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Masterarbeit

The Integration of Electric Vehicles in the Smart Grid

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Abstract

In recent years, the rising trend of Electric Vehicles (EVs) as a clean mode of transportation is regarded crucial for a sustainable future. Impact of heavy traffic flow in the transportation system will have significant implications on distribution network load due to widely varying EV penetration rate and market price incentives. Naturally, it becomes imperative to study the joint stochastic operational planning of ***Transportation Network (TN)*** and ***Power Distribution Network (PDN)*** with targeted service radius. EV routing protocols have stochastic nature owing to several environmental factors and traffic elements which may alter the path chosen by EV users. This ultimately may increase or reduce the energy consumption of EVs limited-resource battery, which in turn has a cascading effect on the power system network since EVs might need to recharge either frequently or sparsely. In this research project, we aim to find the inter-relation between TN and PDN in a complex bi-level optimization problem where operational costs and social welfare is modeled. We take an interdisciplinary approach by establishing a stochastic multi-agent simulation-based platform with the objective of minimizing the social welfare cost of the interdependent TN and PDN systems. The conjunction between overlaid networks has been extensively described. The distributed vehicle load on the TN based on random EV mobility behavior poses a challenge to estimate the charging load on the PDN. The spatial and temporal traffic distribution of TN influences the loads connected to PDN through charging stations. We assess the impact of large-scale EV integration into the PDN through mutual coupling of both the networks. Our methodology aims to solve the coupled optimization problems, i.e., optimal EV routing using traffic assignment problem and optimal power flow (OPF) using branch flow model. The route choice of EV users is determined by Dijkstra's shortest path algorithm which minimizes the travel cost. Utilizing Multi-Agent Systems (MAS), we generate semi-realistic samples of EV mobility trip data to eventually develop an ***Optimal Transportation-Power Network Flow (OTPNF)*** model. We employ a Dynamic User Equilibrium model to get the optimal traffic distribution in TN. Through the joint optimization of both networks taking into consideration network constraints, we try to achieve cost minimal system optimal solution. The IEEE 30 test system is adapted to Low Voltage (LV) network to examine the EV charging impact on grid. Simulation results show mutual economical benefits by maximizing social welfare of both the networks. We optimized total power generation by 10.86% and found an optimal solution for both networks which reduced overall system cost by 35%. We also reduced transmission power losses by 23.5% using the same loads and generator costs with our Genetic Algorithm.

Abbreviations

ABM Agent Based Modeling.

DCOPF Direct Current Optimal Power Flow.

EVs Electric Vehicles.

HVAC Heating, Ventilation, and Air-conditioning.

ICE Internal Combustion Engine.

JADE JAVA Agent Development Framework.

LV Low Voltage.

OPF optimal power flow.

OTPNF Optimal Transportation-Power Network Flow.

PDN Power Distribution Network.

SOC State of Charge.

STM Spatial Temporal Model.

TN Transportation Network.

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Notations Summary

Transportation Network Parameters

τ_e^0	Free flow traveling time on link e
ψ_p	Decision parameter to state if path p is chosen 1 or not 0
w	Cost of travel time estimated in Euros
Ψ	Unit traffic flow charging demand rate
$\eta_{sd}(t)$	Current traffic demand on OD pair s,d during time t
P_{ch}^{ev}	Charging power rate of EV
P_{max}^{ev}	Maximum charging power rate of EV

Power Distribution Network Parameters

r_{ij}	Reactance of Active power line connecting bus node i to j
x_{ij}	Reactance of Reactive power line connecting bus node i to j
$(r_{ij}^2 + x_{ij}^2)$	Impedance of line connecting bus node i to j, squared form.
q_i^{dem}	Reactive power demand of bus i
q_i^r and q_i^f	Reactive power generation limit of bus i

Variables

$f_{p,t}^{sd}$	Traffic flow on path p in the OD pair s,d
$C_{p,t}^{sd}$	Cost of travel on path p in the OD pair s,d
$T_{p,t}^{sd}$	Time to travel on path p in the OD pair s,d
$\tau_{e,t}$	Travel time on link e during time t
$\vartheta_{e,t}$	Total aggregate of traffic flow on link e
$X_{e,t}^{Cg}$	Traffic congestion cost on link e
C_j^{Cs}	Charging cost of EVs at charging station j
N_{ch}^{ev}	Upper bound on charging piles installed at charging station
p_i^{dem}	Total active power demand at bus i
p_i^{gen}	Total active power generated at bus i
P_{ij}	Active Power flow from bus node i to j
Q_{ij}	Reactive Power flow from bus node i to j
I_{ij}	Squared current magnitude from node i to j
C_j^{ev}	Charging costs of EV at charging station j
G_{cg}^{ev}	Aggregated charging costs of all EVs
E_{ch}^j	Charging power (kW) of charging station j

