, including grid search, random search, and more advanced techniques like Bayesian optimization or genetic algorithms. From the aforementioned methods, we utilize grid search since it is capable of exploring a larger number of hyperparameters in the most accurate prediction. The comprehensive and straightforward nature of grid search lies in its ability to consistently examine given hyperparameter combinations, leaving no possibilities missed. This approach not only delivers a clear guideline for optimization but also enhances preciseness by enabling a structured exploration. Grid search offers a distinct advantage by effortlessly allowing parallelization and efficient resource allocation, as each evaluation remains independent.

Here for this research, after the model performance analysis, we set up the hyperparameter tuning loop by implementing a loop that iterates over different combinations of hyperparameters. Then we train the model on the training set and evaluate its performance on the validation set using the chosen metrics. The hyperparameters shown in Table 3.4 are tuned and evaluated in their scopes over the grid search cross-validation hyperparameters fine-tuning technique. The optimal values for the batch size, number of units in the model's layers, model's learning rate, activation function, and optimizer are decided after evaluating our model with the hyperparameters range values and comparing the Mean Squared Error scores after each run. the results are illustrated in Figure 3.4.

Table 3.4: Hyperparameters Search Range

Hyperparameter Name	**Grid Search Range**
Training batch size	[128, 256, 512]
Model's layers units	[32, 64, 128]
Learning rate	[0.001, 0.01, 0.1]
Learning activation function	[ReLU, Tanh]
Training optimizer	[Adam, SGD, Adamax]

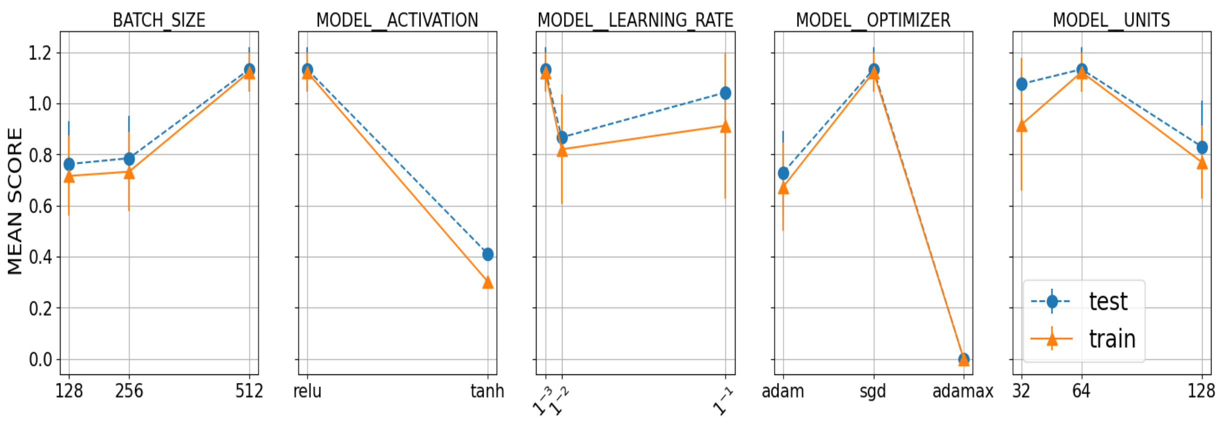


Figure 3.4: Hyperparameters fine-tuning evaluation with GridSearch cross-validation.

3.3.5 Performance Evaluation

To validate our model's prediction performance, we utilized the following metrics based on the true energy consumption values from our database and estimated results from our proposed system.

Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(EC_{ob} - \hat{EC_i})^2. \tag{3.14}$$

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(EC_{ob} - \hat{EC_i})^2}. \tag{3.15}$$

Symmetric Mean Absolute Percentage Error (SMAPE)

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n}(\frac{2|EC_{ob} - \hat{EC_i}|}{|EC_{ob}| + |\hat{EC_i}|}) \times \%. \tag{3.16}$$

Mean Relative Percentage Error (MRPE)

$$MRPE = \frac{1}{n}\sum_{i=1}^{n}(\frac{|EC_{ob} - \hat{EC_i}|}{EC_{ob}}) \times \%. \tag{3.17}$$

where n is the total number of test dataset, EC_{ob} is observed energy consumption, and $\hat{EC_i}$ is estimated energy consumption.

The summary of the prediction performance of our system is presented in Table 3.5. We compared our model with 4 baseline machine-learning algorithms, namely Least Absolute Shrinkage and Selection Operator Regression (LASSO Reg.), Support Vector Machine (SVM), Linear Regression, and LSTM, and 2 TL models with different domain adaptation approaches, namely, Euclidean Distance in Mapped Correlation Alignment-based TL (TL_Euc), and Deep Adaptation Network-based TL (TL_DAN). The experimental results show that we could gain better performance among traditional and TL-based algorithms, and enhance the model operation by applying the optimized knowledge transferring with the following evaluation metrics values of 0.1237 for MSE, 0.1331 for RMSE, 0.3432 for SMAPE, 0.2443 for MRPE, and 0.9056 for R^2 score (The higher the R^2 values, the more goodness in model's fit measurement.) This comparison evidently shows the impact of transferring pre-trained knowledge from a large-scale dataset into an insufficient missing dataset, considering the feature space compatibility.

Table 3.5: The proposed model's performance comparison.

Method	**MSE**	**RMSE**	**SMAPE**	**MRPE**	$\mathbf{R^2}$
Non-TL Models					
LASSO Regression	0.8125	0.9014	1.0326	1.0805	0.7946
SVR	0.7312	0.8551	0.9202	0.9249	0.8152
Linear Regression	0.7197	0.8483	0.9282	0.9518	0.8181
LSTM	0.7046	0.8394	0.9483	06192	0.8939
TL-Based Models					
TL_Euc	0.3626	0.3506	0.6539	0.6534	0.8589
TL_DAN	0.3345	0.1601	0.3977	0.3969	0.8944
Our Model	**0.1237**	**0.1331**	**0.3432**	**0.2443**	**0.9056**

Accordingly, in Figure 3.5, a bar graph vividly depicts the performance comparison of our model with two distinct sets of existing approaches. In the upper section of the graph, our model's performance values, shaded in black color, are compared with those of four basic machine learning models. Simultaneously, the lower section contrasts our model, again highlighted in black color, with two TL-based algorithms. The evaluation metrics employed for comparison encompass MSE, RMSE, SMAPE, and MRPE loss function, and R^2 Score metric (also known as the coefficient of determination) which evaluates the goodness-of-fit of a model. It measures how well the predicted values from the model approximate the actual values of the target variable. Across all metrics and comparisons, the proposed model consistently outperforms the alternatives, underscoring its superior performance in the evaluated scenarios.

Achieving the proposed model's performance results is mainly based on the source electric bus dataset. In Figures 3.6a and 3.7a the prediction accuracy of the source and target models are analyzed. The analysis shows that our base model is capable of estimating the accurate future energy consumption values given the unseen/simulated dataset for other regions planning to adopt electric personal/public transportation. Another evaluation is conducted focusing on the prediction residual errors, and the experimental results are shown in Figures 3.6b and 3.7b, for electric buses and EVs, respectively.

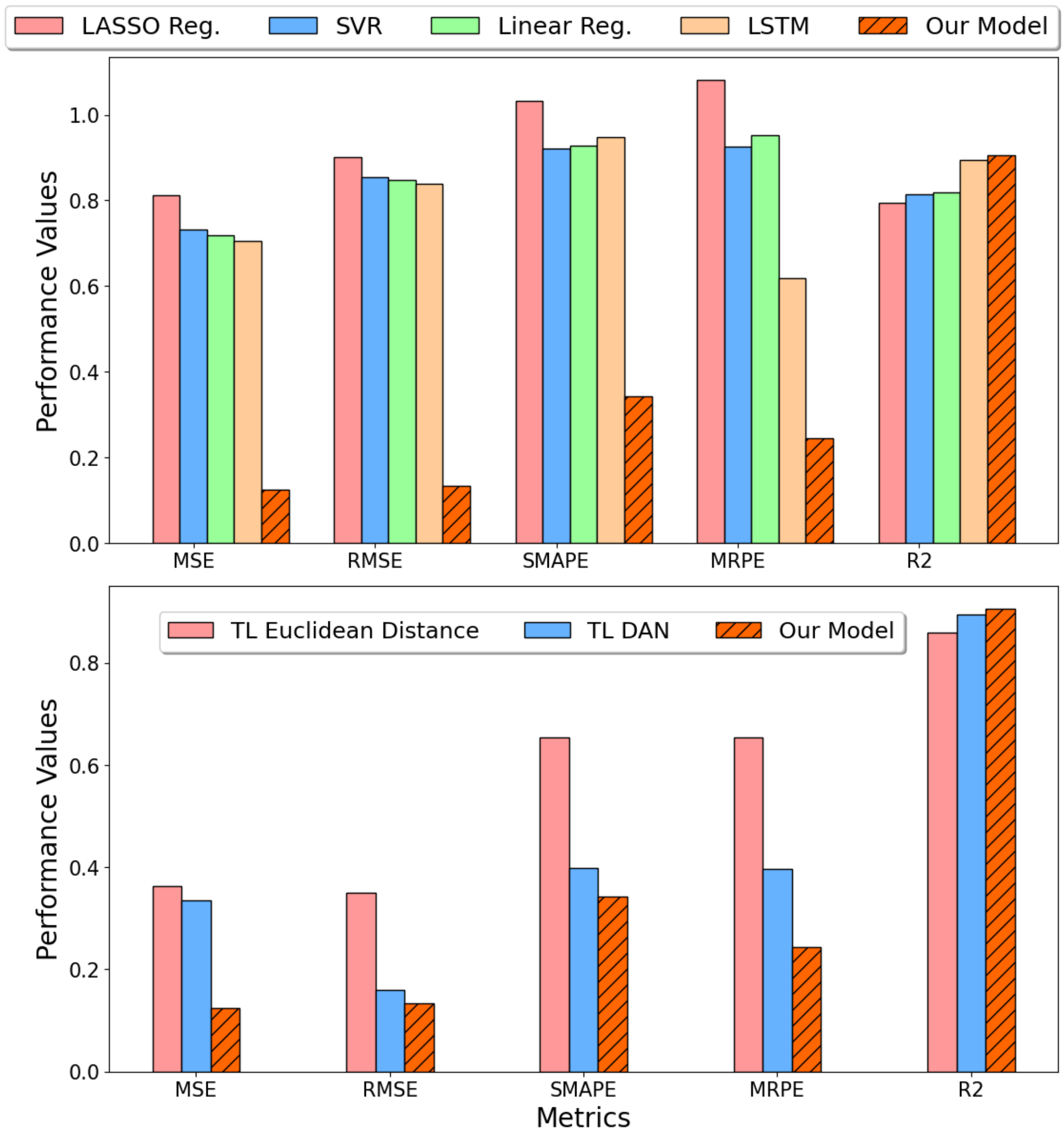
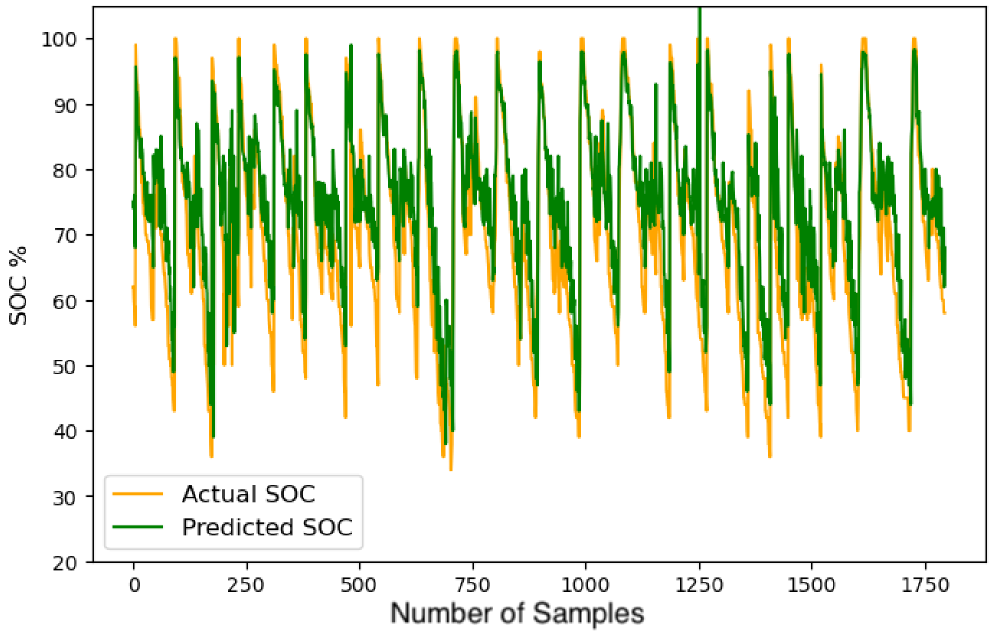
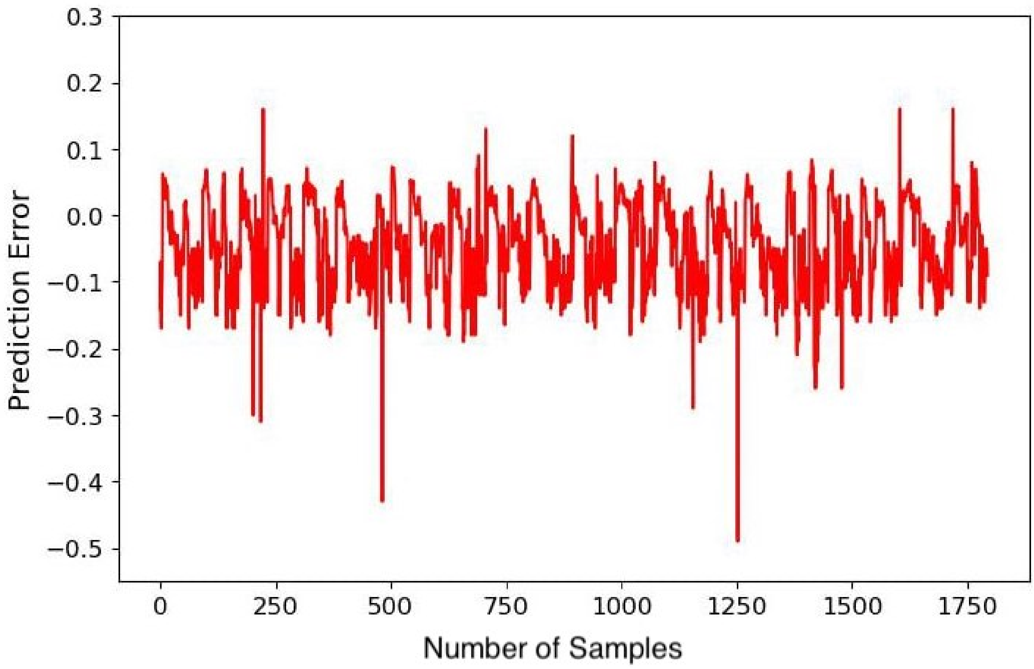


Figure 3.5: Illustration comparing the performance of our model with two distinct groups of existing approaches.

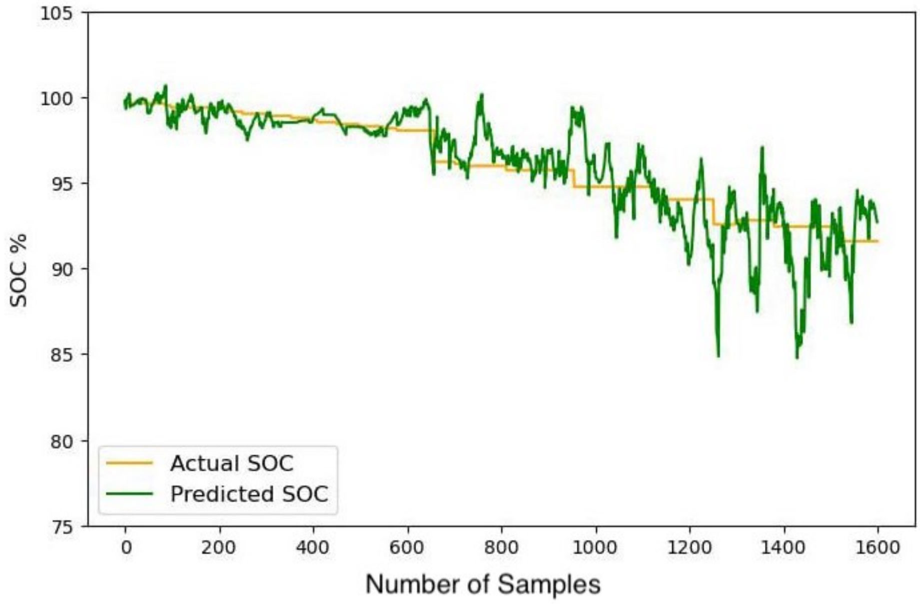


(a) Source Model Energy Prediction Accuracy

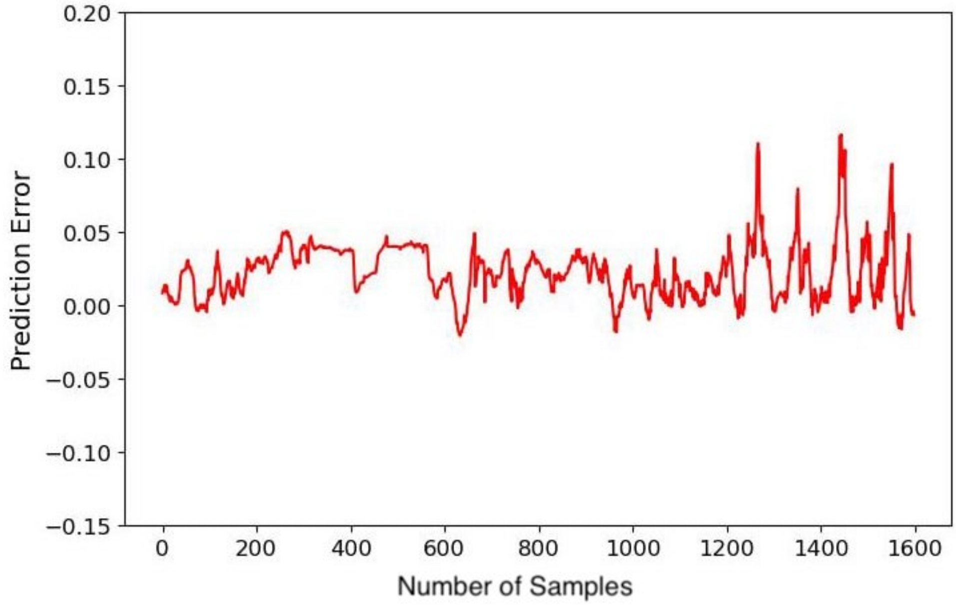


(b) Source Model Energy Prediction Residual and Error

Figure 3.6: Energy consumption prediction performance and residual for the source electric bus dataset model.



(a) Target Model Energy Prediction Accuracy



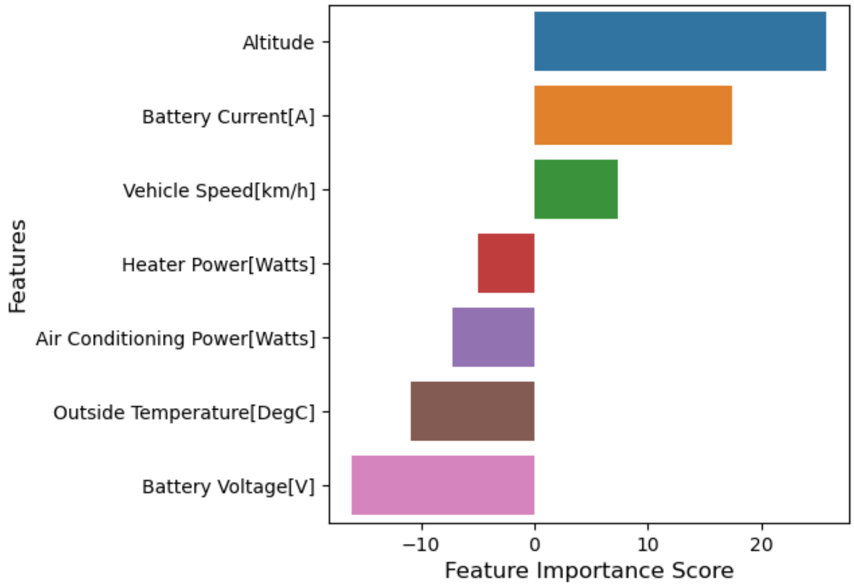
(b) Target Model Energy Prediction Residual and Error

Figure 3.7: Energy consumption prediction performance and residual for the target EV dataset model.

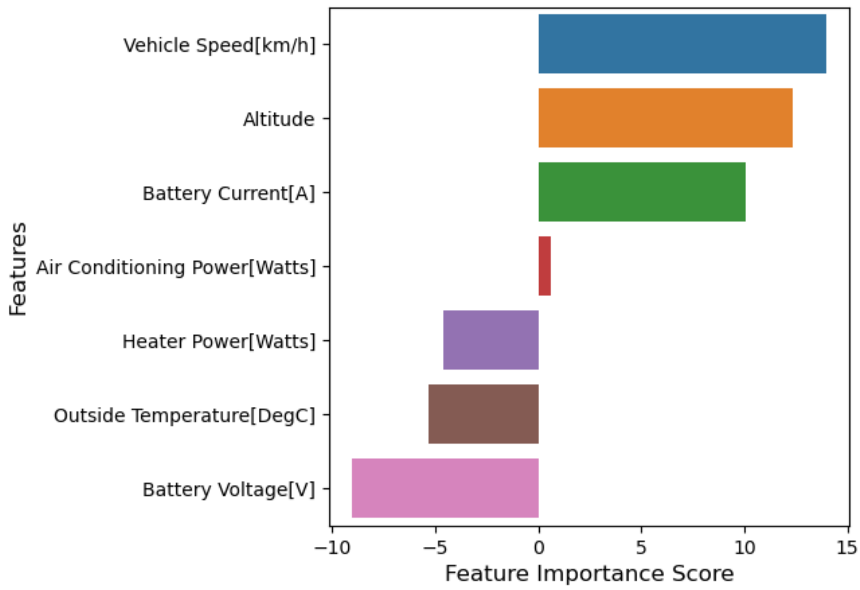
Figure 3.8 compares feature scores within our target dataset (EVs) before and after applying the pre-trained parameter transfer learning. The score list of impactful features changed after transferring the knowledge from electric buses into our EVs dataset.

By replacing feature weights with more accurate ones from our trained source model, we could gain a higher score for Battery Voltage and Heater Power which might be more important features in EV power degradation. The target dataset includes 12 features related to EVs, however, in our analysis, we picked 7 of them with higher gained weights than the threshold $p = -16$ from the target model. This means that Figure 3.8 only visualizes the important factors affecting EVs energy consumption by removing other insignificant features.

In order to better analyze the impact of the features on the proposed model's prediction accuracy, we used the SHAP Python library to illustrate the effect of the features on our model's output in Figure 3.9. SHAP values show how much a given feature changed our prediction, compared to if we made that prediction at some baseline value of that feature. The summary shown in Figure 3.9 gives a global interpretation of the permutation feature importance, which involves systematically excluding individual features from the input feature set, and assessing the extent to which the model's performance declines as a result of each feature's removal. The implemented SHAP graph here involves understanding the contributions of individual features of EVs to the model's energy consumption (SoC) estimation. Starting with the features listed on the y-axis, each bar represents a different feature, and the length of the bar indicates the magnitude of its impact on the model's predictions. Checking the direction of each bar, a bar extending to the right suggests a positive contribution to the prediction, while a bar extending to the left indicates a negative contribution. The longer the bar, the greater the impact of the corresponding feature on the prediction. Features with longer bars have a more substantial influence on the model's output. Here, the attributes Trip, Timestamp, Latitude, and Longitude have the lowest effect on our model's performance, so they are not shown in Figure 3.8 as the important features set.