Chapter 1: Introduction

In an effort to curb greenhouse gas emissions and pave the way for a sustainable transportation future, Electric Vehicles have emerged to be a promising solution. Electricity decarbonisation and tackling climate change calls for the transformation of public transport into a smart electric transportation network. EVs use electrical energy to recharge their batteries instead of burning fossil fuels. However, the changing landscape of urban transportation from conventional Internal Combustion Engine (ICE) cars to EVs have introduced an important load to the electrical distribution network. A larger EV penetration will require installation of more charging stations deployed strategically to meet the demands of EV movement and charging behavior without depleting the EV battery entirely. Also, when several EVs recharge their batteries at the same time, the power grid load impact induced by EV charging scenarios could be outside safe boundaries. Presently, the lack of EV charging station infrastructure is a roadblock to successful EV adoption. In the future, this might not be the case as more EVs are deployed and integrated into the smart grid. Thus it becomes increasingly necessary to investigate and quantify the load impact combining mobility needs with the power system infrastructure.

Since EVs are considered as distributed energy resources [43], this type of mobile energy demand is highly influenced by several factors. These include EV battery State of Charge (SOC), battery type and capacity, travel distance, traffic elements affecting the trip time and arrival at charging stations, charging duration with charge preferences etc. EVs can be recharged at home or any public charging station with low operational cost given market incentives and regulations. Residential EV charging demand is fairly predictable in nature as the average users driving pattern could be identified on a regular basis. However, public EV re-charging scenarios are stochastic and difficult to predict because they are influenced by traffic flow (road congestion level and influx of vehicles). Determining the Spatial Temporal Model (STM) of EV charging load across LV network is critical in optimal operational efficiency of the entire distribution network. The challenges of large-scale EV integration in the power grid is manifold. First, due to uncontrolled charging schemes adopted by EV users, the power load might increase during peak hours. This can be a source of possible grid failures due to voltage instability, power losses etc. Second, due to the power capacity constraints, the charging stations might not be able to fulfill all EV recharge requests when several EVs recharge at the same time. These interactions between TN and PDN poses a complex challenge on the real-time operation and dependencies between the two systems with a higher level of EV penetration [78], [50]. Including the charging load impact of EVs in PDN within the mathematical modeling of TN, through coordinated control of coupled networks could improve the operational integrity of the overall system [21]. Thus, the coupled systems play an important role in the smart grid ecosystem energy market. Several authors have investigated the effects of large scale EV integration on power system.

Authors in [50] have taken an Integrated simulation-based approach to model road traffic and EV battery charging using Multi-agent systems. However, more emphasis has been made on EV agent's characteristics and behavioral modeling rather than inter-relation between TN and PDN. Details of distributed charging stations services are not included in the electricity grid. We try to bridge the research gap by taking into account several aspects of stochastic EV agent behavioral profiles and coupling TN with PDN. Moreover, for calculating the cost function of travel time based on traffic flow in transportation network modeling, in most literature, the widely used Bureau of Public Roads (BPR) function [49] is adopted to model the relation between traffic flow on travel link which is quadratic in nature, however we use the Davidson's function [19] with queuing analysis due to its linear properties.

The current state of the art research in optimal operation of interdependent transportation-power network system is based on graph network approach where nodes and edges are represented as the interlinking elements. The functional characteristic metrics of both TN and PDN are measured considering methods of network analysis. For traffic flow modeling, most authors have used simple static traffic models without dynamic user equilibrium conditions. A table with the current state of the art research on the relations between coupled TN and PDN is given in Table 3.1.