(a) Target Data Important Features Before Transfer Learning



(b) Target Data Important Features After Transfer Learning

Figure 3.8: Important factors on energy consumption for EVs. The level of factors changed after transferring prior parameters weight knowledge from the electric bus model.

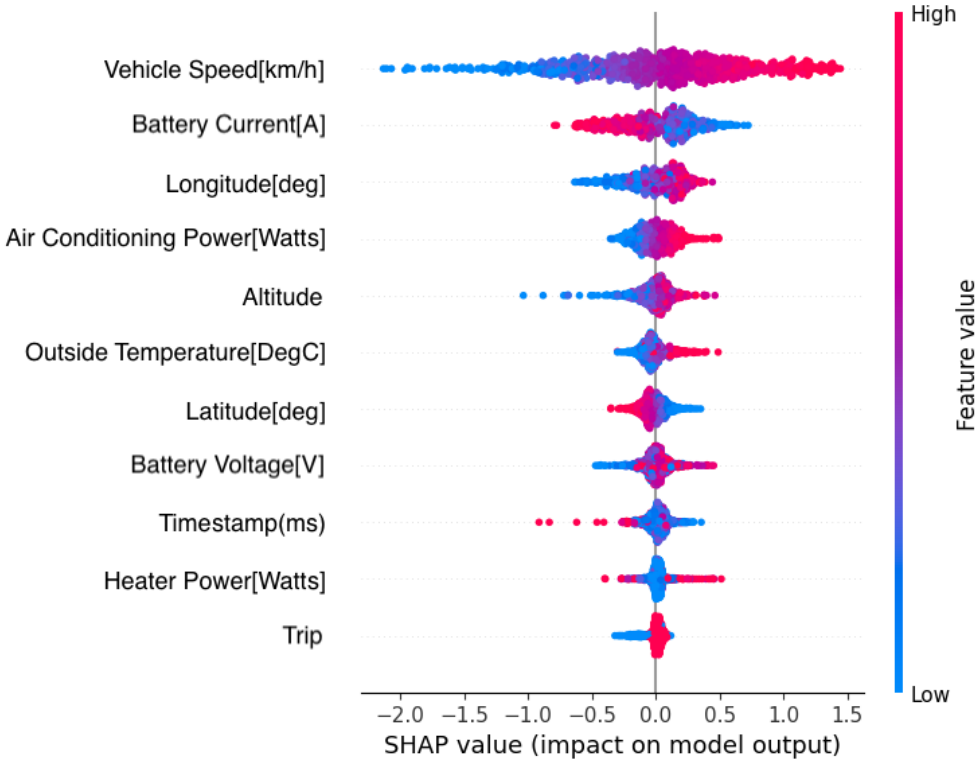


Figure 3.9: SHapely Additive exPlanations. SHAP values explain how much each feature contributes to the output of the model's prediction. Positive values show positive effects on the model's performance.

In our study, we also employed a heat-map graph in Figure 3.10 to illustrate the correlation and similarity between two distinct feature spaces: EVs features on the y-axis and electric buses with 33 features on the x-axis. This graphical representation serves as a visual tool to identify highly correlated features that are well-suited for our transfer learning approach between the e-bus dataset and EVs. The Figure provides an insightful overview of the relationships between the feature sets, helping us pinpoint features that exhibit strong correlation and similarity, thereby informing the selection of optimal features for the transfer learning model. This approach ensures that the knowledge transfer between the e-bus and EV datasets is built upon features that demonstrate significant inter-domain compatibility, contributing to the efficacy of our proposed transfer learning methodology.

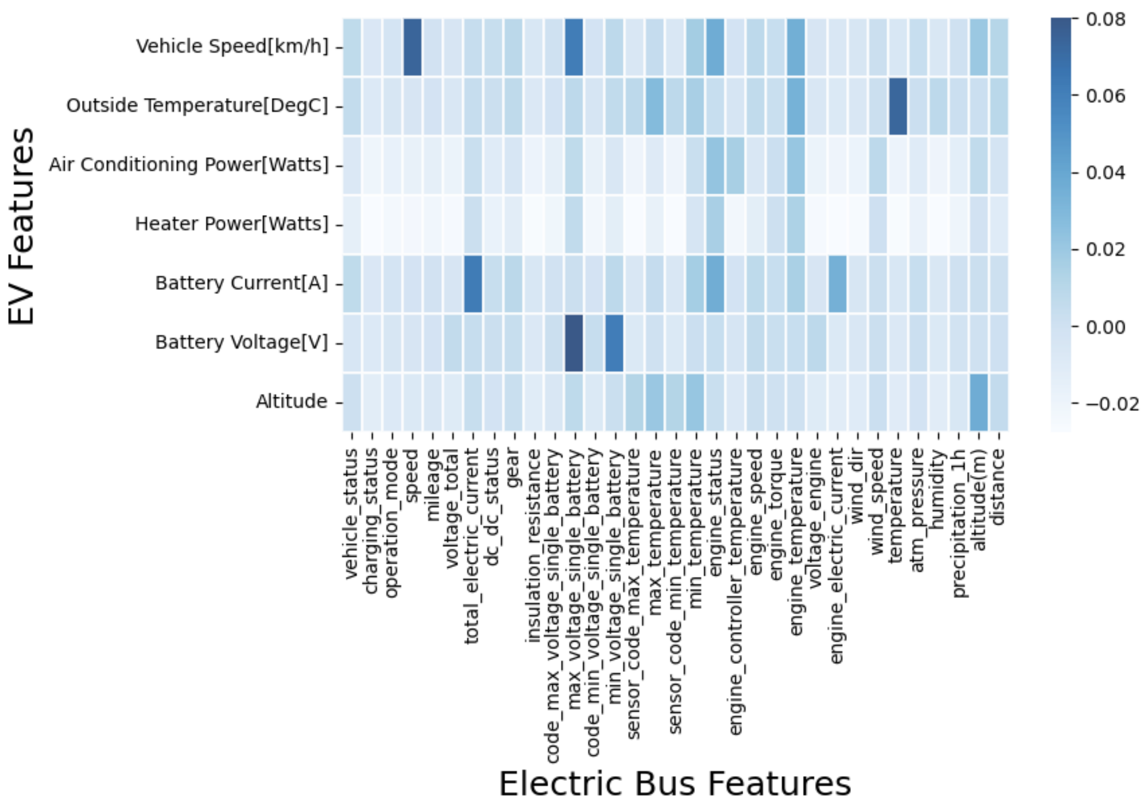


Figure 3.10: Heat-map depicting the correlation of features between the source (electric bus) and target (EV) domains, with the x-axis representing the source domain and the y-axis representing the target domain.

As the final approach to evaluating our proposed solution, we analyzed the improvement of the training evaluation metrics before and after applying the TL method to our target domain. Figure 3.11 illustrates the effectiveness of the transferred pre-trained knowl-

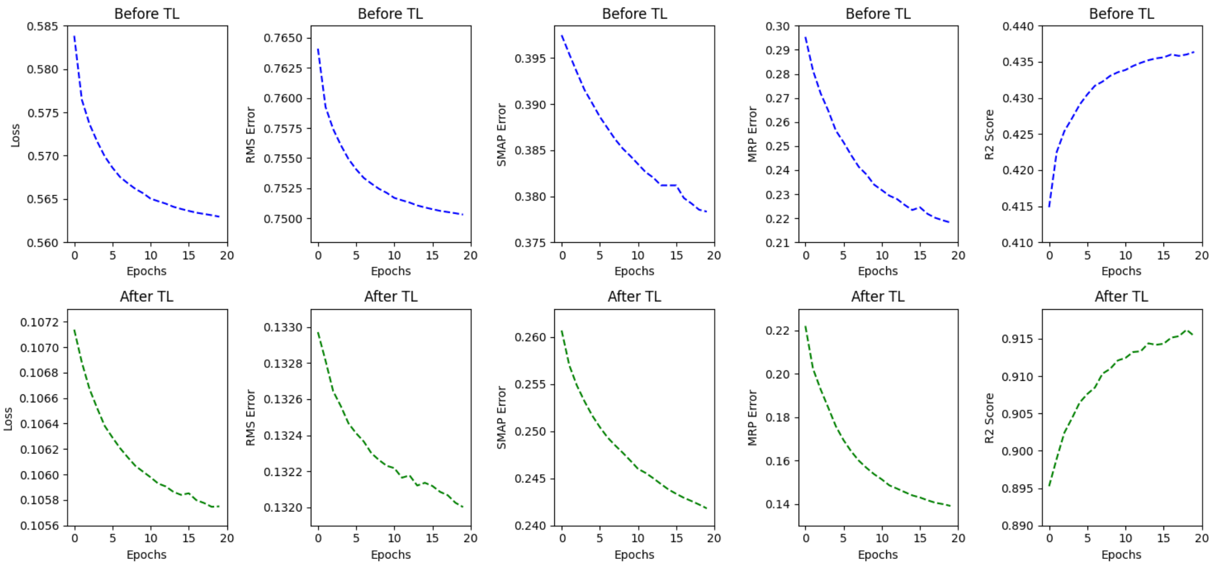


Figure 3.11: Comparing the training metrics in our model before (blue) and after (green) applying the transfer learning technique.

edge from the source domain (electric bus) into the target domain (EV) model's training evaluation metric functions (Loss, Root Mean Squared Error, Symmetric Mean Absolute Percentage Error, Mean Relative Percentage Error, and R^2 Score, respectively). As shown in this Figure, the loss range is drastically improved from [0.560, 0.585] to [0.1060, 0.1090] by approximately 0.46 on average, as well as the RMS Error by 0.62, SMAP Error by 0.137, MRP Error by 0.076, and R^2 Score by 0.48. In this Figure, we assessed the model's performance on the initial target dataset.

Additionally, to better illustrate the practicality of our proposed model, we conduct a thorough evaluation of its performance on a second, more constrained EV dataset, as depicted in Figure 3.12. The line graph within this Figure presents the decreasing loss values before TL on the left y-axis and after TL on the right y-axis across 20 training epochs. The graph distinctly shows that the loss values diminish further after employing our proposed TL-based framework, highlighting its effectiveness in enhancing model performance.

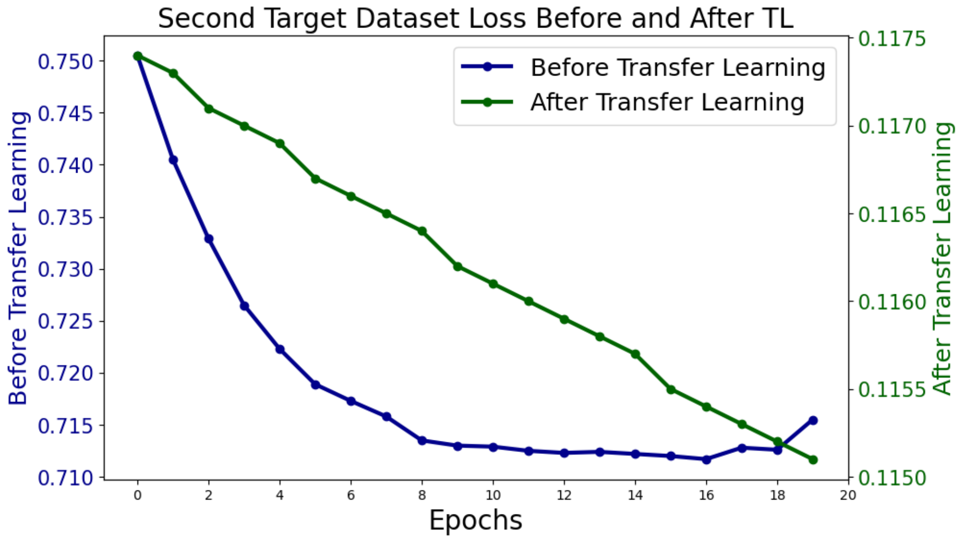


Figure 3.12: Performance evaluation of the proposed model on the supplementary EV dataset. The line graph illustrates the decreasing loss values after applying TL on the right y-axis compared to the left y-axis range values over 20 training epochs.

3.4 Chapter 3 Summary

To construct an effective energy consumption detector for EV power management, a comprehensive model is essential to reduce range anxiety among EV owners. In this study, we identified the parameters with the highest impact on EV charging consumption and scheduling, both while parked and during journeys. Given the challenge of insufficient available datasets, we employed the DTL technique to mitigate the issues of inadequate and sparse data. We used the MMD method to compute feature distribution differences, capturing highly correlated attributes before transferring knowledge among datasets. Our analysis included diverse driving areas such as rural regions, urban routes, and highways, allowing us to evaluate the impact of traffic density and speed on EV power consumption. This comprehensive approach enabled us to model energy consumption more accurately, addressing critical variables like stop-and-go traffic, continuous high-speed travel, and mixed driving conditions.

Additionally, we implemented a multi-task learning framework to enhance the predictive capabilities of our model. By pre-training on a large-scale source domain dataset and extracting trained weights, parameters, and features from the early layers of the source model, we ensured a robust foundation for transfer learning. These pre-trained components were then evaluated for domain compatibility using an optimized discrepancy loss function. Adjusting task-specific final layers to fit the target model allowed for precise adaptation to the unique characteristics of EV datasets. This methodological exactness, combined with detailed consideration of various driving environments, resulted in a powerful tool for predicting EV energy consumption, ultimately supporting more efficient EV power management and reducing range anxiety for EV owners.

Chapter 4

Smart Vehicles Recommendation System for Artificial Intelligence-enabled Communication

4.1 Introduction to Chapter 4

In this chapter, we provide a model for a secure recommendation system for EV consumer electronics. Our model considers both fixed and mobile charging locations, with a focus on optimizing the well-being of EV consumers and owners. Unlike traditional methods that involve direct data sharing among data holders during model training, our approach employs a secure VFL technique. This ensures that data from EVs and charging sources remains within their respective platforms, thereby enhancing data security and privacy. By leveraging the strengths of FL, our system facilitates the training of models without the need for raw data exchange, ensuring that sensitive information is kept secure. The best solution to a recommendation system should achieve a more optimal distribution of EVs within designated areas, addressing the pressing issue of limited charging infrastructure and improving the overall charging experience for EV users.

In this chapter, we delve into an extensive analysis of the fundamental knowledge prerequisites for immersing ourselves in this study. Our exploration encompasses foundational definitions and crucial theoretical frameworks, equipping our readers with the essential resources to approach upcoming discussions with a profound understanding and clear insight.

4.2 System Model and Problem Formulation

In this section, we present an in-depth explanation of the structure and operational process of our system. Our approach's objective is to optimize EV owners' satisfaction by minimizing their costs to gain the desired level of power supply, implementing a securely decentralizing FL recommendation model, taking into account both stationary/fixed charging stations and mobile charging stations.

Figure 4.1 illustrates the key steps in our model designed to ensure an efficient charging source recommendation system with secure data sharing within the IoT network for EVs, encompassing both Fixed and MCSs. The primary steps of the presented model are detailed as follows.

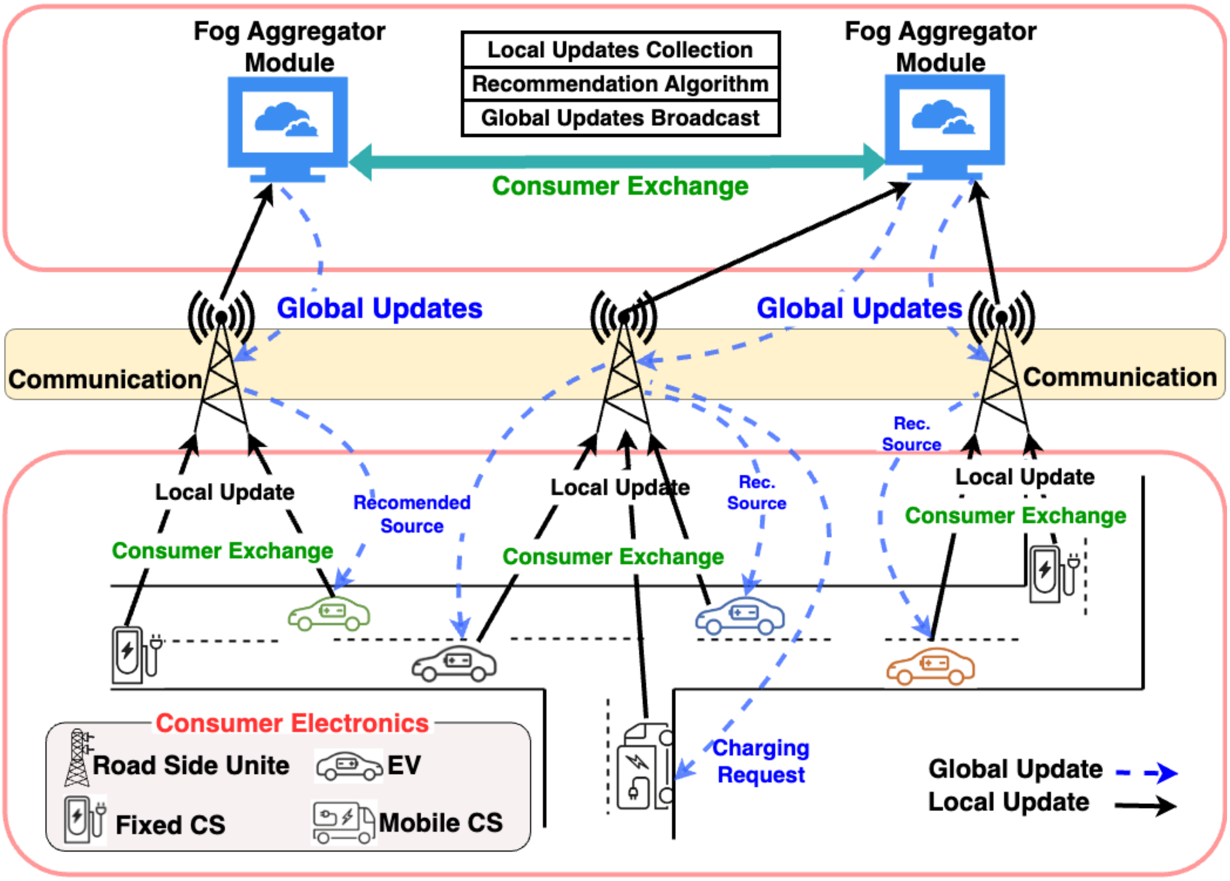


Figure 4.1: Consumer electronics recommendation model framework with secure federated learning-based decentralized fog-edge network communication, considering both fixed and mobile charging points for an EV with charging demand.

4.2.1 Intelligent User-centric Recommendation

In our system design, we consider three primary elements: EVs, FCSs, and MCSs. The set of EVs is denoted as:

$$\{v_i \in EV = \{v_1, v_2, ..., v_i\}\},$$

where v_i represents an individual EV within the system. Similarly, we have the set of FCSs denoted as:

$$\{cs_j \in FCS = \{c_1, c_2, ..., cj\}\},$$

with cs_j representing each FCS available for use. Additionally, we include MCSs, represented as:

$$\{ms_k \in MCS = \{m_1, m_2, ..., ms_k\}\},$$

where ms_k signifies each MCS in the system. These elements form the foundation of our system architecture, enabling the efficient recommendation and utilization of charging sources within the IoT network for electric vehicles.

The distance between the current location of an EV and the charging source location is $\Lambda_{(v_i,x)}$, with the service fee Φ_x, where $x \in \{cs_j, ms_k\}$ is either a FCS or a MCS.

Each charging source in the service area has an availability indicator ρ. For a FCS,

$$\rho_{cs_j} = \langle n, q.(\overrightarrow{\mathrm{t_{req}}}), \vec{t}\rangle,$$

shows the number of empty charging spots (n) at station cs_j, the number of EVs waiting outside the station to get charged (q) with their charging request times ($\overrightarrow{\mathrm{t_{req}}}$) at station cs_j, and the remaining charging session time at the occupied spots by EVs ($\vec{t} = [t_1, t_2, ..., t_S]$) at station cs_j with the total number of S charging spots. And for a MCS,

$$\rho_{ms_k} = \langle n', q'.(\overrightarrow{\mathrm{t'_{req'}}}), \vec{t'}, \vec{\delta}\rangle,$$

where, n' is the number of idle battery(ies) mounted at station ms_k, q' shows the number of EVs waiting to get charged at station ms_k with their charging request times ($\overrightarrow{\mathrm{t'_{req'}}}$), then $\vec{t'} = [t'_1, t'_2, ..., t'_B]$ shows the remaining charging session time at the busy batteries by EVs installed at station ms_k with the total number of B batteries, and $\vec{\delta}$ displays the remaining capacity of battery(ies) at station ms_k.

First, we need to calculate the availability indicator ρ_x for both a FCS cs_j and a MCS ms_k to indicate the charging source availability ratio.

For a FCS with the station availability parameter, we are looking for higher values in ρ_{cs_j}:

$$n = S - \sum_{s=1}^{S} o_s, \tag{4.1}$$

$$\rho_{cs_j} = n - q - (\sum_{s=1}^{S} t_s.o_s + \sum_{req=1}^{q} t_{req}). \tag{4.2}$$

Referring to the equation (4.2), we have o_s which is a binary decision variable that equals 1 if spot s is occupied and 0 if it's empty.

$$o_s \in \{0,1\}, for \quad s = \{1,...,S\}.$$

In order to calculate the availability indicator ρ_{cs_j}, shown in equation (4.2), we need to define constraints ensuring the applicability of the proposed availability indicator parameter, as follows.

1. Each EV must be assigned to exactly one spot (if allocated):

$$\sum_{s=1}^{S} o_s.v_i = 1, for \quad i = \{1,...,q\}.$$

2. The total number of spots allocated cannot exceed the number of empty spots:

$$\sum_{s=1}^{S} o_s \leq n.$$

3. If $o_s = 1$ (spot s is occupied), then it must be allocated to exactly one EV:

$$\sum_{i=1}^{q} v_i.o_s = o_s, for \quad s = \{1,...,S\}.$$

4. Each EV can only be assigned to a spot if there's enough time to charge before the EV's remaining charging time expires:

$$t_s \leq \mathcal{R}.(1 - o_s), for \quad s = \{1,...,S\},$$

   where $\mathcal{R}$ is a very large positive number, and this constraint ensures that if $o_s = 1$, then t_s must be less than $\mathcal{R}$, allowing charging to complete.

Similarly, for a MCS with the source availability parameter, we are looking for higher values in ρ_{ms_k}:

$$n' = B - \sum_{b=1}^{B} a_b, \tag{4.3}$$

$$\rho_{ms_k} = n' - q' - (\sum_{b=1}^{B} t'_b.a_b + \sum_{req'=1}^{q} t'_{req'}) + \sum_{b=1}^{B} \delta_b. \tag{4.4}$$

Considering the availability indicator parameter ρ_{ms_k} in equaiotn (4.4) for a MCS, we define the following variables:

- a_b: Binary decision variable that equals 1 if battery b is active and 0 if it's idle.

$$a_b \in \{0, 1\}, for \quad b = \{1, ..., B\}.$$

- $m_{k,t}$: Binary decision variable that equals 1 if MCS ms_k is moving at time t, and 0 is it not moving.

$$m_{k,t} \in \{0, 1\}, for \quad MCS = \{m_1, m_2, ..., ms_k\}.$$

- $m^B_{k,i,t}$: Binary decision variable that equals 1 if MCS ms_k with B batteries is assigned to charge EV i at time t.

$$m^B_{k,i,t} = \begin{cases} 0, & \text{if } \forall a_b = 0, \\ 1, & \text{if } \exists a_b = 1, \end{cases}$$

$$for \quad i = \{1, ..., q\} \quad b = \{1, ..., B\}.$$

- $m_{k,j,t}$: Binary decision variable that equals 1 if MCS ms_k is charging itself at a FCS j at time t.

$$m_{k,j,t} \in \{0, 1\}, for \quad FCS = \{c_1, ..., cs_j\}.$$

Then to compute the availability indicator ρ_{ms_k} as illustrated in equation (4.4), it is imperative to establish constraints that guarantee the suitability of the proposed availability indicator parameter. These constraints can be defined as follows.

Constraints (1), (2), (3), and (4) are similar to the FCS.

5. If $a_b = 1$ (battery b is actively charging an EV), then the remaining capacity of the battery must be greater than zero:

$$\delta_b \leq \mathcal{R}.(1 - a_b), for \quad b = \{1, ..., B\}.$$

6. Each MCS should exclusively be in one of two states: either linked to a FCS within the microgrid or actively recharging EVs. A third state is also included in this constraint to more efficiently restrict a MCS.

$$m^B_{k,i,t} + m_{k,j,t} + m_{k,t} = 1.$$

The probability ratio of a charging source to be chosen is a softmax function P_x where $x \in \{cs_j, ms_k\}$. To formulate P_x, we use a utility-based approach where we compute a utility value based on distance $\Lambda_{(v_i,x)}$ and charging service fee Φ_x, which needs to be minimized as a cost that an EV must pay to reach its preferred battery SoC level. The *Service_Area (SA)* parameter in equation (4.6) ensures that only charging sources located near the requested EV will be taken into account within the recommendation model by limiting the distance to be less than the threshold τ_{dis}. Then, we calculate the probability of selecting a charging source based on the different utility values that an EV will receive for the source x compared to the other sources.

$$P_x = \frac{\exp_x U(v_i)}{\sum_{x=1}^{SA} \exp_x U(v_i)}. \tag{4.5}$$

$$\begin{gathered} SA = c \cup m = \\ \{x \mid x \subset FCS = \{c_1, c_2, ..., c_j\} \leq \tau_{dis}\} \\ \{x \mid x \subset MCS = \{m_1, m_2, ..., m_k\} \leq \tau_{dis}\} \end{gathered} . \tag{4.6}$$

Since P_x may recommend either a MCS or a FCS, we are adding a selection constraint on the P_x proportional to the availability of each charging source (overall waiting time for an EV to start the charging state). Here we say the source availability indicator $\rho_x \geq z$, where z is the threshold of availability value calculated from equations (4.2) and (4.4) for FCS and MCS, respectively, which is a selection constraint as follows:

$$x = \begin{cases} \text{FCS}, & \text{if } z \geq \zeta \\ \text{MCS}, & \text{if } z \geq \kappa \end{cases}.$$

Equation (4.7) defines a utility function for each EV v_i which requests to be charged at the preferred battery percentage SoC_{sit}. Reaching the desired SoC level costs the EV to travel to the charging source x location by U_D with $\Lambda_{(v_i,x)} \leq \tau_{dis}$, which is a threshold for distance to limit the number of charging sources (Fixed and Mobile) to the ones in the vicinity of the service area. Traveling to the location of the charging source results in the EV experiencing a reduction in its SoC, incurring an energy consumption cost ranging between [0.125, 0.19] kWh per kilometer on average. This cost is influenced by the driving pattern and speed [101]. To incorporate this cost into the utility function $U(v_i)$, we introduce the term "unit of energy consumption" ($unit_{(EC)}$). Additionally, the EV, denoted as the energy requester v_i, is required to pay the charging service fee U_F, as specified by the service provider. The SoC level decreases with every kilometer traveled to the charging source, and the difference between the current SoC and the desired amount is added to the requested quantity, leading to an increase in the charging service fee.

Accordingly,

$$\underset{\forall x \in SA}{\operatorname{argmax}} U(v_i) = SoC_{sit} - [\Upsilon_1 U_D(\Lambda_{(v_i,x)}) + \Upsilon_2 U_F(\Phi_x)], \tag{4.7}$$

$$\underset{\forall x \in SA}{\operatorname{argmin}} [\Upsilon_1 U_D(\Lambda_{(v_i,x)}) + \Upsilon_2 U_F(\Phi_x)]. \tag{4.8}$$

In this context, Υ_1 and Υ_2 serve as weights to balance the significance of distance and charging fees for each EV. To maximize the utility function of EV v_i, minimizing the associated costs is imperative. Essentially, the closer the charging source and the lower the fee, the more cost-effective the EV becomes. The system regulates and selects these weights based on the longest distance threshold (τ_{dis}) that an EV can cover given its current battery SoC. This approach allows the system to prioritize charging source assignments in urgent scenarios by emphasizing the distance utility function—achieved by setting Υ_2 to zero—since selecting the nearest charging source becomes crucial for maximizing $U(v_i)$. These two utility function values are calculated from equations (4.9) and (4.10) for distance, and equations (4.11) and (4.12) for fee.

$$\underset{\forall x \in SA}{\operatorname{argmin}} U_D(\Lambda_{(v_i,x)}) = R \times (2 \times atan2(\sqrt{h}, \sqrt{(1-h)}), \tag{4.9}$$

$$h = \sin^2(\frac{\Delta lat}{2}) + \cos lat_1 \times \cos lat_2 \times \sin^2(\frac{\Delta lon}{2}), \tag{4.10}$$

which is the haversine formula for computing the great-circle distance between two coordinates, representing the shortest path across the Earth's surface [94].

$$\underset{\forall x \in SA}{\operatorname{argmin}} U_F(\Phi_x) = [Quantity\, of\, Electricity(kW)] \times [Unit\, Price(\$)], \tag{4.11}$$

$$Qty\, of\, Etc(kW) = SoC_{sit} - SoC_{current} + (unit_{EC} \times \Lambda_{(v_i,x)}). \tag{4.12}$$

where the result of this calculation represents the cost that must be paid for the electricity requested/consumed in dollars ($) for a given amount of electricity usage, measured in kilowatts (kW).

4.2.2 Secure Data Sharing with Federated Learning

One significant aspect of the FL approach lies in its capacity to maintain the confidentiality of all raw training data, including feature names and values, within the devices owned by the data providers, as highlighted in [91]. Within the realm of smart grids, data is inherently partitioned across various data-holding entities. Recognizing this fundamental characteristic in data analytics simplifies the process of establishing a collaborative learning model for discerning shared information among disparate data holders, particularly when dealing with data samples that exhibit similarity.

This distinction can be categorized into two primary types of collaborative learning settings. The first category involves parties with distinct sets of training samples, yet they share the same feature attributes and labels. On the other hand, the second category, known as Vertical Federated Learning as mentioned in [102], encompasses different data providers possessing unique feature sets for the same set of data samples. Consequently, to train a model, the aggregator must combine features from these distinct parties, all while ensuring that raw data remains confined within their respective platforms.

Using Vertical FL in our recommendation model, we have $d = \{1, ...D\}$ number of data holders with a local dataset $\mathcal{D}_d$ including EVs, FCSs, and MCSs. Each entity has its own local model, $\theta_E, \theta_C, \theta_M$ for an EV, FCS, and MCS, respectively. These local models at each entity are trained using their own data $\mathcal{D}_d$. Each entity's training model tries to minimize the training loss $\mathcal{L}$, by applying the additive homomorphic encrypted function $[[HM]]$, as represented below:

$$\theta_E^* = \underset{\theta_E}{\text{argmin}} \quad [[\mathcal{L}(\theta_E, \mathcal{D}_E)]], \tag{4.13}$$

$$\theta_C^* = \underset{\theta_C}{\text{argmin}} \quad [[\mathcal{L}(\theta_C, \mathcal{D}_C)]], \tag{4.14}$$

$$\theta_M^* = \underset{\theta_M}{\text{argmin}} \quad [[\mathcal{L}(\theta_M, \mathcal{D}_M)]]. \tag{4.15}$$

Then, the model updates, such as gradients, are securely shared with the aggregator node, which collects model updates from all entities and computes the weighted average to create a global model, as follows:

$$\theta_{global} = \frac{\sum w_E \times \theta_E + \sum w_C \times \theta_C + \sum w_M \times \theta_M}{\sum w_E + w_C + w_M}, \tag{4.16}$$

where w_E, w_C, and w_M represent the weights assigned to each entity, reflecting its contribution to the global model. The aggregator node sends the updated global model θ_{global} back to the entities, and each entity receives the global model, refines its local model, and generates recommendations using its updated local model, shown in equations (4.17), (4.18), and (4.19), with ϑ as a hyperparameter that controls the extent to which the global model is incorporated.

$$\theta_E = (\vartheta \times \theta_E) + ((1 - \vartheta) \times \theta_{global}), \tag{4.17}$$

$$\theta_C = (\vartheta \times \theta_C) + ((1 - \vartheta) \times \theta_{global}), \tag{4.18}$$

$$\theta_M = (\vartheta \times \theta_M) + ((1 - \vartheta) \times \theta_{global}). \tag{4.19}$$

The underlying goal of minimizing these training losses is to enhance the efficiency of each entity in making charging-related decisions for EVs, based on the local models of FCSs, and MCSs within the FL framework. The FL process iterates over several rounds, with each round involving local model training, model sharing, global model update, and local model refinement.

4.2.3 Implementation of the Secure Intelligent Recommendation Algorithm

Algorithm 2 illustrates the steps of the developed system, which allows participant entities to safely share their personal data. This process aims to identify the most suitable charging source for an EV while considering the desired SoC battery level, all while minimizing travel expenses and service fees.

Examining Algorithm 2, the efficiency of our proposed model becomes apparent as it demonstrates commendable computational complexity. The scalability of the model is reflected in its time complexity, denoted by $O(V * (C + M))$. Here, V signifies the number of EVs, while C and M represent the cumulative count of charging sources. This time complexity analysis underscores the model's ability to handle an increasing number of EVs and charging sources without a disproportionate increase in computational demands. The linear relationship between time complexity and the variables V, C, and M underscores the scalability of our algorithm, ensuring that as the system grows, the computational load remains manageable. This scalability is particularly crucial for real-world applications where the number of EVs and charging sources may vary dynamically, and our model adapts seamlessly to these changes while maintaining efficient computational performance.

Algorithm 2 : Secure charging source recommendation for consumer electric vehicles

Given: $SoC_{sit}, \theta_E, \theta_C, \theta_M, \Upsilon_1, \Upsilon_2, z$
Output: Charging Source P_x, EV Utility $U(v_i)$

for each EV i **do**
  Receive FL global model θ_{global}
  for each FCS j **do**
    Receive FL global model θ_{global}
    Compute Availability Indicator ρ_{cs_j}
    Compute local model θ_F^*
    Broadcast the secure local model θ_F^* parameters
    Calculate the distance utility function
      $\operatorname{argmin} U_D = R \times (2 \times atan2(\sqrt{h}, \sqrt{(1-h)})$
    Calculate the fee utility function
      $\operatorname{argmin} U_F = [Qty\,of\;Etc(kW)] \times [Unit\,Price(\$)]$
    Calculate EV utility function
      $\operatorname{argmax} U(v_i) = SoC_{sit} - [\Upsilon_1 U_D + \Upsilon_2 U_F]$
  end for
  for each MCS k **do**
    Receive FL global model θ_{global}
    Compute Availability Indicator ρ_{ms_k}
    Compute local model θ_M^*
    Broadcast the secure local model θ_M^* parameters
    Calculate the distance utility function
      $\operatorname{argmin} U_D = R \times (2 \times atan2(\sqrt{h}, \sqrt{(1-h)})$
    Calculate the fee utility function
      $\operatorname{argmin} U_F = [Qty\,of\;Etc(kW)] \times [Unit\,Price(\$)]$
    Calculate EV utility function
      $\operatorname{argmax} U(v_i) = SoC_{sit} - [\Upsilon_1 U_D + \Upsilon_2 U_F]$
  end for
  Choose a source based on the probability scores
    $P_x = \frac{\exp_x U(v_i)}{\sum_{x=1}^{SA} \exp_x U(v_i)}$
      subject to $\rho \geq \zeta$ and $\rho' \geq \kappa$
  Compute local model θ_E^*
  Broadcast the secure local model θ_E^* parameters
end for

Accordingly, the sequence diagram in Figure 4.2 provides a detailed view of the steps involved in our recommendation model. It shows how EVs initiate requests to locate and access nearby charging spots. This diagram highlights the interaction between the EVs and the charging infrastructure, ensuring an efficient and secure process for energy acquisition. This systematic flow of actions underscores the model's capability to dynamically allocate charging resources based on the near-real-time demands of EVs, enhancing overall charging efficiency and user experience. The shaded area in this diagram represents the secure data transfer process, where local models from each entity are needed to update the global model, which is the recommendation.

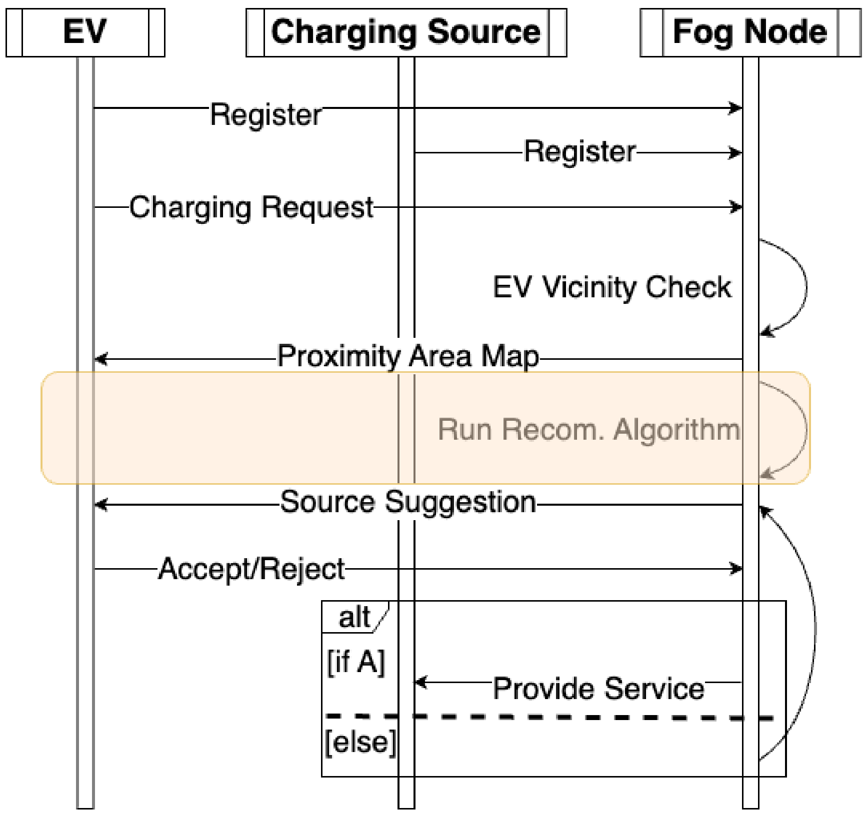


Figure 4.2: A diagram that shows the order of actions in the suggested recommendation model, where requests come from EVs to get energy from nearby charging spots, which can be either fixed or mobile.

As can be seen in Algorithm 2, and Figure 5.1, FL is used to enhance the security of our recommendation model. This approach leverages the power of fog-computing decentralized learning by training the model locally on each charging source and EV data without centralizing sensitive information and the risks of data breaches and privacy violations. Furthermore, the FL-enabled model makes it a robust and secure solution for optimizing EV charging recommendations while safeguarding sensitive data. This not only bolsters the security of the recommendation system but also promotes trust and cooperation among charging providers, ultimately fostering a more secure and efficient EV charging infrastructure.

4.3 Model Evaluation and Results Analysis

In this section, we evaluate the performance of our model and analyze the results of our experiments. We will also demonstrate the effectiveness of our proposed approach and offer insights into the outcomes achieved.

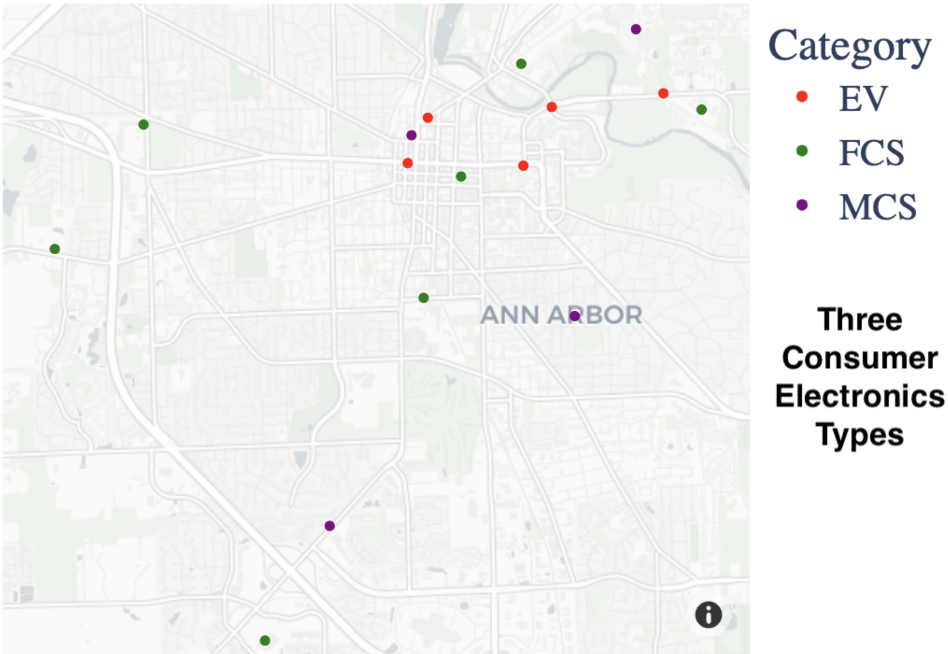
4.3.1 Datasets

To analyze the proposed model, we are using a simulated dataset for MCSs that reflects real-world data from the city of Ann Arbor in MI, USA. This dataset includes various parameters and scenarios to ensure the model's robustness and applicability. Additionally, a list of real FCS data has been gathered to provide a comprehensive overview of the existing infrastructure. We also incorporate collected EV datasets from [103], which include both static and dynamic data of EVs driving in Ann Arbor, Michigan in 2018. This rich dataset allows us to capture the variability in EV usage patterns, charging behaviors, and mobility trends, thus enabling a thorough evaluation of the model's performance under diverse conditions. The combination of simulated and real-world data ensures that our analysis is grounded in practical realities, enhancing the reliability and validity of our findings.

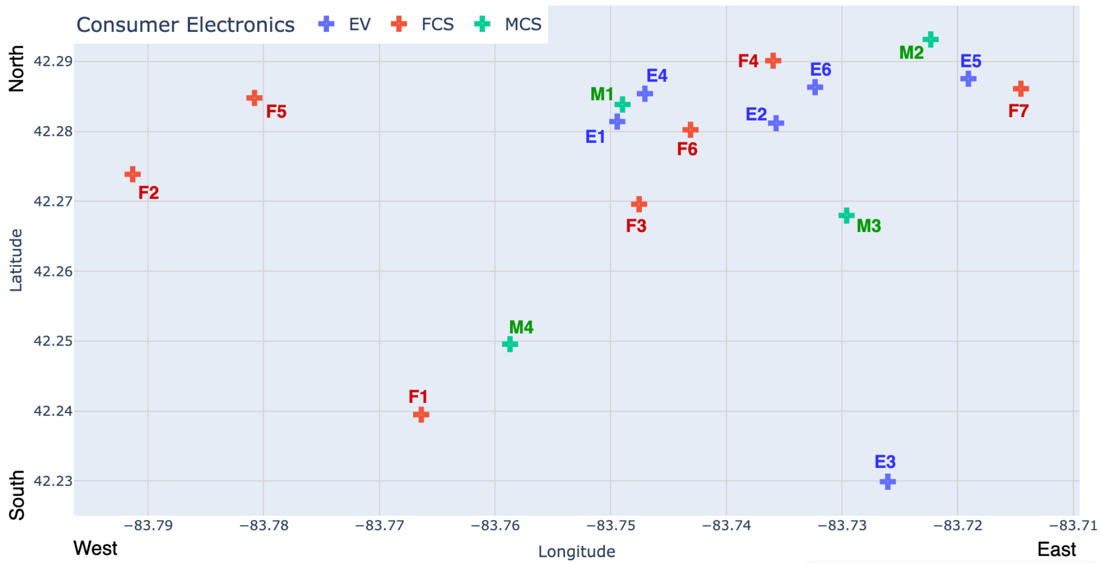
4.3.2 Results and Analysis

Figures 4.3a, and 4.3b illustrate a part of the participants' geographical distribution on the map, featuring 6 EVs with charging requests at different locations, 7 FCSs positioned in distinct areas, and 4 MCSs scattered across various locations within the city scope.

Specifically, in Figure 4.3b EVs are represented by a blue color, FCSs by a red color, and MCSs by a green color.



(a) A region of the dataset is chosen to display the grid-based distribution of labeled EVs, stationary SCs, and MCSs in our specific scenario.



(b) A region of the dataset is chosen to display the grid-based distribution of labeled EVs, stationary SCs, and MCSs in our specific scenario.

Figure 4.3: Distribution of labeled Electric entities in a selected region of Ann Arbor city, illustrating their spatial arrangement and density.

4.3.3 Experimental Setup

To confirm the consistency and trustworthiness of the model outcomes, we conducted the experiments iteratively, implemented in Python programming language on a MacBook Pro M1 with 16 GB of RAM. Multiple runs were performed to ensure the robustness of our findings, and various metrics were used to assess the model's accuracy and efficiency. The iterative approach allowed us to fine-tune the model parameters and optimize the performance, providing a comprehensive evaluation of its capabilities.

4.3.4 Performance Evaluation

In the first part of the proposed algorithm, the availability indicator parameters ρ and ρ' for the FCS and MCS, are calculated. These values then will be used in the recommendation step as a constraint to limit the number of suggested charging sources. In Figure 4.4, an EV can decide which charging source to choose by analyzing its availability values. The ranked list of suggested charging sources is subjective to these parameters' values, which shortens the list to the ones that EV desires. Here the values are scaled from the range [-1.89, 6.6] to [18.11, 26.6] for better illustration in this Figure.

Table 4.1 presents the actual availability values for these seven FCSs. As discussed, the values are determined based on the current availability attributes of these FCSs, providing a comprehensive overview of their readiness for serving EVs. Specifically, the availability parameter values reflect factors such as the number of available charging slots, the average wait time, and the queue list at each station.

For instance, FCS #1 has an availability parameter value of 0.58, indicating a relatively low readiness level, possibly due to limited available slots or higher usage demand. On the other hand, FCS #2 shows a high value of 5.8, suggesting a higher availability, likely due to more available slots or efficient service times. Negative values, such as -1.89 for FCS #3, might indicate stations that are currently very crowded or non-operational affecting their service availability.