1.1 Problem statement and research questions

Power distribution grids aim to operate smoothly to supply local energy consumption with increased reliability and efficiency. However, increasing EV adoption will add significant load to the demand profile for each distribution network, posing challenges to its robust operation and infrastructural integrity. The various influencing factors that could impact the EV charging load has paramount importance in modeling the grid stability. Intermittent charging patterns induced by stochastic travel behavior of several EV users will create load variations and imbalances in the grid components. Considering these stochastic parking and complex charging events, the daily trip pattern will have an impact on the energy requirements from the grid causing disruptions. The electrical energy impact could be substantial if a large fleet of EVs connect to the charging stations while they move in their daily recharge habits. Owing to the restricted publicly available EV charging data primarily due to low EV market share, the work on data driven models can only be applied to participating regions where these data sets (Traffic and weather data, vehicle trip data, EV charging records and load measurements in Voltage, power factor etc.) originate from.

A. Research Question

To address the above issues, the following research question can be constructed: **"What is the impact of Electric Vehicles energy load in a smart-grid distribution network considering traffic movement and charging behavior?"**

B. Sub Questions

To answer the above main research question, the following sub questions should be answered:

- What is the impact of EV charging strategies on Low Voltage Distribution Network?
- How does the TN and PDN relate with each other?
- What is the impact of EV movement in traffic and energy consumption at charging stations?
- Strategies to optimize the social welfare cost of overlaid TN and PDN?

1.2 Methodology

We provide a mathematical description of the individual TN and PDN models after setting up the agent based abstraction platform to collect EV mobility and behavioral profile data. Fig. 1.1 shows the hierarchy of elements which constitute the methodological approach of our thesis. A theoretical analysis is presented supported by simulation based on distributed network mobility using a mathematical model and multi-agent systems. The TN comprises of EVs and EV agent characteristics such as driver behavioral profiles, traffic elements, Origin-Destination points realized by OD-Matrix, trip travel time, energy consumption, EV battery capacity, battery SOC. The parameters have been identified based on stochastic travel behavior and traffic flow. The fundamental Wardrop principle [75] is adopted to estimate the distribution of EV flows in the TN which leads to a stable equilibrium of traffic-flow pattern known as Dynamic User Equilibrium (DUE) in Dynamic Traffic Assignment (DTA) setup. The DUE model can be computationally very expensive [36] because enumerating all possible paths in the OD pair requires accurate O-D trip data and computational resources. Hence, the DTA model was developed to generate approximate solutions to

DUE which can be applied to larger networks [36]. We adopt the Semi-Dynamic Traffic Assignment model (SDTA) owing to less computational complexity and OD trip data. The mobility and charging demand of EV users are assessed using traffic elements. The charging station load is captured within the boundaries of a TN system. By modeling both TN and PDN networks independently and then linking them with coupling constraints, an optimized traffic constrained transportation power flow solution is developed. The parameters for each of the networks have been discussed in Chapter 4. When several EVs charge at the same time it may negatively impact the local electrical distribution network. Several research works have proposed individual operational methodologies and optimization techniques to ensure secure operation under peak demands when EVs are connected to the power grid. We aim to propose a refined model with through interdependent Transportation and Power Distribution Networks which transcends the existing literature on energy impact of EV on distribution networks. In this thesis we have considered the bottom-up approach to model the characteristics of individual EV driving and charging behavior creating an unique load profile. However, the energy consumption of EVs at charging stations are accumulated over time periods to ascertain the electrical impact on power grid. Ultimately, we aim to maximize the social welfare of the system.

In Chapter 4, the detailed models are described in regards to two main aspects: *Mobility Model* and *Power Flow Model*. For data collection and analysis we have primarily used quantitative techniques with agent-based simulation technique coupled with MATLAB for power flow analysis. The mobility model is realized by JAVA Agent Development Framework (JADE) and power flow model calculations are done in MATLAB using radial distribution network. Also, we have used the ACN-Dataset for public EV charging for realistic charging session information [11].