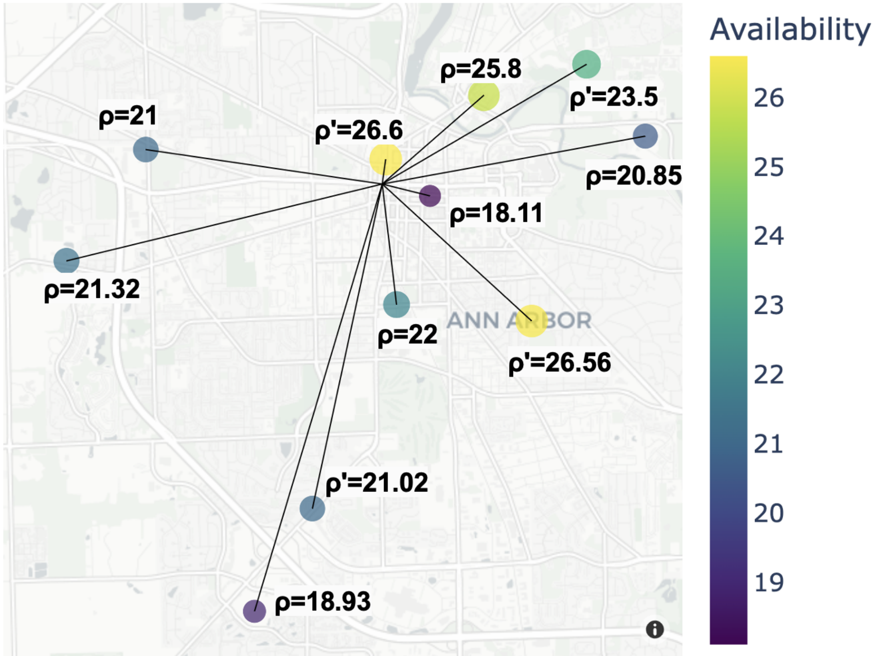


Figure 4.4: Availability Indicator values (ρ for FCS, and ρ' for MCS) to an EV with the charging request. The size and color of the points (which have been enlarged for finer illustration), show the range of the sources' availability.

Table 4.1: Fixed Charging Stations Availability Values

Charging Service Index	Availability Parameter Value
FCS #1	0.58
FCS #2	5.8
FCS #3	-1.89
FCS #4	2
FCS #5	1
FCS #6	1.32
FCS #7	-1.07

Table 4.2: Mobile Charging Stations Availability Values

Charging Service Index	Availability Parameter Value
MCS #1	3.5
MCS #2	6.56
MCS #3	6.6
MCS #4	1.02

In the same manner, in Table 4.2, a similar approach is taken to list the scaleless availability values for the other four MCSs. The values in this table are derived from the current availability features and the remaining battery SoC of the MCSs. For example, MCS #1 has a value of 3.5, which reflects its readiness to provide charging services based on its battery SoC and mobility status. Higher values, such as 6.6 for MCS #3, indicate a higher capacity to serve EVs, whereas lower values, like 1.02 for MCS #4, suggest limited availability possibly due to lower SoC or higher current demand.

Together, these tables offer valuable insights into the readiness and capacity of both FCSs and MCSs in the specified scenario.

Moreover, Figure 4.5 illustrates the total utility achieved by EVs for a given SoC from each EV to maximize their battery levels. The shaded area represents the difference between the SoC_{sit} value and the received SoC value at each charging source, highlighting the efficiency of the charging process. The Figure shows the maximum utility values gained for every six EV consumer electronics from the MCSs and FCSs, demonstrating how the system effectively meets the requested SoC levels (indicated by the dashed red line) from their current SoC. This visual representation underscores the model's ability to manage and optimize charging resources, ensuring EVs receive the necessary energy to maintain optimal performance.

To demonstrate the optimization performance of our models, we contrast the charging source recommendation for EV #3 using a straightforward distance-based selection method, without considering other critical factors, with our proposed optimized utility approach. As depicted in Figure 4.6, the distance between the MCSs and the EV is set to 0 since the MCS will drive to the EV, making them the initial preferences. However, the green line represents the waiting time in minutes that an EV must endure to receive the desired charging level.

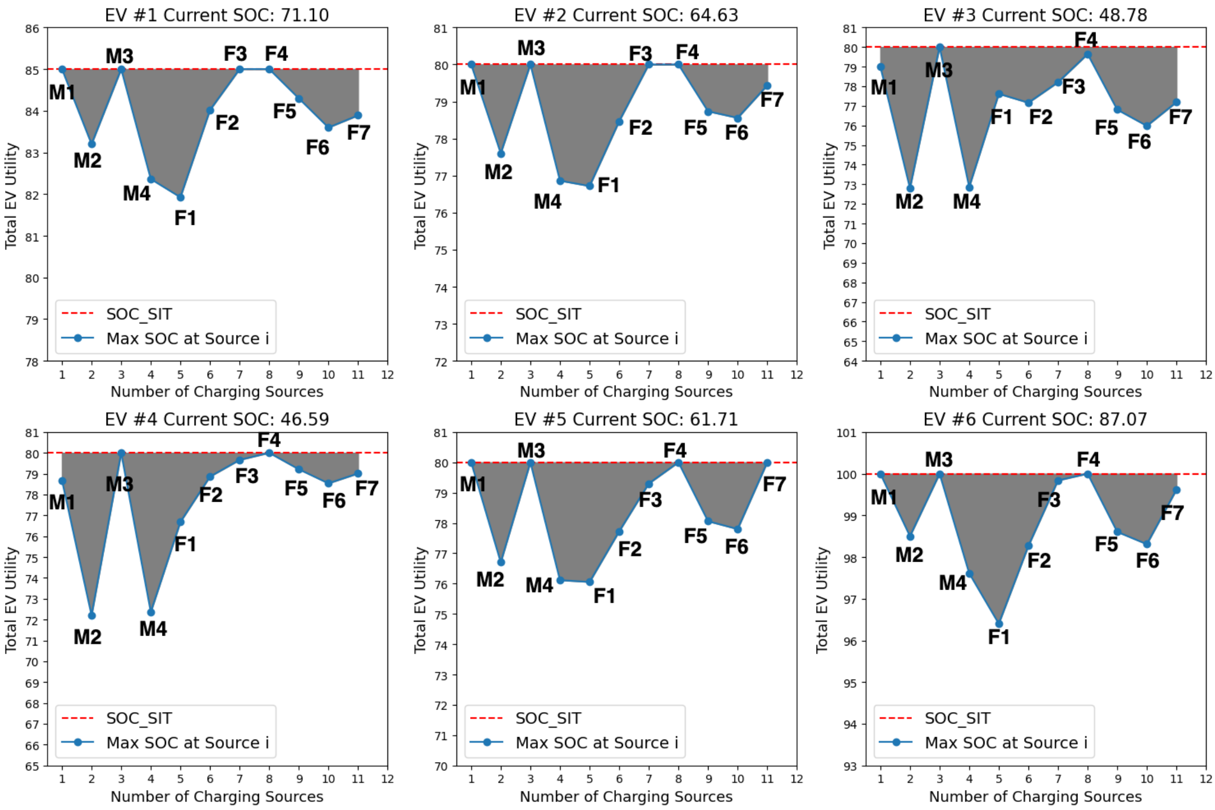


Figure 4.5: Gained maximum utility values for every 6 EV consumer electronics from the MCSs and FCSs to get to their requested SoC level (dashed red line) from their current SoC.

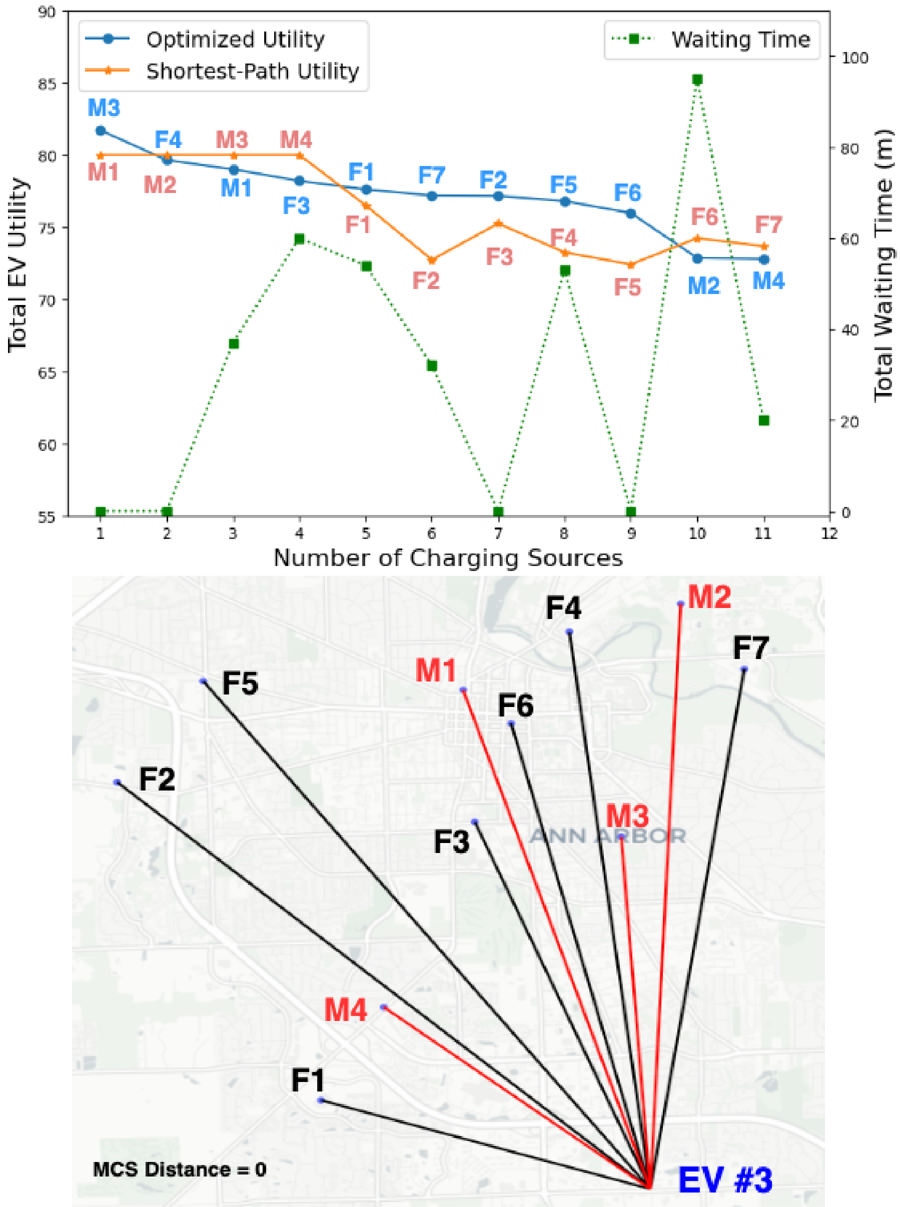
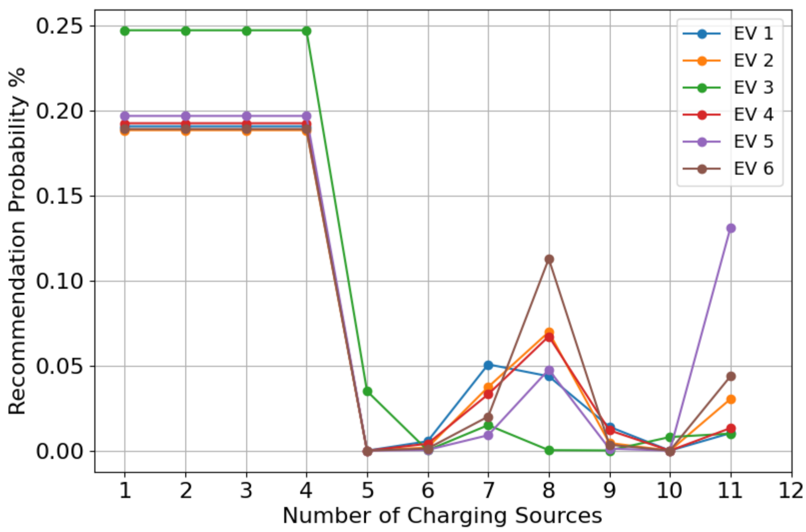
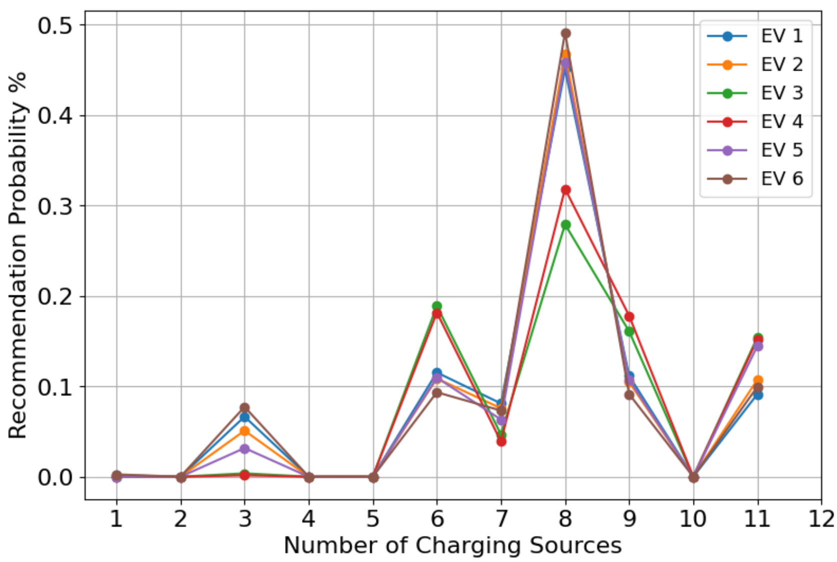


Figure 4.6: Total gained utility (SoC%) of EV consumer #3, comparing the simple distance_based charging source selection, and our optimized recommendation.

To better evaluate the efficacy of the proposed optimized charging source recommendation, we employed two distinct scenarios illustrated in Figure 4.7. In Figure 4.7a, wherein the nearest charging source is obligatory, MCSs represented by charging sources 1 to 4 receive the highest recommendations due to the convenience of drivers not having to travel; the source can instead move to their location. Subsequently, FCSs #1, #3, and #6 are recommended, capitalizing on their proximity to EV #3. Conversely, Figure 4.7b depicts a scenario where drivers can set parameters to minimize waiting time and identify the most cost-effective options. In this context, FCS #4 emerges as a prominent recommendation for EVs, having 7 out of 10 available spots and an occupied spot with a charging time of less than 5 minutes. Among the MCSs, source#3 earns higher recommendations, featuring 2 out of 3 idle batteries and the other being available in less than 12 minutes, and an attractive price of 0.72$/kWh (which is taken from the simulated dataset for this MCS in our scenario), surpassing the other three MCSs in terms of affordability.



(a) Electricity Urgency scenario where the closest charging source must be recommended.



(b) Most-available-cheapest scenario to recommend.

Figure 4.7: The likelihood of suggesting a charging source in (a): when the nearest charging source is mandated for recommendation due to the pressing electricity demand for EVs, and in (b): when an EV seeks the most available and cost-effective charging source for efficient charging.

Finally, in this section, we present Figure 4.8 which compares the computation delay in centralized and FL environments with varying numbers of EVs. The left y-axis represents the computation delay in seconds, showcasing the computation efficiency of both centralized and FL recommendation approaches. The right y-axis represents the differences in computation delay between the two approaches, providing insights into the performance gap across different numbers of EVs. As can be seen, the FL model demonstrates superior computation times compared to the centralized approach. With FL, the computation times range from 0.0022 to 0.0056 seconds, outperforming the corresponding times in the centralized model (ranging from 0.0457 to 0.0709 seconds). This substantiates the efficiency and effectiveness of the FL model, making it a compelling choice for optimizing computation dynamics in EV charging recommendation systems.

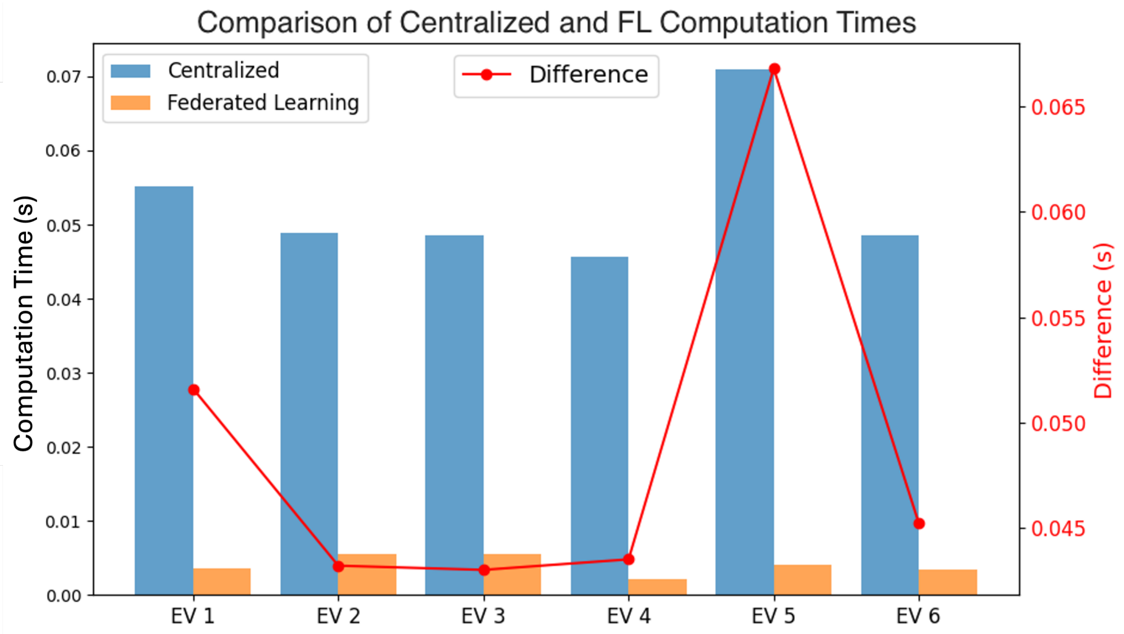


Figure 4.8: Comparative computation times in seconds in Centralized vs. Federated Learning with Differences in second across 6 numbers of EVs. The graph highlights the impact of computation efficiency and the corresponding differences between the two recommendation approaches.

4.4 Chapter 4 Summary

Based on the insights gathered from our research on the integration of a secure recommendation system for EVs, leveraging both Stationary CSs and MCSs, along with the implementation of advanced fog-based recommendation frameworks, we draw several conclusive remarks.

Firstly, our study in this chapter underscores the pressing need for innovative solutions to address the challenges faced by EV owners, particularly concerning the accessibility and availability of charging infrastructure. The introduction of MCSs alongside traditional FCSs presents a promising avenue to mitigate range anxiety and enhance the QoE for urban EV users. By incorporating mobility and flexibility into the recommendation system, we offer a comprehensive approach that adapts to the dynamic needs of EV owners, thereby enabling a more user-centric charging ecosystem.

Secondly, our research highlights the significance of integrating secure fog-based recommendation systems within the IoT paradigm. By leveraging the power of fog computing at the network's edge, we ensure low-latency data processing, near-real-time decision-making, and enhanced data aggregation, all crucial elements for optimizing the efficiency and responsiveness of the recommendation system. Moreover, our approach prioritizes user privacy and data security through the utilization of FL, thereby addressing growing concerns surrounding data protection and safeguarding user privacy in the IoT ecosystem for EVs.

In conclusion, this study contributes to the advancement of ITSs by proposing a robust recommendation framework that not only enhances the accessibility and efficiency of EV charging but also prioritizes user satisfaction and data security.

Chapter 5

Empowering Consumer Electric Vehicle Mobile Charging Services with Secure Profit Optimization

5.1 Introduction to Chapter 5

In this chapter, we present the development of an optimized mobile charging service system designed to minimize operational costs and maximize profits for MCSs within the Consumer IoT framework. Developing an on-demand mobile charging service system aims primarily at minimizing daily operational costs incurred during self-charging, while simultaneously optimizing total profits to the highest degree possible. This initiative focuses on enhancing the performance and functionality of MCSs.

Our approach integrates FL with fog computing to enhance the security and reliability of vehicle communication, prioritizing user data confidentiality. By replacing traditional centralized models with FL, we mitigate data leakage risks and improve the overall security and responsiveness of the recommendation system. This collaborative profit optimization system effectively addresses key challenges in EV charging infrastructure, ensuring secure and efficient interactions within the consumer electronics network. Through these innovations, we enhance the user experience by providing a more secure, efficient, and responsive mobile charging service system.

5.2 System Model and Problem Formulation

Within this section of our study, we represent the architecture and mathematical depiction of a model designed to enhance the performance and profitability of MCSs, while also attempting to fulfill as many charging requests by EVs as feasible.

Similar to many edge consumer electronic devices [104], MCSs require the use of a smart system to oversee the charging process and determine the optimal locations for deploying them to provide energy to EVs. To enhance the solution in this co-management situation, the suggested system needs the capability to address queries regarding the optimal placement and dispatch of a MCS to provide energy to an EV, while also minimizing the idle time of MCSs.

To mathematically denote entities and system's items, similar to chapter 4, we used a set of I number of EVs as $\{v_1, v_2, ..., v_i\}$, $i \in I$, and $v_i \in EV$ to be the entity demanding energy from a MCS. Each MCS is identified from a set of K number of MCSs as $\{m_1, m_2, ..., ms_k\}$, $k \in K$, and $ms_k \in MCS$ to be the entity responding to energy-delivery request and also requesting electricity from a FCS. The last entity providing energy is indicated within a set of J number of FCSs as $\{f_1, f_2, ..., f_j\}$, $j \in J$, and $f_j \in FCS$.

The primary purpose of the system is to increase the entire amount of profit a MCS ms_k can gain by increasing the number of service deliveries, and less self-charging payments from the equation (5.1).

$$max\, Profit_k^{(total)} = \sum_{i=1}^{I} Profit(ms_k, v_i) - \sum_{j=1}^{J} Cost(ms_k, f_j). \tag{5.1}$$

In general, the primary factors influencing the optimal dispatch of a MCS ms_k for energy delivery and self-charging scheduling revolve around the SoC level of the MCS battery(ies), with the overall count of installed batteries B, along with the charging prices (Φ) they offer to other EVs or they must pay to FCSs. This Φ can be calculated from equation (5.2) for each MCS ms_k, by multiplying the amount of energy (Qnt) by unit price, as follows.

$$\Phi = Qnt\,(kW) \times Selling\,Price\,(\$). \tag{5.2}$$

The $Profit(.)$ function here aggregates the revenue earned by the MCS ms_k from each EV v_i it served. Therefore, by increasing the number of EVs receiving assistance, the MCS is able to correspondingly enhance its profit. To refine the optimization process, we introduced two principle constraints into the system to mitigate the occurrence of inaccurate results.

1. We assume that during the transit of a MCS to an EV or a FCS, the sole expense caused is the travel time, with no associated energy consumption cost, as these MCSs are typically moved by ICE vehicles.
2. Once a charging phase begins, whether it is initiated at a FCS for self-charging purposes or with an EV for energy delivery, it cannot be interrupted.

Whenever there is a request for charging from an EV v_i, denoted as r_i, the system collects the required data and generates a set consisting of the quantity of electricity needed, available start time, departure time, and location, respectively, as shown in equation (5.3).

$$r_i =< Qnt,\, t_i^{start},\, t_i^{end},\, [lat, long] >, \tag{5.3}$$

$$\Lambda(v_i, ms_k) = R \times (2 \times arctangent_2(\sqrt{h}, \sqrt{(1-h)}), \tag{5.4}$$

$$h = \sin^2(\frac{1}{2}\Delta lat) + [\cos{(lat_1)} \times \cos{(lat_2)} \times \sin^2(\frac{1}{2}\Delta long)]. \tag{5.5}$$

Equations (5.4), and (5.5) demonstrate the calculation of the distance $\Lambda(.)$ between the EV v_i and the MCS ms_k by utilizing the provided latitude and longitude data. Similarly, the Haversine formula is used to calculate the most direct route over the surface ground [94].

The system then proposes those requests r_i to the MCS by identifying candidates closer to the MCS and subjecting them to the optimization constraints applied to the $Profit(.)$ function in equation (5.1). These constraints include:

- Each MCS ms_k can be in one of three phases: en route or idle, self-charging at a FCS f_j, EV v_i charging. It cannot be engaged in more than one phase simultaneously.

$$\sum_{k=1}^{K} ms_k + m_{kj} + m_{ki} = 1, \forall j \in J, \forall i \in I. \tag{5.6}$$

- The energy requested by an EV v_i must always be lower than the remaining energy stored in the battery of the MCS ms_k.

$$Qnt_{v_i} < \sum b_{ms_k}, \forall b \in B. \tag{5.7}$$

- The timestamp of the energy request submitted to the system by an EV v_i must always precede the dispatch time for a MCS ms_k.

$$t_i^{request} < t_k^{dispatch}, \forall i \in I, \forall k \in K. \tag{5.8}$$

- In our optimization model, we incorporate a priority factor to address EVs with battery SoC levels below a specified threshold (τ_{SoC}) within our model.

On the other hand, when the SoC level of each MCS ms_k, falls below a predetermined threshold (τ_{SoC}) each MCS, equipped with a b number of batteries, $b \in B$, must initiate self-charging. Subsequently, it must identify and travel to a FCS f_j for the purpose of recharging. Therefore, the ms_k demanding recharging will be provided with a list of available FCSs in the area selected by ms_k.

This aspect of the MCS ms_k affects its operational expenses, as it incurs costs for recharging and becoming ready to provide service to other EVs. Hence, the second segment of the optimization problem centers on minimizing the $Cost(.)$ function in equation (5.1), enabling the MCS to minimize expenses and maximize profits.

The creation of a list of suggested accessible FCSs, as facilitated by our model, depends on several factors, including the number of occupied charging spots, the number of vehicles waiting in line (q) along with their respective charging session durations ($t_{waiting}$)(if all spots are occupied), the remaining time for ongoing charging sessions (t), price per charging unit and the distance to the MCS ms_k, which is obtained from equation (5.4).

$$f_j =< S,\ \vec{o_s},\ \vec{t},\ q,\ \overrightarrow{t_{waiting}},\ \$\$,\ [lat, long] >, \tag{5.9}$$

where o_s is a categorical parameter that represents whether spot s is occupied (assigned a value of 1) or empty (assigned a value of 0).

Each FCS f_j with the aggregate quantity of S charging plugs is required to share this information as a set with the system. Generation of an optimized solution for ms_k in selecting a recharge location by minimizing the total cost it will pay is the main objective in the $Cost(.)$ function definition, used in the primary optimization function (5.1).

However, to enhance the performance of our system optimization, we conducted an additional analysis considering the waiting time at a FCS f_j as another factor influencing the total profit earned by the MCS. This factor is denoted as the station's crowdedness or accessibility value (ρ_{f_j}), which is calculated by equation (5.10) and subsequently used as a subjective in the creation of the suggested list.

$$\rho_{f_j} = \sum_{s=1}^{S} t_s.o_s + \sum_{waiting=1}^{q} t_{waiting}. \tag{5.10}$$

Therefore, the higher the ρ_{f_j} value, the more crowded the station is, which leads to becoming less available and in a lower rank of the suggested list.

Our mathematical model contributes to the optimization of MCS operations by formulating the problem of profit maximization through a combination of energy delivery to EVs and self-charging from FCSs. The model takes into account various operational factors such as energy requests, battery levels, charging prices, and travel distances. The primary objective is to maximize the total profit ($Profit_k^{(total)}$) for each m_k by increasing service deliveries and minimizing self-charging expenses. In order to provide economic justification, the selling price (ϕ) per unit of energy is determined based on market conditions, demand, and operational costs. This price ensures that the MCS can cover its expenses while making a profit. Also, charging prices at FCSs are considered to ensure that the self-charging costs do not exceed the revenues earned from delivering energy to EVs.

There might be scenarios where the MCS might incur losses or negative utilities. These scenarios include (a) High self-charging costs at FCSs due to increased demand or higher prices. (b) Low demand for energy from EVs, resulting in fewer service deliveries. (c) Long travel distances to deliver energy or reach FCSs increase operational costs. To address these scenarios, our model incorporates constraints and optimization techniques to minimize losses. We include a priority factor for EVs with low SoC levels to ensure that the MCS can prioritize high-demand requests. Additionally, the model evaluates the crowdedness value (C_{f_j}) of FCSs to avoid long wait times and high costs.

To further enhance the mathematical modeling, we proposed adding the following equation (5.11) to capture the dynamics of losses and negative utilities and adjust to minimize losses and optimize profits under varying operational conditions.

$$Loss_k = \sum_{j=1}^{J} \left(Cost(m_k, f_j) \times \frac{t_{waiting_j}}{T} \right) - \sum_{i=1}^{I} Profit(m_k, v_i), \tag{5.11}$$

where $Loss_k$ represents the potential losses for MCS m_k, $t_{waiting_j}$ is the waiting time at FCS f_j, T is the total operational time, $Cost(m_k, f_j)$ and $Profit(m_k, v_i)$ are as previously defined.

Up to this point in our system model, we clarified the profit optimization undertaken for the MCSs registered in our model. In order to ensure system safety and protect user data, we integrated FL as a recognized method to strengthen the security of a distributed model across the CIoT network [105][106]. By employing FL, each MCS can learn from decentralized data without sharing sensitive information, thus maintaining privacy while benefiting from collective insights. This approach allows each MCS to make more informed decisions regarding charging/discharging scheduling and service delivery, ultimately maximizing its own profit [106].

FL as demonstrated by its utilization of a secure framework and the integration of homomorphic encryption, serves as a potent security remedy within the proposed model [107]. The application of homomorphic encryption to the parameters transmitted during the FL process is an essential element in fortifying the security landscape. By allowing computations to be executed on encrypted computed data on-device, homomorphic encryption ensures that sensitive information remains confidential during transmission. This inherent privacy-preserving feature significantly mitigates the risk of data exposure, unauthorized access, and potential breaches [108]. As a result, FL not only provides an innovative approach to collaborative model training but also establishes itself as a proactive security measure, fostering a secure environment for the exchange of model updates and contributing to the overall robustness of the proposed model.

In the FL setup for the MCS profit optimization model, since each entity (MCS, FCS, EV) computes its own local model with distinct datasets, the choice of parameters must align with the characteristics of the individual datasets and the overall model structure. The implementation setup involves configuring each entity to perform local computations.

FL involves communication between entities and aggregator nodes, so the setup includes defining the security measures (homomorphic encryption), and the frequency of model updates, as they are responsible for appropriately balancing the contributions from different entities. Similar to chapter 4, section 4.2.2, we will utilize the VFL formulation to securely enable data sharing between the entities. Equations (4.13) to (4.15) represent the mathematical formulations used in FL local training (θ, θ^*) before sharing the private data, to enforce security measures with the additive homomorphic encrypted function $[[HM_{\theta,\theta^*}]]$

on our model with three decentralized private local datasets $\mathcal{D}_{mcs}$, $\mathcal{D}_{fcs}$, and $\mathcal{D}_{ev}$.

Similarly, equation (4.16) is used to update the global model θ_{global}, and then By receiving the global model, entities refine and update their local models, as shown in equations (4.17) to (4.19).

5.2.1 Implementation of the Secure Profit Optimization Algorithm

The sequence diagram in Figure 5.1 shows the steps in the recommendation and profit optimization model for MCSs. This involves four key entities: MCS, FCS, EV, and a Fog Node. The process starts with registering these entities. After registration, EVs send energy requests to nearby MCSs to recharge. The optimization algorithm then recommends an action. If an MCS has a low battery of less than the threshold, it suggests an FCS for recharging. If the MCS is ready, the model directs it to an EV with a charging request. Based on this, the MCS selects either an FCS or an EV. Fog Nodes help by ensuring smooth communication and coordination among EVs and charging services, therefore, optimizing the energy supply process. The practicality of the proposed model lies in its ability to act as an intelligent system that continuously updates and refines models, allowing it to adapt to changing conditions in near-real-time for efficient and responsive operations. Additionally, the system must monitor MCS operational costs and assist operators in maximizing their profits.

Algorithm 3 illustrates a comprehensive approach aimed at optimizing profit margins within the domain of MCSs for consumer electronics. The algorithm not only focuses on maximizing profitability but also emphasizes efficient resource allocation. By strategically allocating resources, the aim is to incentivize the widespread adoption of MCSs as a reliable asset for charging station infrastructure consumers. This entails not only considering immediate profitability but also fostering a sustainable ecosystem where MCSs play a central role in meeting the evolving needs of consumers and the broader energy landscape.

The algorithm incorporates various factors such as demand forecasting, dynamic pric-

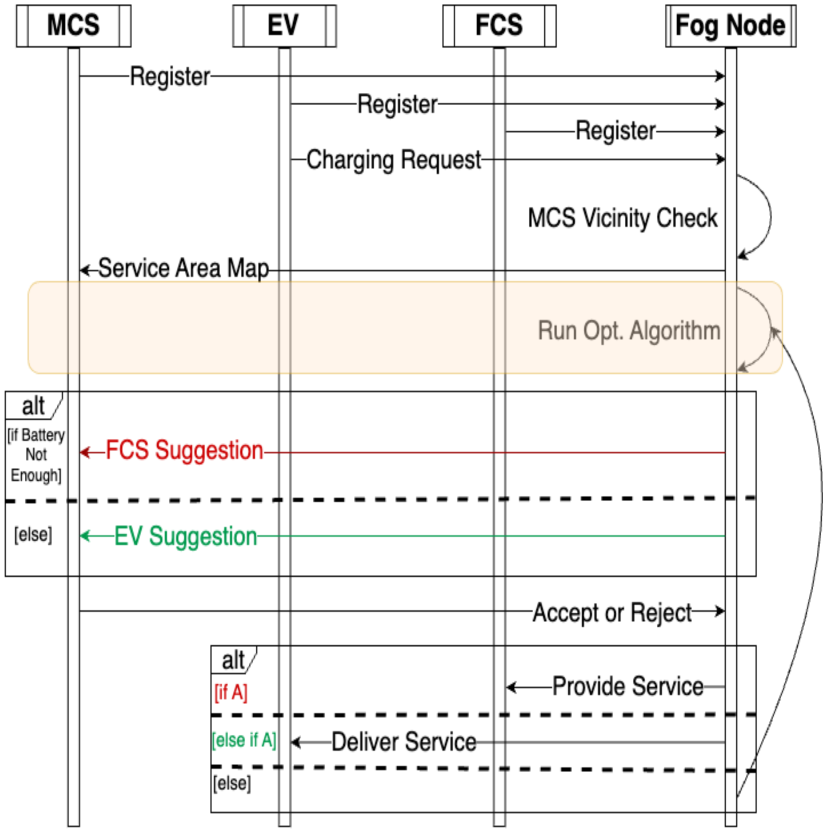


Figure 5.1: Sequence diagram showing the actions in the MCS optimization process. It includes registration, EVs sending requests, and the algorithm directing MCSs to either recharge at FCSs or service EVs, with Fog Nodes enabling communication.

ing models, and intelligent scheduling algorithms to ensure that MCSs operate at peak efficiency while maximizing revenue streams. Additionally, it takes into account factors such as energy efficiency, infrastructure costs, and user preferences to strike a balance between profitability and consumer satisfaction. Through this approach, the algorithm seeks to establish MCSs as indispensable components of the consumer electronics ecosystem, driving both economic growth and environmental sustainability.

The time complexity calculated from the model's proposed algorithm is represented by the expression $O(M*(V+C))$, where M denotes the quantity of MCSs, and V and C symbolize the combined total of profit-influencing elements from EVs and FCSs, respectively. The evaluation of the model's time complexity and scalability ratio is especially important for scenarios where the overall number of EV charging requests and energy services may change actively, the system's perfect adjusting enhances its computational performance.

Algorithm 3 : Secure MCSs consumer electronics profit optimization

Given: $\Phi, < r >, < f >, \theta_{mcs}, \theta_{fcs}, \theta_{ev}, \theta_{global}$
Output: MCS $Profit^{(total)}$

for each MCS k **do**
  Collect θ_{global} initial parameters
  if $|r| > 0$ **then**
    for each EV i **do**
      Collect θ_{global} initial parameters
      Check Qnt_i
      Compute distance
        $\Lambda(v) = R \times (2 \times arctangent_2(\sqrt{h}, \sqrt{(1-h)})$
      Calculate θ_{ev} local model
      Publish encrypted $[[\theta_{ev}]]$ parameters
    end for
  end if
  if $|b_k| < \tau_{SoC}$ **then**
    for every FCS j **do**
      Collect θ_{global} initial parameters
      Compute crowdedness value
        $\rho_j = \sum_{s=1}^{S} t_s.o_s + \sum_{waiting=1}^{q} t_{waiting}$
      Compute distance
        $\Lambda(f) = R \times (2 \times arctangent_2(\sqrt{h}, \sqrt{(1-h)})$
      Calculate θ_{fcs} local model
      Publish encrypted θ_{fcs} parameters
    end for
  end if
  Compute $\Phi^{+} = Qnt\,(kW) \times Selling\,Price\,(\$)$
  Calculate $Profit(ms_k)$ function
      subject to τ_{dist}
  Compute $\Phi^{-} = Qnt\,(kW) \times Selling\,Price\,(\$)$
  Calculate $Cost(ms_k)$ function
      subject to τ_{dist}
  Compute $max\,Profit^{(total)}$
end for

5.3 Model Evaluation and Results Analysis

In this section, we will conduct a performance evaluation of our model and examine the outcomes of our experiments. Furthermore, we will demonstrate the effectiveness of our proposed approach and offer insights into the attained results.

5.3.1 Datasets

To demonstrate the efficacy of the proposed model in this chapter, it underwent testing using the same case study from chapter 4 section 4.3.1, based on a real-world dataset sourced from Ann Arbor City in Michigan, during 2018. The collected dataset features both static and dynamic data from consumer electronics activities [103]. On that account, Table 5.1 displays a representative sample extracted from the available datasets for MCSs, FCSs, and EVs. It provides insight into their structure and contents and serves as a valuable resource for understanding the characteristics and dynamics of the MCS, FCS, and EV ecosystem.

Table 5.1: Consumer Electronics dataset samples.

MCS	**Time**	**Lat/Long [deg]**	**Fee [$]**	**Max Power [kW]**	**Battery #**	**Start/Stop Sess. [h]**	**SoC [%]**
	12:36:08	[42.28,-83.74]	1.6	25	2	[13:24,13:50]	[92,86]
FCS	**Lat/Long [deg]**	**Fee [$]**	**Spots #**	**Type**	**Available #**	**Start Sessions [h]**	**End Sessions [h]**
	[42.23,-83.76]	0	2	Slow	1	[9:46,10:12]	[10:43, -]
EV	**Time**	**Speed [km/h]**	**Outside Temp. [c]**	**Voltage [V]**	**Current [A]**	**Lat/Long [deg]**	**SoC [%]**
	20180609051222	27.02	9	374.5	15.5	[42.22,-83.72]	48.78

5.3.2 Experimental Setup

Constant testing of experimental results was undertaken to guarantee the reliability and precision of the model's outcomes. These experiments were conducted using the Python programming language on a MacBook Pro equipped with an M1 chip and 16 GB of RAM. The effectiveness of our proposed model is evident in its notable computational efficiency and scalability.

5.3.3 Performance Evaluation

In this study, we accurately examined different aspects of our proposed optimization model. We carried out experiments to assess the performance of the model in diverse scenarios and to ensure the efficacy of incorporating federated learning as a replacement for the conventional centralized architecture by having the users' data and computation on-device.

The analysis shown in Figures 5.2, 5.3, and 5.4 sheds light on the relationship between the booking times for charging services requested by EVs and the resulting revenue attainable by an MCS through its charging fee structure through different timing scenarios. It explains how the timing of these booking requests directly impacts the potential profit generated by the MCS, particularly MCS #4, which serves as the focal point of the study. Each booking period from the 6 EVs within the service zone of MCS #4 is examined, alongside the corresponding charging fees offered by the station. This overall view allows for a refined understanding of how variations in booking times influence the revenue potential of the MCS.

Figure 5.2 presents the scenario under normal traffic conditions, showing the profit generated based on the booking times with a selling price of $2.5. This Figure complements the analysis by incorporating data on MCS #4's driving distance to deliver charging services to the 6 EVs, along with their respective booking request times. This addition underscores the various natures of profit optimization for MCSs and highlights the fact that while charging fee offerings play a principal role in determining potential revenue, other factors such as travel distance must also be taken into account. The travel time required for MCS #4 to reach each EV is a determinant of operational costs and, consequently, overall profitability.

In Figure 5.3, the scenario during peak hours is depicted, where the demand for charging services is higher, resulting in increased profits from \$2.5 to \$2.8 as shown by the adjusted booking times and fees. Figure 5.3 continues to emphasize the importance of travel distance in profit optimization under these conditions.

Furthermore, Figure 5.4 illustrates the off-peak hours scenario, where the demand for charging services is lower. The impact of reduced booking times on profit is evident in this figure with a price of \$2.0. This Figure maintains the focus on travel distance, reinforcing its significance in the overall profitability of MCS #4 during off-peak hours.

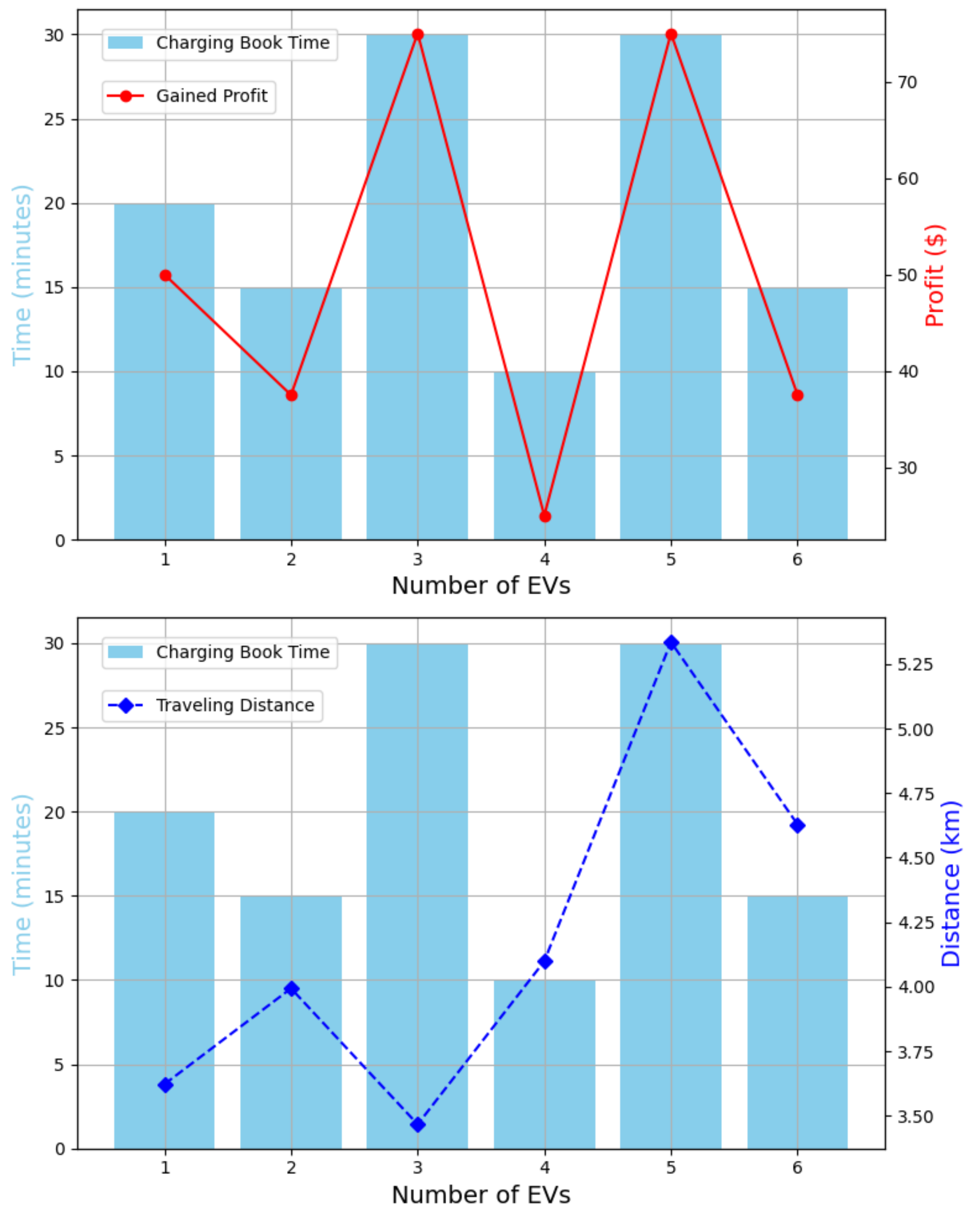


Figure 5.2: Depiction of the relationship between the booking times for charging requests from 6 EVs within the service zone of MCS #4 and the potential profit generated based on a charging price of $2.5 during **normal traffic conditions**. The figure also shows the corresponding traveling distances for MCS #4 to deliver charging services to these EVs, illustrating how both booking times and travel distances influence the MCS's profitability.

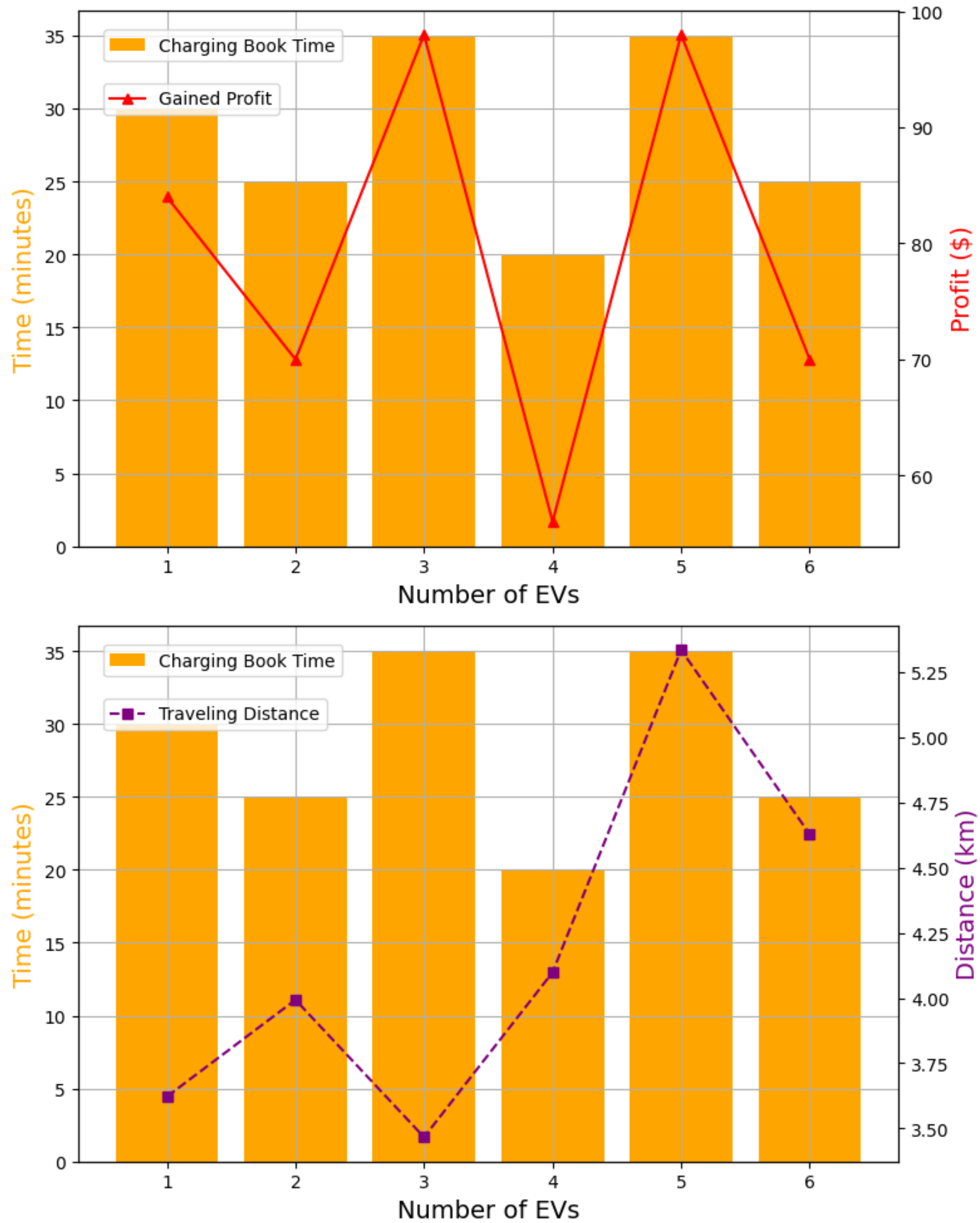


Figure 5.3: Representation of the interaction between the booking times for charging requests from 6 EVs within the service zone of MCS #4 and the potential profit generated at a charging price of $2.8 during **peak hours**. This figure includes the travel distances for MCS #4 to reach each EV, highlighting the impact of higher demand periods on both profit and operational logistics.

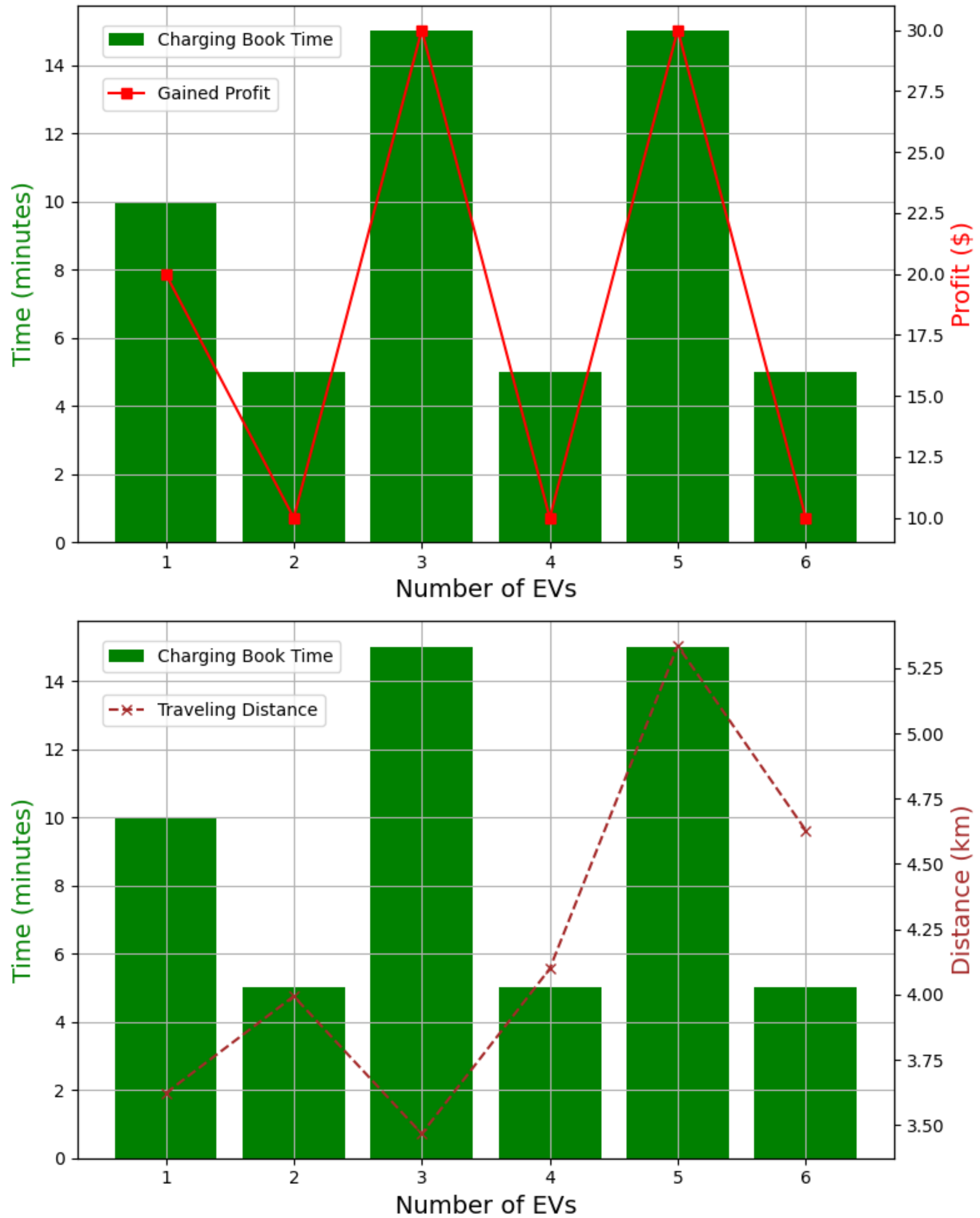


Figure 5.4: Visualization of the relationship between the booking times for charging requests from 6 EVs within the service zone of MCS #4 and the potential profit generated at a charging price of $2.0 during **off-peak hours**. The figure also details the traveling distances for MCS #4 to provide charging services, emphasizing how reduced demand and travel requirements affect the MCS's overall profitability during less busy times.

Utilizing the charging/discharging scheduling mechanism to maximize profit for MCSs proposed in this study by considering profit-influencing parameters, Figure 5.5 illustrates the operational scheduling scenario for MCS#1 during peak hours operation, strategically selecting 2 adjacent EVs for service delivery after checking SoC level to fulfill the service. Initiating with energy provision to EV#1, succeeded by EV#4, the MCS stands to earn \$90 approximately (normal hours \$1.6, peak hours \$1.8, and off-peak hours \$1.2). Following this, in order to be able to continue the service delivery, the MCS is confronted with the decision of where to recharge itself, as the SoC level is reaching its minimum threshold. Given the present position of the MCS, the system presents a choice among 3 proximate FCSs, taking into account their queue times and charging prices. Here, using the color-coded arrows, for clarity, the system outlines the available options, ordered from the closest most available to the furthest least available, arranged in a left-to-right sequence.

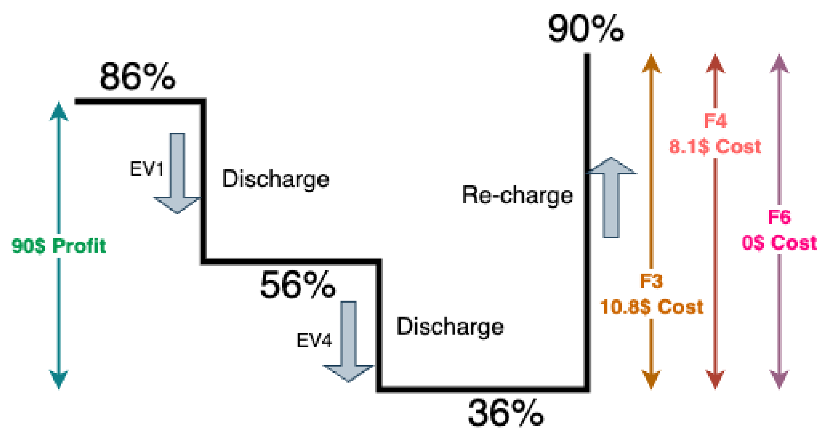


Figure 5.5: The operational scheduling scenario for MCS#1 selecting 2 nearby EVs for service delivery. By providing energy to EV#1 followed by EV#4, the MCS can earn \$90 during peak hours. Subsequently, the MCS must decide where to recharge itself, selecting from 3 nearby FCSs based on their queue times and charging prices. The color-coded arrows indicate the available options, extending from the nearest to the most distant, arranged from left to right.

Additionally, Figure 5.7 shows the optimized profit for each MCS. It analyzes the energy buying and selling between MCSs, EVs, and FCSs at different locations. Each subplot represents one of the four MCSs that highlights three key metrics: profit (the income from selling energy to EVs), cost (the expense of recharging at different FCSs), and total profit (net profit, calculated as profit minus cost).

The bar graphs in each subplot show these metrics for each MCS when choosing from seven different FCSs. Moreover, each subplot includes a line graph that shows the distance between the MCS and each FCS. This helps to understand how distance affects costs and total profit. Figure 5.7 tries to underline the importance of strategic choices for MCSs to maximize profit. By selecting the best FCSs for recharging, MCSs can balance energy costs with revenue from EVs. The distance to each FCS and the station's crowdedness value impact the cost and influence the overall profit margins.

For clarity, we included the geographical distribution of EVs and charging sources in our scenario, as illustrated in Figure 5.6.

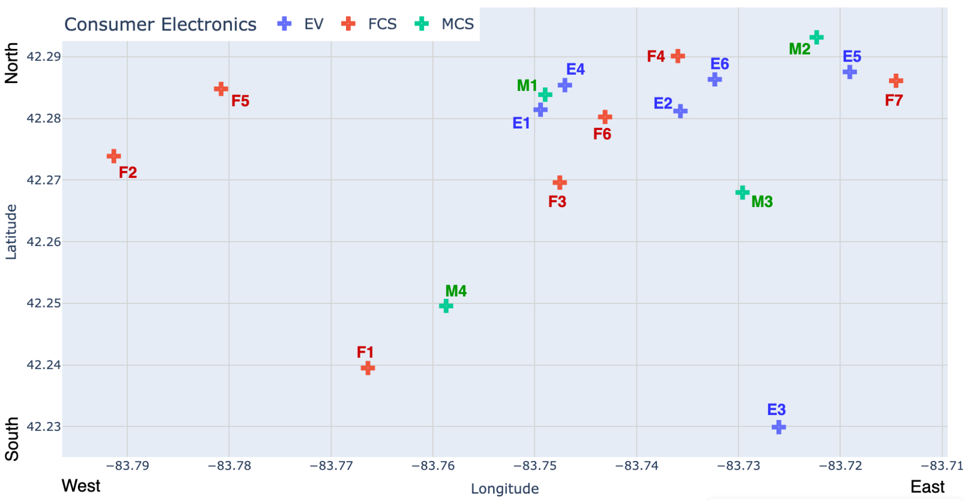


Figure 5.6: Distribution of labeled Electric entities in a selected region of Ann Arbor city, illustrating their spatial arrangement and density.

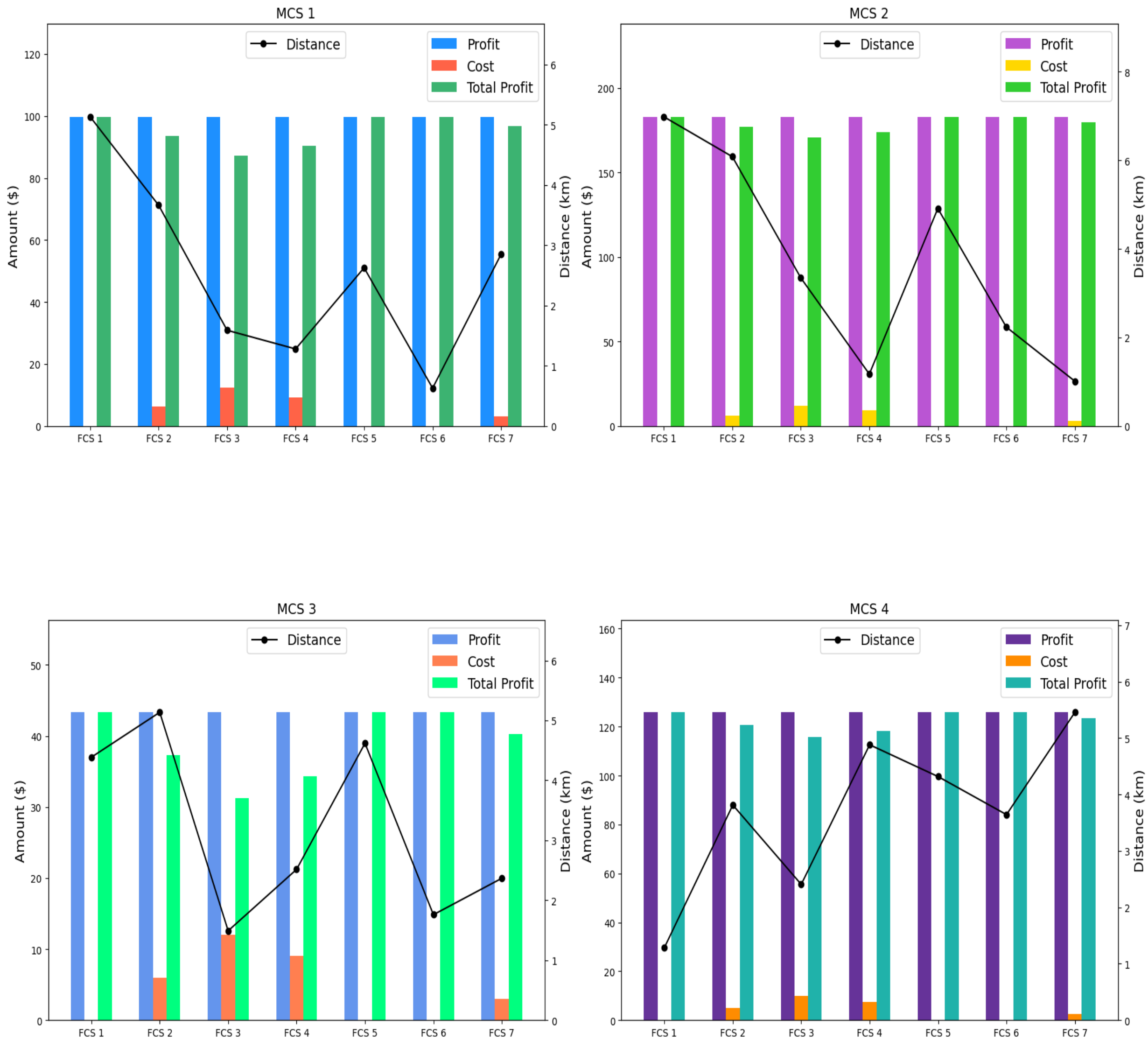


Figure 5.7: Optimized profit for each MCS by analyzing energy transactions with EV and FCSs at various locations. The subplots show profit, cost, and total profit (net profit) for each MCS when choosing from seven different FCSs. FCSs 1, 5, and 6 offer free charging, but they may be far and crowded, potentially leading to time wasted traveling there. The line graph in each subplot represents the distance between the MCS and each FCS, highlighting the spatial considerations influencing costs and profits.

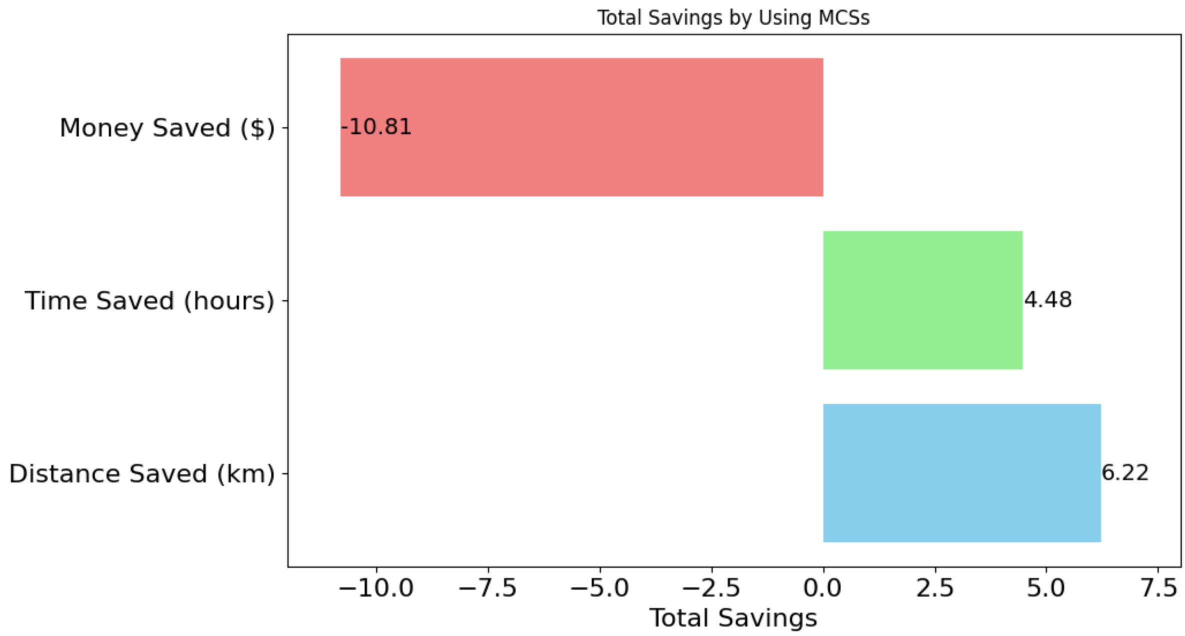


Figure 5.8: Total distance, time, and money saved by EVs using nearest MCSs instead of traveling to nearest FCSs, highlighting the benefits of MCSs in the ITS.

Lastly, Figure 5.8 demonstrates the benefits of MCSs in terms of distance, time, and money saved for EVs when these EVs choose to have the nearest MCSs come to them instead of going to the nearest FCSs.

Here to evaluate the Distance Saved, Time Saved, and Money Saved parameters, we calculated the distance from each EV to the nearest FCS, to compare the distances. The Time Saved parameter uses the average travel speed ([30-50] km/h in city roads in Ontario [109]), and the differences in waiting times at the nearest charging sources, as shown in equation (5.12)

$$time\_saved = \frac{max(distance\_saved, 0)}{average\_speed} + (fcs\_waiting\_time - mcs\_waiting\_time). \quad (5.12)$$

The Money Saved parameter is then calculated considering the driving cost per kilometer, which as reported is on average 12 cents/km [110]. Equation (5.13) explains the used variables for this parameter.

$$\begin{aligned} &money\_saved = max(distance\_saved, 0) \times cost\_per\_km + \\ &(fcs\_charging\_price - mcs\_charging\_price). \end{aligned} \tag{5.13}$$

As illustrated, these results highlight the advantages of using MCSs in terms of reducing travel distance and saving time, though they do not significantly lower costs for EV users.

5.4 Chapter 5 Summary

In conclusion, this chapter has highlighted the importance of enhancing EV charging infrastructure within the CIoT network through the integration and extension of MCSs. Our primary aim was to emphasize the need to incorporate dynamic factors into the stochastic optimization problem faced by MCS drivers and operators to achieve the highest possible daily profits. By proposing a secure and optimized approach, we sought to maximize profit potential while reducing operational costs. To address data sharing security concerns, we integrated FL for data privacy and proposed a fog-edge communication framework to enhance communication. These contributions have significantly improved the efficiency and capabilities of MCSs within the CIoT network, ensuring a consumer-centric, secure, and reliable experience.

Moreover, a prudent approach to maximizing profitability requires balancing potential profits with logistical considerations. This includes evaluating the revenue potential of each charging request and factoring in the distance to be traveled by the MCS. By integrating these insights into their decision-making processes, MCS operators can devise strategies that optimize profit margins by minimizing driving distances while capitalizing on lucrative charging opportunities. Ultimately, this nuanced understanding of the relationship between booking times, charging fees, travel distances, and profitability empowers MCS operators to make informed decisions that enhance financial success and operational efficiency.

Chapter 6

Blockchain and Federated Learning for Electric Vehicle Charging Station Recommendation

6.1 Introduction to Chapter 6

In this chapter, we introduce a secure mechanism for fog nodes, granting access only to authorized aggregators who manage shared parameters. This mechanism enhances privacy by requiring fog nodes to register within a distributed blockchain network, ensuring verification by other network participants. This architecture is pivotal in preventing malicious users from infiltrating the fog network to conduct data theft or tampering attacks. This proposed approach decentralizes the aggregator role, traditionally vulnerable to single points of failure, by employing decentralized fog nodes located near data holders (EVs, FCSs, MCSs). It improves communication latency for near-real-time applications by reducing communication delays and access latencies, creating a flexible and scalable network of aggregators.

6.2 System Model and Problem Formulation

In this section, the architecture, and workflow of our proposed system, which is based on the idea of securely decentralizing a VFL model by integrating blockchain and fog technologies, is described in detail.

Distributed fog-based nodes are designed to manage training parameters exchanged among all the parties in our system. A distant computation center infrastructure might not perform well for a near-real-time interactive system such as a recommender for on-the-move EVs. Shifting to the fogs is one possible solution to increase an end-to-end response time by locally processing the parameters at the edge of the network within the geographical location of EVs [28]. Flexible high-performance fogs can reduce traffic and computing loads on the central server since they are provided with storage and processors to aggregate and analyze localized training models.

Let $\bar{\mathcal{C}} = \{\mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_P\}$ be the set of fogs that perform the decentralized local model aggregation task in our recommender system. As the fogs are responsible for parameter exchanging between entities, blockchain can help enhance the fog network reliability by recording and sharing the list of only validated nodes via a distributed ledger. The blockchain can create a secure network consisting of only trusted data aggregators. It facilitates tracking the security of our distributed scalable network of fogs [81] By doing so, the authenticity of an aggregator node $\mathcal{C}_p \in \mathcal{C}$ within the set of fogs is proven, and no misleading user can alternate the network to steal or tamper the data. Integrating the blockchain into the proposed recommendation system assures the data providers (i.e., FCSs, MCSs, EVs) to connect to a tamper-proof network of distributed fog nodes. Below is the overall operation of the blockchain-based fogs (fogChain), implemented in the proposed system model.

1. Requests for adding a new fog node $\mathcal{C}_{new}$ to the blockchain are submitted by generating a new transaction TX from a cloud Service Provider (SP) in a new area, which includes the actual transaction information and the hashed value $hash(TX)$.

When $\mathcal{C}_{new}$ wants to be registered as a new fog node in the recommender system, it generates a TX using its public (PBK) and private (PK) keys, Figure 6.1. All the transactions are first entered into the transaction pool (mempool) to be validated by the blockchain network.

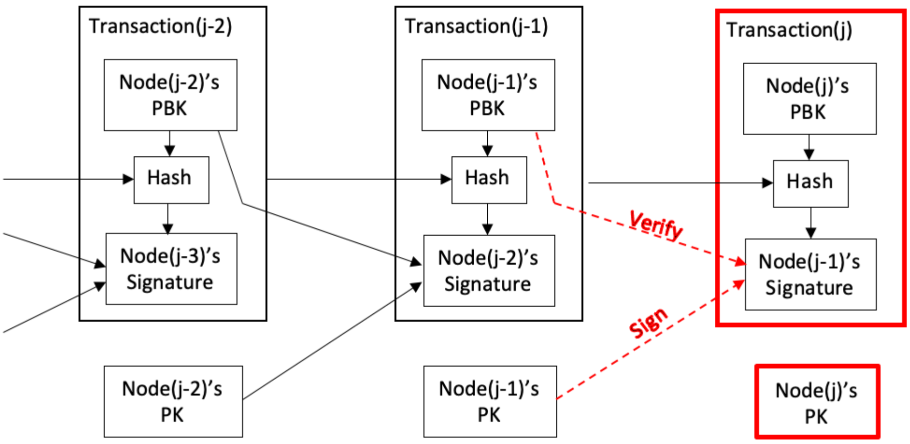


Figure 6.1: New transaction generation by a new fog node.

2. We defined t_{pool} as the waiting time for initiating the block-mining process by the blockchain miners. After t_{pool} period, a miner node $\mathcal{C}_{miner}$, which is one of the fog nodes, is selected randomly to validate, verify, and authenticate the TX. In our system, one $\mathcal{C}_{miner}$ is picked randomly to avoid forking (as there is always a possibility of generating the same block by different miners) and to prevent delays in the near-real-time system performance. Then $\mathcal{C}_{miner}$ picks available transaction(s) from the mempool and place them into a block b_{ready}. There might be one or maximum $\mathcal{T}$ number of transactions inside the b_{ready}, depending on the scale of our recommender system. When b_{ready} is created, it will be broadcasted to all the other nodes.

3. $\mathcal{C}_{miner}$ starts mining b_{ready} using the data stored in the block header, which holds the previous block's hash, nonce, and the Merkle tree root hashed value $H(TX_1...TX_j)$. This value is the combined hash of all the transactions, and it is calculated using the following equations.

$$
\begin{aligned}
H(TX_1 + TX_2) &= H(hash(TX_1) + hash(TX_2)), \\
&\vdots \\
H(TX_{j-1} + TX_j) &= H(hash(TX_{j-1}) + hash(TX_j)).
\end{aligned} \tag{6.1}
$$

Having this iterative process from TX_j all the way back to the TX_1 confirms the integrity of the blockchain network.

4. The miner $\mathcal{C}_{miner}$ stops its proof-of-work after the final generated size of the hash satisfies the target value. The newly generated block b_{new} is then propagated into the blockchain system, and $\mathcal{C}_{miner}$ broadcasts an acknowledgment message to all the other nodes to update their ledger.

The framework of the implemented fogChain recommendation system is provided in Figure 6.2. As can be seen from this depiction, there are two main parts in this collaborative learning system, the VFL Model Training and the Secure Communication with fogChain.

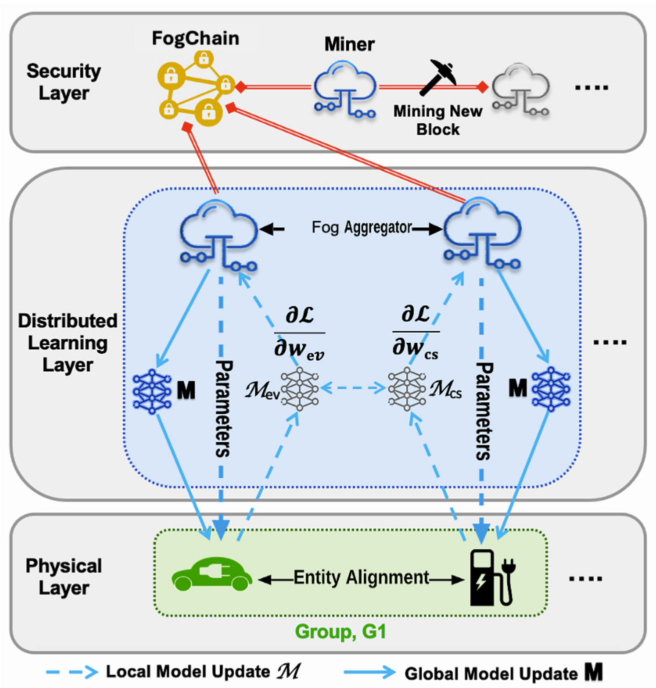


Figure 6.2: Proposed model architecture. The VFL-based fogChain framework is used to establish a decentralized secure communication between parties.

6.2.1 Implementation of the fogChain Algorithm

The top layer in Figure 6.2 describes the security layer mechanism applied in this work. Charging services and EVs can connect to the nearby fogs through an Access Point (AP) to exchange their locally computed parameters with other parties. The fogs communicate periodically after the period of τ_{period} to keep themselves updated on charging sources status and the recently trained global model. While $\mathcal{C}_p$ is performing a recommendation training model, another fog node $\mathcal{C}_{miner}$ has been selected randomly to authenticate the registration of the new fog by mining the block b_{ready}. When a new block has been added to the ledger, then the information inside the block is available to the fogs, charging sources, and EVs. The fog nodes responsible for passing the data between parties are irreplaceable by other fake nodes since all nodes have been authorized and recorded in a transparent public ledger [111].

Accordingly, the overall procedure of the secure fogChain framework is shown in Algorithm 4 which illustrates the process of generating the secure blockchain-based fog network $\bar{\mathcal{C}}$ in which the participating fogs are registered and verified via the blockchain. The registration requests are stored inside the mempool at line 2. Then at t_{pool}, the miner node ($\mathcal{C}_{miner}$) generates a new block b_{ready} from lines 4 to 8. $\mathcal{C}_{miner}$ verifies b_{ready} by mining the target hash value at line 10. At this time, $\mathcal{C}_{miner}$ adds the newly authorized block b_{new} to the ledger by broadcasting the b_{new} and an ACK message inside $\bar{\mathcal{C}}$ from lines 12 to 16.

Algorithm 4 : fogChain

Given: miner node $\mathcal{C}_{miner}$, TX
Output: b_{new}

for each transaction TX **do**
    Add TX to mempool
end for
if $timer = t_{pool}$ **then**
    A miner node $\mathcal{C}_{miner}$ is selected randomly
    $\mathcal{C}_{miner}$ picks TX from mempool
    $\mathcal{C}_{miner}$ generates block b_{ready}
end if
while hash satisfies **do**
    $\mathcal{C}_{miner}$ mines b_{ready}
end while
$\mathcal{C}_{miner}$ creates a new block b_{new}
$\mathcal{C}_{miner}$ broadcasts b_{new} to the network $\bar{\mathcal{C}}$
$\mathcal{C}_{miner}$ sends an ACK message into $\bar{\mathcal{C}}$
Updates the public ledger
Network size + 1

6.3 Model Evaluation and Results Analysis

In this section, we will showcase the effectiveness of our proposed approach by analyzing the results of our experiments. Through evaluating our model's performance, we aim to offer insights into the outcomes achieved and demonstrate the efficacy of our secure algorithm.

6.3.1 Datasets

For the purpose of this chapter we conduct the analysis based on 20 FCSs selected from a real dataset, gathered from Dundee city in Scotland between June and September in 2018, including FCS *id*, the history of charged vehicles, cost, longitude, latitude, etc. In this experiment, 50 EVs data with *id*, battery capacity, remaining battery, longitude, latitude, charging duration, etc., is utilized. Ten fog nodes are located in different positions to cover fast communication over the geographical area. These fogs are securely recorded inside the blockchain.

6.3.2 Performance Evaluation

In this section, we assess the effectiveness of our proposed algorithm. By conducting several experiments, we analyze various metrics to determine the model's accuracy, efficiency, and scalability. The results are then compared based on different scenarios to highlight improvements and validate the advantages.

Figure 6.3 compares the execution time of the secure recommender system for a different number of FCSs and EVs. This Figure shows that the system running time increases linearly as the number of participating parties increases. The process starts with 5 EVs and 1 FCS, and it is scaled to 50 EVs and 20 FCSs.

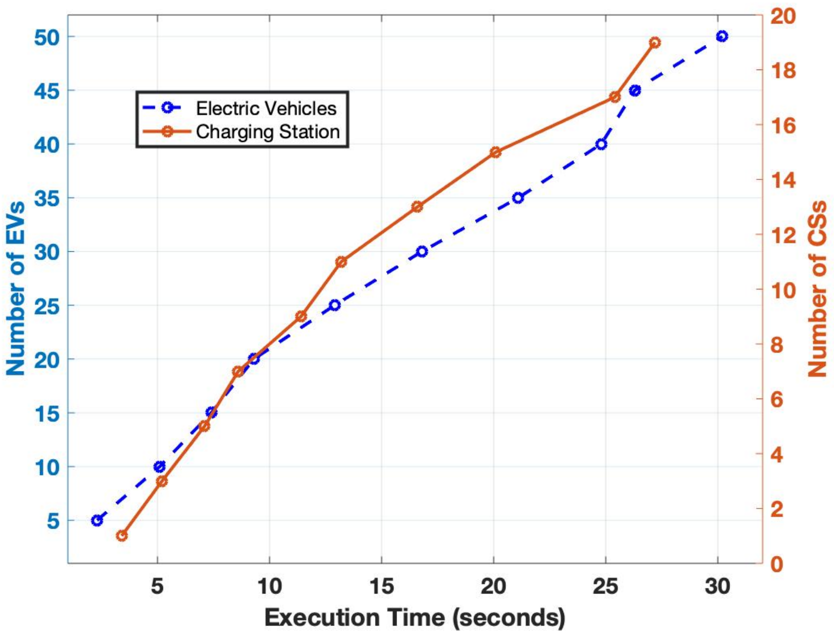


Figure 6.3: The secure recommender system execution time with different numbers of EVs and FCSs.

As our system is designed to be secure from attackers outside the fog network, preserving the security of the aggregator nodes is assured while scaling up the network inside the blockchain. If there is a new registration of a fog node into the network, a miner node must validate the new transaction to be recorded transparently inside a new block in the ledger. Therefore, the validation time increases as the number of nodes (fogs) increases. The security of the fogChain is proved, since the consensus algorithm is determined to be tamper-proof [112]. However, by increasing the number of fogs, mining a new block's execution time also increases.

Figure 6.4 shows the mining execution time to add a new block inside the public ledger. The results are generated by a modified version of a blockchain network simulator (HyperLedger Fabric) to see the impact of the ledger size on the new block-generating time. As the miner node $\mathcal{C}_{miner}$ is selected randomly in fogChain, we analyzed the block mining process within five iterations at each size of the network and recorded the minimum and maximum execution time in that Figure. When the network size is small, the variance of recorded mining time is short, and around 22 seconds. By adding more fog nodes to the network $\bar{\mathcal{C}}$ from 6 to 10, the variance of generating a new block increases too.

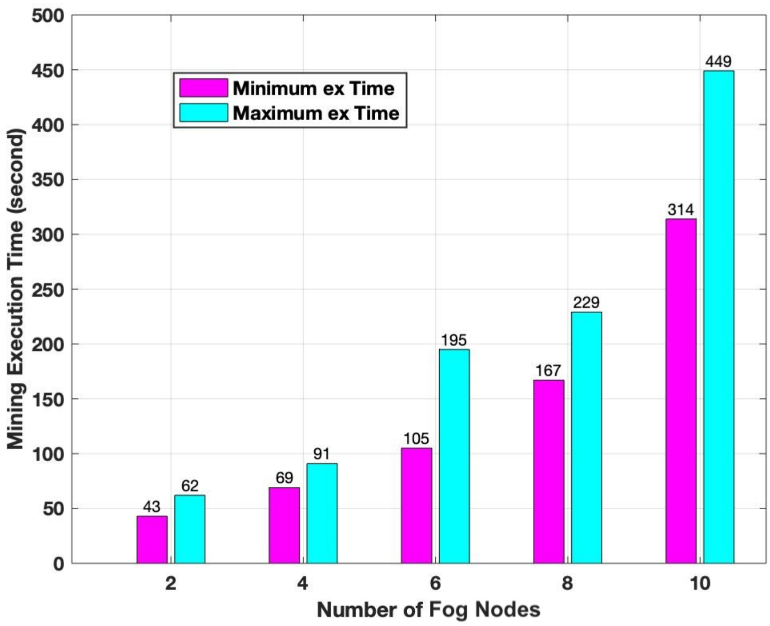


Figure 6.4: New block mining execution time by scaling the fogChain from two fog nodes to ten.

6.4 Chapter 6 Summary

This chapter aims to design a secure recommendation system for EVs to find the best charging source. A decentralized fog-edge architecture is employed as aggregators to help summarize and transmit encrypted training parameters among FCSs and MCSs and EVs, enabling the selection of the most suitable charging service based on an EV's requirements, charging point status, and vehicle status. Replacing centralized units with fog nodes provides a scalable infrastructure for both private and public EVs within a specific area, ensuring a flexible and efficient network.

To further enhance the security of the fog-based network, nodes are protected against malicious users through the integration of blockchain technology. This ensures that no unauthorized device can enter the chain, as the blockchain-enabled network (fogChain) is tamper-proof and transparent to all other blocks (fog nodes). Consequently, this architecture not only secures data transmission and storage but also maintains the integrity and reliability of the network. By leveraging these advanced technologies, our system offers a robust, scalable, and secure solution for EV charging infrastructure.

Chapter 7

Conclusions and Future Research

7.1 Conclusions

In recent years, the promotion of EVs by various governments has aimed to reduce carbon emissions and improve air quality. However, this shift has introduced significant challenges, particularly the imbalance between electricity demand and energy production, especially during peak hours. Addressing these energy congestion issues is crucial for achieving net-zero emission goals and increasing the public's adoption of EVs. Another key challenge is the mismatch between the number of charging facilities and the locations where EVs need to charge. Given the substantial time and financial investments required to expand EV charging infrastructure, researchers are exploring practical solutions to mitigate range anxiety for EV owners.

Effectively managing EV energy consumption and demand, optimally scheduling charging times, and accurately locating ideal charging sources can significantly alleviate pressure on smart grids. To enhance the performance and applicability of these solutions, an in-depth analysis of EV driving behavior and energy consumption patterns is essential. By identifying the most impactful factors, optimal demand-side energy scheduling can be implemented to systematically control energy loads and reduce peak demands. Proposing effective EV charging strategies requires an intensive analysis of behavioral characteristics to accurately predict charging loads and identify the best charging stations for EVs in need.

An accurate charging service recommendation system must aggregate parameters from various entities, including EVs, charging sources, power distributors, and producers, to provide comprehensive energy scheduling, demand estimation, and charging source recommendations. However, increasing data security and privacy protection requirements limit the sharing of data between different entities and institutions. To overcome this, a recommendation system must ensure user data privacy. FL offers a promising solution by enabling cross-platform joint data analysis without data leaving its original platform. This approach only requires the sharing of locally trained parameters, which are aggregated and updated centrally before being distributed back to participating platforms.

While centralized aggregators in an FL-based energy management system can introduce a single point of failure, replacing them with decentralized fog nodes enhances performance by reducing communication delays and ensuring constant availability. Integrating blockchain technology further secures the fog-based network by preventing unauthorized access and ensuring transparent and tamper-proof monitoring of activities.

In conclusion, this thesis aims to develop a comprehensive intelligent secure recommendation system for EVs. The system will analyze behavioral factors affecting energy consumption, optimize a secure decentralized charging scheduling mechanism, and design an accurate user-centric distributed charging source selection algorithm while ensuring data security and privacy. Additionally, a lightweight blockchain-based security layer is added to the model. This approach leverages a decentralized fog architecture and FL to provide a scalable, efficient, and secure solution for managing EV energy consumption and charging infrastructure.

The following section summarizes our plan for future work to further enhance the proposed system.

7.2 Future Research Directions

While this thesis presents a comprehensive and secure recommendation system for EVs, several areas require further investigation to enhance and expand the proposed solutions. Future research could focus on the following directions:

- **Recommendation System Performance:** We plan to further explore the potential scalability of the system to larger EV networks and discuss the potential impact of different user preferences on the recommendation outcomes. Also, to compare MCS service performance to other research, in terms of economic factors, and different pricing models. In this regard, further research on scenarios could be done where a MCS might incur losses or negative utilities. Moreover, additional in-depth analysis of Autonomous MCSs that rely on batteries rather than ICEs for their operations could be performed.

- **Integration with Renewable Energy Sources:** Further studies could examine the integration of renewable energy sources, such as solar and wind power, into the charging infrastructure. This would involve developing algorithms to predict renewable energy availability and optimize EV charging schedules accordingly.

- **Enhanced FL Techniques:** Improving FL techniques to handle more complex data scenarios and increase the robustness of the learning process is essential. This includes developing methods to handle heterogeneous data and ensuring scalability as the number of participating entities grows.

- **Cybersecurity Measures:** Strengthening cybersecurity measures to protect against emerging threats in EV charging networks is vital. Future research could develop advanced encryption techniques and intrusion detection systems to safeguard data privacy and network integrity.

- **Advanced Behavioral Analysis:** A deeper more advanced analysis of EV driver behavior using machine learning and big data analytics could yield more accurate predictions of energy consumption patterns. Future research could focus on personalizing recommendations based on individual driving habits and preferences.

- **Blockchain Scalability and Efficiency:** Addressing the scalability and efficiency challenges of blockchain technology is crucial. Future work could explore lightweight consensus algorithms and sidechain technologies to reduce the time needed for mining and verifying transactions within the fog network.

- **Advanced Communication Technologies:** Investigating the role of advanced communication technologies, such as 6G and beyond networks, in enhancing the performance of EV charging systems is crucial. Future research could explore how ultra-fast, low-latency communication can improve near-real-time data exchange and coordination between EVs, charging stations, and the grid.

By addressing these future research directions, the potential of intelligent and secure EV charging systems can be fully realized, providing the way for more sustainable and efficient transportation solutions.

References

[1] Canada.ca. New electric vehicle availability standard will give canadians better access to more affordable cars and cleaner air. Available online: https://www.canada.ca/en/environment-climate-change/news/2023/12/new-electric-vehicle-availability-standard-will-give-canadians-better-access-t html. (accessed on 07 2024). 1

[2] Canada Energy Regulator. Market snapshot: Levelized costs of driving evs and conventional vehicles. Available online: https://www.cer-rec.gc.ca/en/data-analysis/energy-markets/market-snapshots/2019/market-snapshot-levelized-costs-driving-evs-conventional-vehicles.html. (accessed on 07 2024). 2

[3] Andri D. Setiawan, Akhmad Hidayatno, Bramanda Dwi Putra, and Irvanu Rahman. Selection of charging station technology to support the adoption of electric vehicles in indonesia with the ahp-topsis method. In *2020 3rd International Conference on Power and Energy Applications (ICPEA)*, pages 85–88, nov 2020. 5, 37

[4] Li Yujing, Su Su, Zhao Yuming, and Zhang Renzun. Personalized navigation of electric vehicle charging station based on collaborative filtering. In *2019 IEEE Sustainable Power and Energy Conference (iSPEC)*, pages 849–855, 2019. 5, 39

[5] Shubham Goel, Ravinder Kumar, Ashwani Kumar, and Reetu Malhotra. Smart station search assistance for electric vehicle—a step toward smart city. *IEEE Consumer Electronics Magazine*, 9, July 2020. 5, 23, 39, 46

[6] Bo Sun, Tongxin Li, Steven H. Low, and Danny H. K. Tsang. Orc: An online competitive algorithm for recommendation and charging schedule in electric vehicle charging network. In *Proceedings of the Eleventh ACM International Conference on Future Energy Systems*, pages 144–155, 2020. 5, 37, 39

[7] Wen Wang, Xiaofeng Peng, Jun Jia, Ji Zhao, and Wei Xiao. Optimal user oriented multi-level experience planning strategy for electric automobile charging path. *E3S Web of Conferences*, 218:02028, 2020. 5

[8] Yongmin Zhang, Pengcheng You, and Lin Cai. Optimal charging scheduling by pricing for ev charging station with dual charging modes. *IEEE Transactions on Intelligent Transportation Systems*, 20:3386–3396, 2019. 5

[9] WESLEY VAN BARLINGEN and JOSEPH D. SIMPSON. Electric car range and 5 reasons why your range anxiety is unwarranted. Available online: https://blog.evbox.com/eliminate-range-anxiety. (accessed on 05 2022). 6

[10] George F. Savari, Vijayakumar Krishnasamy, Jagabar Sathik, Ziad M. Ali, and Shady H.E. Abdel Aleem. Internet of things based real-time electric vehicle load forecasting and charging station recommendation. *ISA Transactions*, 97:431–447, feb 2020. 6, 37

[11] Hai Lin, Xiang Lin, Houda Labiod, and Lin Chen. Toward multiple-phase mdp model for charging station recommendation. *IEEE Transactions on Intelligent Transportation Systems*, pages 1–13, 2021. 6, 22, 39

[12] Abdulsalam Yassine, Shailendra Singh, M. Shamim Hossain, and Ghulam Muhammad. Iot big data analytics for smart homes with fog and cloud computing. *Future Generation Computer Systems*, 91:563–573, Feb. 2019. 6

[13] Mohammed Shurrab, Shakti Singh, Hadi Otrok, Rabeb Mizouni, Vinod Khadkikar, and Hatem Zeineldin. Ran efficient vehicle-to-vehicle (v2v) energy sharing framework. *IEEE Internet of Things Journals*, 9:5315–5328, 2022. 6

[14] Dhaou Said. A decentralized electricity trading framework (detf) for connected evs: A blockchain and machine learning for profit margin optimization. *IEEE Transactions on Industrial Informatics*, 17:6594–6602, 2021. 6

[15] Gaurang Bansal and Ashutosh Bhatia. A fast, secure and distributed consensus mechanism for energy trading among vehicles using hashgraph. In *2020 International Conference on Information Networking (ICOIN)*, pages 772–777, 2020. 7

[16] Youyang Qu, Shiva Raj Pokhrel, Sahil Garg, Longxiang Gao, and Yong Xiang. A blockchained federated learning framework for cognitive computing in industry 4.0 networks. *IEEE Transactions on Industrial Informatics*, 17(4):2964–2973, 2021. 7, 12

[17] Weizheng Wang et al. Secure-enhanced federated learning for ai-empowered electric vehicle energy prediction. *IEEE Consumer Electronics Magazine*, pages 1–1, 2021. 7

[18] Jinshi Liu, Manzoor Ahmed, Muhammad Ayzed Mirza, Wali Ullah Khan, Dianlei Xu, Jianbo Li, Abdul Aziz, and Zhu Han. Rl/drl meets vehicular task offloading using edge and vehicular cloudlet: A survey. *IEEE Internet of Things Journal*, 9(11):8315–8338, 2022. 7

[19] Zeinab Teimoori and Abdulsalam Yassine. A review on intelligent energy management systems for future electric vehicle transportation. *Sustainability*, 14(21):14100, 2022. 9

[20] Yuechuan Tao, Jing Qiu, and Shuying Lai. A hybrid cloud and edge control strategy for demand responses using deep reinforcement learning and transfer learning. *IEEE Transactions on Cloud Computing*, 10(1):56–71, 2022. 10

[21] Yu-Jin Lin, Yu-Cheng Chen, Jun-Yi Zheng, Dan-Wei Shao, Dan Chu, and Hong-Tzer Yang. Blockchain-based intelligent charging station management system platform. *IEEE Access*, 10:101936–101956, 2022. 10, 43

[22] Zeinab Teimoori, Abdulsalam Yassine, and M Shamim Hossain. Smart vehicles recommendation system for artificial intelligence-enabled communication. *IEEE Transactions on Consumer Electronics*, 2024. 11

[23] So Rim Han and Byung Duk Song. Optimal operation scheduling of mobile hydrogen charging stations: A mathematical optimization model and heuristic approach. *International Journal of Hydrogen Energy*, 2023. 11, 43, 44, 45

[24] Morteza Nazari-Heris, Abdolah Loni, Somayeh Asadi, and Behnam Mohammadi-ivatloo. Toward social equity access and mobile charging stations for electric vehicles: A case study in los angeles. *Applied Energy*, 311:118704, 2022. 11, 42, 43, 45

[25] Mohammed Aledhari, Rehma Razzak, Reza M. Parizi, and Fahad Saeed. Federated learning: A survey on enabling technologies, protocols, and applications. *IEEE Access*, 8:140699–140725, 2020. 12

[26] Kia Yang Tao Jiang Yuanming Shi and Zhi Ding. Federated learning via over-the-air computation. *IEEE Transactions on Wireless Communications*, 19:2022–2035, March 2020. 12

[27] Sangyoon Lee and Dae-Hyun Choi. Federated reinforcement learning for energy management of multiple smart homes with distributed energy resources. *IEEE Transactions on Industrial Informatics*, 2020. 12, 23

[28] Abdulsalam Yassine, M. Shamim Hossain, Ghulam Muhammad, and Mohsen Guizani. Cloudlet-based intelligent auctioning agents for truthful autonomous electric vehicles energy crowdsourcing. *IEEE Transactions on Vehicular Technology*, 69:5457–5466, May 2020. 13, 128

[29] Yunlong Lu, Xiaohong Huang, Ke Zhang, Sabita Maharjan, and Yan Zhang. Blockchain empowered asynchronous federated learning for secure data sharing in internet of vehicles. *IEEE Transactions on Vehicular Technology*, 69:4298–4311, 2020. 13, 31

[30] Emiliano Sisinni, Abusayeed Saifullah, Song Han, Ulf Jennehag, and Mikael Gidlund. Industrial internet of things: Challenges, opportunities, and directions. *IEEE Transactions on Industrial Informatics*, 14(11):4724–4734, 2018. 22, 23

[31] Li Da Xu, Wu He, and Shancang Li. Internet of things in industries: A survey. *IEEE Transactions on Industrial Informatics*, 10(4):2233–2243, 2014. 22

[32] Shuohan Liu, Yue Cao, Wenjie Ruan, Qiang Ni, Michele Nati, and Chakkaphong Suthaputchakun. Ev charging recommendation concerning preemptive service and charging urgency policy. In *2020 IEEE 92nd Vehicular Technology Conference (VTC2020-Fall)*, pages 1–5, 2020. 23, 39

[33] Benjamin Maschler and Michael Weyrich. Deep transfer learning for industrial automation: a review and discussion of new techniques for data-driven machine learning. *IEEE Industrial Electronics Magazine*, 15(2):65–75, 2021. 24

[34] Yining Hua, Michele Sevegnani, Dewei Yi, Andrew Birnie, and Steve Mcaslan. Fine-grained rnn with transfer learning for energy consumption estimation on evs. *IEEE Transactions on Industrial Informatics*. 24, 34, 52

[35] Yuefeng Liu, Jiaqi Li, Gong Zhang, Bin Hua, and Neal Xiong. State of charge estimation of lithium-ion batteries based on temporal convolutional network and transfer learning. *IEEE Access*, 9:34177–34187, 2021. 24

[36] Nan Wang, Guangcai Zhao, Yongzhe Kang, Wei Wang, Alian Chen, Bin Duan, and Chenghui Zhang. Core temperature estimation method for lithium-ion battery based on long short-term memory model with transfer learning. *IEEE Journal of Emerging and Selected Topics in Power Electronics*, 11(1):201–213, 2023. 24

[37] Xi Fang, Guangcai Gong, Guannan Li, Liang Chun, Wenqiang Li, and Pei Peng. A hybrid deep transfer learning strategy for short term cross-building energy prediction. *Energy*, 215:119208, 2021. 24

[38] Hongwen He, Yunlong Wang, Jianwei Li, Jingwei Dou, Renzong Lian, and Yuecheng Li. An improved energy management strategy for hybrid electric vehicles integrating multistates of vehicle-traffic information. *IEEE Transactions on Transportation Electrification*, 7(3):1161–1172, 2021. 25

[39] Shahab Afshar, Pablo Macedo, Farog Mohamed, and Vahid Disfani. Mobile charging stations for electric vehicles—a review. *Renewable and Sustainable Energy Reviews*, 152:111654, 2021. 26

[40] Luyang Hou, Omar E Herrera, and Walter Mérida. Charging scheduling and energy management for mobile chargers in a grid-interactive transportation system. *Journal of Energy Storage*, 65:107305, 2023. 26

[41] Konečný Jakub, McMahan H. Brendan, Ramage Daniel, and Richtárik Peter. Federated optimization: Distributed machine learning for on-device intelligence. *arXiv:1610.02527 [cs]*, October 2016. 28

[42] Qiang Yang, Yang Liu, Tianjian Chen, and Yongxin Tong. Federated machine learning: Concept and applications. *arXiv:1902.04885 [cs]*, Feb 2019. 28, 29

[43] Robin C. Geyer, Tassilo Klein, and Moin Nabi. Differentially private federated learning: A client level perspective. *arXiv:1712.07557*, 2018. 29

[44] Payman Mohassel and Peter Rindal. Aby¡sup¿3¡/sup¿: A mixed protocol framework for machine learning. CCS '18, page 35–52, New York, NY, USA, 2018. Association for Computing Machinery. 29

[45] Jie Zhao, Xinghua Zhu, Jianzong Wang, and Jing Xiao. Efficient client contribution evaluation for horizontal federated learning. In *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 3060–3064. IEEE, 2021. 30

[46] Zhaomin Wu, Qinbin Li, and Bingsheng He. Exploiting record similarity for practical vertical federated learning. *arXiv:2106.06312 [cs]*, 2021. 30

[47] Zehui Zhang, Ningxin He, Dongyu Li, Hang Gao, Tiegang Gao, and Chuan Zhou. Federated transfer learning for disaster classification in social computing networks. *Journal of Safety Science and Resilience*, 3:15–23, 2022. 30

[48] Shashi Raj Pandey, Nguyen H. Tran, Mehdi Bennis, Yan Kyaw Tun, Aunas Manzoor, and Choong Seon Hong. A crowdsourcing framework for on-device federated learning. *IEEE Transactions on Wireless Communications*, 19:3241–3256, 2020. 30

[49] Satoshi Nakamoto. Bitcoin: A peer-to-peer electronic cash system. *Decentralized Business Review*, page 21260, 2008. 30

[50] Philipp Frauenthaler, Marten Sigwart, Christof Spanring, Michael Sober, and Stefan Schulte. Eth relay: A cost-efficient relay for ethereum-based blockchains. In *2020 IEEE International Conference on Blockchain (Blockchain)*, pages 204–213, 2020. 30, 31

[51] Vittorio Astarita, Vincenzo Pasquale Giofrè, Giovanni Mirabelli, and Vittorio Solina. A review of blockchain-based systems in transportation. *Information*, 11:21, 2020. 31

[52] Mehdi Bennis Hyesung Kim, Jihong Park and Seong-Lyun Kim. Blockchained on-device federated learning. *IEEE Communications Letters*, 24:1279–1283, June 2020. 31, 40

[53] Ziming Liu, Dazhi Wang, Jiaxing Wang, Xinghua Wang, and Hao Li. A blockchain-enabled secure power trading mechanism for smart grid employing wireless networks. *IEEE Access*, 8:177745–177756, 2020. 32

[54] Ziyou Song, Jun Hou, Shaobing Xu, Minggao Ouyang, and Jianqiu Li. The influence of driving cycle characteristics on the integrated optimization of hybrid energy storage system for electric city buses. *Energy*, 135:91–100, 2017. 32, 36

[55] Guang Wang et al. Pricing-aware real-time charging scheduling and charging station expansion for large-scale electric buses. *ACM Transactions on Intelligent Systems and Technology*, 12:1–26, February 2021. 32, 36

[56] Hussein Basma, Charbel Mansour, Marc Haddad, Maroun Nemer, and Pascal Stabat. Energy consumption and battery sizing for different types of electric bus service. *Energy*, 239:122454, 2022. 33

[57] Tianwei Lu, Enjian Yao, Yongsheng Zhang, and Yang Yang. Joint optimal scheduling for a mixed bus fleet under micro driving conditions. *IEEE Transactions on Intelligent Transportation Systems*, 22(4):2464–2475, 2021. 33, 36

[58] Yang Xing, Chen Lv, Xiaoyu Mo, Zhongxu Hu, Chao Huang, and Peng Hang. Toward safe and smart mobility: Energy-aware deep learning for driving behavior analysis and prediction of connected vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 22(7):4267–4280, 2021. 33, 36

[59] Mehdi Jafari, Antonio Gauchia, Kuilin Zhang, and Lucia Gauchia. Simulation and analysis of the effect of real-world driving styles in an ev battery performance and aging. *IEEE Transactions on Transportation Electrification*, 1(4):391–401, 2015. 33, 36

[60] H. Palahalli, P. Maffezzoni, and G. Gruosso. Statistical simulation of electric vehicle behaviour applied to low voltage distribution network. In *2021 22nd IEEE International Conference on Industrial Technology (ICIT)*, pages 657–662, 2021. 33, 36

[61] Qian Hu, Haiyu Li, and Siqi Bu. The prediction of electric vehicles load profiles considering stochastic charging and discharging behavior and their impact assessment on a real uk distribution network. *Energy Procedia*, 158:6458–6465, 2019. 33, 36

[62] Kalle Rauma, Alexander Funke, Toni Simolin, Pertti Järventausta, and Christian Rehtanz. Electric vehicles as a flexibility provider: Optimal charging schedules to improve the quality of charging service. *Electricity*, 2(3):225–243, Jun. 2021. 34

[63] Feng Chen, Minling Feng, Bing Han, and Shaofeng Lu. Multistage and dynamic layout optimization for electric vehicle charging stations based on the behavior analysis of travelers. *World Electric Vehicle Journal*, 12(4):243, 2021. 34, 36

[64] Yue Wang, Enjian Yao, and Long Pan. Electric vehicle drivers' charging behavior analysis considering heterogeneity and satisfaction. *Journal of Cleaner Production*, 2021. 34, 36

[65] Iman Babaeiyazdi, Afshin Rezaei-Zare, and Shahab Shokrzadeh. Transfer learning with deep neural network for capacity prediction of li-ion batteries using eis measurement. *IEEE Transactions on Transportation Electrification*, 9(1):886–895, 2023. 34, 36

[66] Yunhong Che, Yusheng Zheng, Yue Wu, Xianke Lin, Jiacheng Li, Xiaosong Hu, and Remus Teodorescu. Battery states monitoring for electric vehicles based on transferred multi-task learning. *IEEE Transactions on Vehicular Technology*, pages 1–11, 2023. 34, 36

[67] Isaiah Oyewole, Abdallah Chehade, and Youngki Kim. A controllable deep transfer learning network with multiple domain adaptation for battery state-of-charge estimation. *Applied Energy*, 312:118726, 2022. 35, 36

[68] Jingcheng Song, Zhaoyang Han, Weizheng Wang, Jingxue Chen, and Yining Liu. A new secure arrangement for privacy-preserving data collection. *Computer Standards & Interfaces*, 80:103582, 2022. 37

[69] Ramkumar Devendiran, Padmanathan Kasinathan, Vigna K. Ramachandaramurthy, Umashankar Subramaniam, Uma Govindarajan, and Xavier Fernando. Intelligent optimization for charging scheduling of electric vehicle using exponential harris hawks technique. *International Journal of Intelligent Systems*, 36(10):5816–5844, 2021. 37

[70] Binod Vaidya and Hussein T. Mouftah. Smart electric vehicle charging management for smart cities. *IET Smart Cities*, 2:4–13, 2020. 37, 39

[71] Tai-Yu Ma and Sébastien Faye. Multistep electric vehicle charging station occupancy prediction using mixed lstm neural networks. *arXiv:2106.04986 [cs]*, jun 2021. 37

[72] Yue Cao, Tao Jiang, Omprakash Kaiwartya, Hongjian Sun, Huan Zhou, and Ran Wang. Toward pre-empted ev charging recommendation through v2v-based reservation system. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 51:3026–3039, May 2021. 37

[73] Yanheng Zhao, Chunxiao Song, Kai Zhang, Xiaoyong Wang, and Chao Zhang. Method for finding the best charging station in the power internet of things. In *2020 IEEE/IAS Industrial and Commercial Power System Asia (I CPS Asia)*, pages 1720–1726, jul 2020. 37

[74] Yue Cao, Omprakash Kaiwartya, Yuan Zhuang, Naveed Ahmad, Yan Sun, and Jaime Lloret. A decentralized deadline-driven electric vehicle charging recommendation. *IEEE Systems Journal*, 13:3410–3421, September 2019. 38

[75] Wei Tu et al. Real-time route recommendations for e-taxies leveraging gps trajectories. *IEEE Transactions on Industrial Informatics*, 17:3133–3142, May 2021. 38, 39

[76] Jing Zhang, Taoyong Li, Aiqiang Pan, Xuemei Long, Linru Jiang, Zhe Liu, and Yuanxing Zhang. Charging time and location recommendation strategy considering taxi user satisfaction. In *2020 Asia Energy and Electrical Engineering Symposium (AEEES)*, pages 257–264, 2020. 38, 39

[77] Simon Steinschaden and José Baptista. Development of an efficient tool for solar charging station management for electric vehicles. *Energies*, 13:2979, 2020. 39

[78] Yuris Mulya Saputra, Dinh Thai Hoang, Diep N. Nguyen, Eryk Dutkiewicz, Markus Dominik Mueck, and Srikathyayani Srikanteswara. Energy demand prediction with federated learning for electric vehicle networks. *arXiv:1909.00907 [cs, eess]*, 2019. 40, 41

[79] Hongyi Zhang, Jan Bosch, and Helena Holmström Olsson. Real-time end-to-end federated learning: An automotive case study. In *2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC)*, pages 459–468, 2021. 40, 41

[80] Xiaohui Wang, Xiaokun Zheng, and Xiao Liang. Charging station recommendation for electric vehicle based on federated learning. *Journal of Physics: Conference Series*, 1792:012055, February 2021. 40, 41

[81] Kentaroh Toyoda, Jun Zhao, Allan Neng Sheng Zhang, and P. Takis Mathiopoulos. Blockchain-enabled federated learning with mechanism design. *IEEE Access*, 8:219744–219756, 2020. 40, 128

[82] Shiva Raj Pokhrel and Jinho Choi. Federated learning with blockchain for autonomous vehicles: Analysis and design challenges. *IEEE Transactions on Communications*, 68:4734–4746, August 2020. 40, 41

[83] Syed Muhammad Danish, Kaiwen Zhang, and Hans-Arno Jacobsen. A blockchain-based privacy-preserving intelligent charging station selection for electric vehicles. In *2020 IEEE International Conference on Blockchain and Cryptocurrency (ICBC)*, pages 1–3, May 2020. 40, 41

[84] Zhishang Wang, Mark Ogbodo, Huakun Huang, Chen Qiu, Masayuki Hisada, and Abderazek Ben Abdallah. Aebis: Ai-enabled blockchain-based electric vehicle integration system for power management in smart grid platform. *IEEE Access*, 8:226409–226421, 2020. 40

[85] Yuris Mulya Saputra, Diep Nguyen, Hoang Thai Dinh, Thang X. Vu, Eryk Dutkiewicz, and Symeon Chatzinotas. Federated learning meets contract theory: Economic-efficiency framework for electric vehicle networks. *IEEE Transactions on Mobile Computing*, 2020. 41

[86] Weizheng Wang, Memon Hussain Fida, Zhuotao Lian, Zhimeng Yin, Quoc-Viet Pham, Thippa Reddy Gadekallu, Kapal Dev, and Chunhua Su. Secure-enhanced federated learning for ai-empowered electric vehicle energy prediction. *IEEE Consumer Electronics Magazine*, 2021. 41

[87] Ahmed Khoumsi. An efficient blockchain-based electric vehicle charging management system. In *2021 IEEE Symposium on Computers and Communications (ISCC)*, pages 1–7, 2021. 41

[88] Zeinab Teimoori and Abdulsalam Yassine. User-centric charging service recommendation for electric vehicles. In *IEEE 22nd Mediterranean Electrotechnical Conference (MELECON)*. IEEE, 2024. 42

[89] Ubaid Qureshi, Arnob Ghosh, and Bijaya Ketan Panigrahi. Scheduling and routing of mobile charging stations with stochastic travel times to service heterogeneous spatiotemporal electric vehicle charging requests with time windows. *IEEE Transactions on Industry Applications*, 58(5):6546–6556, 2022. 42, 43, 44, 45

[90] Oanh Tran Thi Kim, Tra Huong Thi Le, Michael J Shin, Vandung Nguyen, Zhu Han, and Choong Seon Hong. Distributed auction-based incentive mechanism for energy trading between electric vehicles and mobile charging stations. *IEEE Access*, 10:56331–56347, 2022. 42

[91] Huasheng Liu, Yu Li, Chongyu Zhang, Jin Li, Xiaowen Li, and Yuqi Zhao. Electric vehicle charging station location model considering charging choice behavior and range anxiety. *Sustainability*, 14(7), 2022. 42, 44, 89

[92] R Gopalakrishnan, D Sri Vidhya, R Gowshickraaj, E Kamalakannan, and S Narendran. Design and implementation of roving charging station for electric vehicles. In *2023 7th International Conference on Trends in Electronics and Informatics (ICOEI)*, pages 255–258. IEEE, 2023. 43

[93] Shahab Afshar and Vahid Disfani. Optimal scheduling of electric vehicles in the presence of mobile charging stations. In *2022 IEEE Power & Energy Society General Meeting (PESGM)*, pages 1–5. IEEE, 2022. 43, 45

[94] Andreas Andreou, Constandinos X Mavromoustakis, Jordi Mongay Batalla, Evangelos K Markakis, George Mastorakis, and Shahid Mumtaz. Uav trajectory optimisation in smart cities using modified a* algorithm combined with haversine and

vincenty formulas. *IEEE Transactions on Vehicular Technology*, 2023. 43, 44, 45, 89, 109

[95] Bülent Çatay and İhsan Sadati. An improved matheuristic for solving the electric vehicle routing problem with time windows and synchronized mobile charging/battery swapping. *Computers & Operations Research*, page 106310, 2023. 43, 45

[96] Marija Zima-Bockarjova, Antans Sauhats, Lubov Petrichenko, and Roman Petrichenko. Charging and discharging scheduling for electrical vehicles using a shapley-value approach. *Energies*, 13:1160, 2020. 46

[97] Weijia Zhang, Hao Liu, Fan Wang, Tong Xu, Haoran Xin, Dejing Dou, and Hui Xiong. Intelligent electric vehicle charging recommendation based on multi-agent reinforcement learning. In *Proceedings of the Web Conference 2021*, WWW '21, page 1856–1867. Association for Computing Machinery, 2021. 46

[98] Odd André Hjelkrem, Karl Yngve Lervåg, Sahar Babri, Chaoru Lu, and Carl-Johan Södersten. A battery electric bus energy consumption model for strategic purposes: Validation of a proposed model structure with data from bus fleets in china and norway. *Transportation Research Part D: Transport and Environment*, 94:102804, 2021. 58

[99] Geunseob Oh, David J. Leblanc, and Huei Peng. Vehicle energy dataset (ved), a large-scale dataset for vehicle energy consumption research. *IEEE Transactions on Intelligent Transportation Systems*, 23(4):3302–3312, 2022. 58

[100] D3 2013 nissan leaf sv. https://www.anl.gov/taps/d3-2013-nissan-leaf-sv. Accessed: 2023-12-08. 59

[101] Virta.global. Ev charging - how much electricity does an electric car use? Available online: https://www.virta.global/blog/ev-charging-101-how-much-electricity-does-an-electric-car-use. Accessed on 12 2023. 88

[102] Zeinab Teimoori, Abdulsalam Yassine, and M Shamim Hossain. A secure cloudlet-based charging station recommendation for electric vehicles empowered by federated learning. *IEEE Transactions on Industrial Informatics*, 2022. 89

[103] Geunseob Oh, David J Leblanc, and Huei Peng. Vehicle energy dataset (ved), a large-scale dataset for vehicle energy consumption research. *IEEE Transactions on Intelligent Transportation Systems*, 23(4):3302–3312, 2020. 95, 116

[104] Jia-Hao Syu, Jerry Chun-Wei Lin, Gautam Srivastava, and Keping Yu. A comprehensive survey on artificial intelligence empowered edge computing on consumer electronics. *IEEE Transactions on Consumer Electronics*, 69(4):1023–1034, 2023. 107

[105] Preeti Rani, Chandani Sharma, Janjhyam Venkata Naga Ramesh, Sonia Verma, Rohit Sharma, Ahmed Alkhayyat, and Sachin Kumar. Federated learning-based misbehaviour detection for the 5g-enabled internet of vehicles. *IEEE Transactions on Consumer Electronics*, pages 1–1, 2023. 112

[106] Mohammad Kamrul Hasan, Nusrat Jahan, Mohd Zakree Ahmad Nazri, Shayla Islam, Muhammad Attique Khan, Ahmed Ibrahim Alzahrani, Nasser Alalwan, and Yunyoung Nam. Federated learning for computational offloading and resource management of vehicular edge computing in 6g-v2x network. *IEEE Transactions on Consumer Electronics*, pages 1–1, 2024. 112

[107] Hafsa Bousbiat, Roumaysa Bousselidj, Yassine Himeur, Abbes Amira, Faycal Bensaali, Fodil Fadli, Wathiq Mansoor, and Wilfried Elmenreich. Crossing roads of federated learning and smart grids: Overview, challenges, and perspectives. *arXiv preprint arXiv:2304.08602*, 2023. 112

[108] Xinran Zhang, Zheng Chang, Tao Hu, Weilong Chen, Xin Zhang, and Geyong Min. Vehicle selection and resource allocation for federated learning-assisted vehicular network. *IEEE Transactions on Mobile Computing*, 2023. 112

[109] DestinationOntario.com. Rules of the road. https://www.destinationontario.com/en-ca/travel-resources/rules-of-the-road#: :text=Speed 125

[110] EnergyRates.ca. How much does it cost to charge an electric car? the true costs of powering an ev. https://energyrates.ca/how-much-does-it-cost-to-charge-an-electric-car-the-true-costs-of-powering-an-ev/#: :text=Let's 125

[111] Hemant Ghayvat et al. Cp-bdhca: Blockchain-based confidentiality-privacy preserving big data scheme for healthcare clouds and applications. *IEEE Journal of Biomedical and Health Informatics*, 2021. 131

[112] Hassan Mansur Hussien, Sharifah Md Yasin, Nur Izura Udzir, and Mohd Izuan Hafez Ninggal. Blockchain-based access control scheme for secure shared personal health records over decentralised storage. *Sensors*, 21(7):2462, 2021. 134