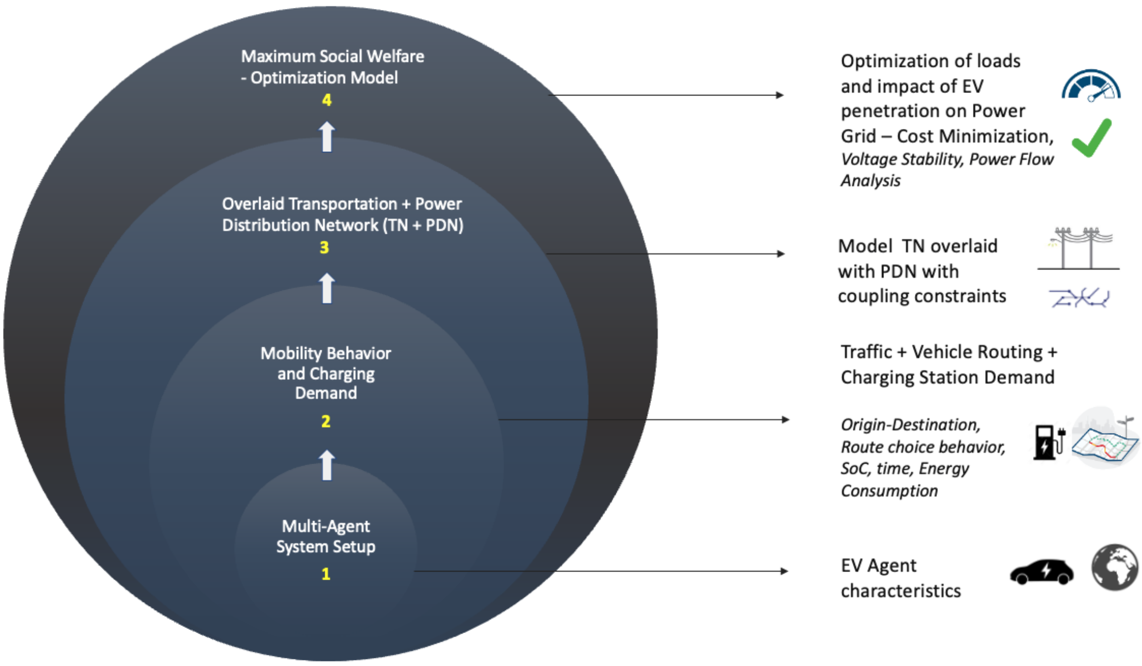

Figure 1.1: Process hierarchy of elements within our modeling technique. A bottom-up approach is presented to analyze a complex system from individual smaller components.

1.3 Assumptions

The following assumptions are taken into account while modeling relevant scenarios in this thesis:

1. The economic aspect in terms of cost efficiency for EV integration in smart grid is not discussed in this work. Also EV discharging behavior (Vehicle to Grid [V2G]) and related ancillary services are not modeled.

2. The vehicle considered is purely electric, i.e Battery Electric Vehicles (BEVs). Other types of Electric Vehicles such as Hybrid Electric Vehicles (HEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) are not modeled.

3. EV batteries have different stages in the charging process with variable charging power and mixture of constant current (CC) and Constant Voltage (CV) charging.

1.4 Contributions

The aim of this thesis is to develop a realistic framework to integrate the power network with transportation network and find its impact on smart grid due to massive EV penetration. We aim to minimize the social benefit costs mutual to both networks. Our methodology takes an unique interdisciplinary approach of finding the inter-relation between TN and PDN by combining Multi-Agent System framework into the TN with traffic information. The interactions between EV users are captured in semi-realistic distributed environment where samples are generated to capture traffic flow and energy consumption due to change in charging behavior. The research study presented in our work addresses the following problems.

- Large-scale EV penetration in an overlaid distribution and transportation network system, linking and optimizing the joint operation of both networks. As traffic behavior changes, it creates variable load distributions in terms of the EV charging process.
- An OTPNF optimization problem is formulated which aims to minimize the social system optimal cost of both TN and PDN.
- Develop an integrated agent based traffic assignment model for Transportation Network Impact Analysis and its cascading effect on power systems.
- Through an Agent Based Modeling (ABM) technique, EV driving behavioral data samples are collected and energy requirement at charging stations are defined as loads connected to the power network bus nodes. The collected load profiles of EVs charging load for 24 hour period is used to analyze the impact on Low Voltage (LV) distribution network node voltage profile. This approach is an unique simulation based optimization of coupled networks.
- An optimization algorithm is developed for optimal route selection to nearby charging stations which eliminates the need for long waiting periods at public charging spots thereby reducing the load curve. A controlled smart-charging technique is also applied to reduce voltage problems which may arise in the distribution network due to multiple EVs recharging at the same time.

1.5 Model Overview

Fig.1.2 shows the overview of our model with the functional elements within the transport and power system linked together. The agents are setup in the simulation platform as individual EVs with unique characteristics. Trips are generated stochastically considering the latitude and longitudinal values between each driving location, for ex. Home to Work. The duration of each workday is assigned by the user and the charging strategy is also selected. During each trip, the EV users can choose to charge on their way if the battery SoC is below a certain threshold value. Also, keeping in mind traffic conditions and route deviations, agents might choose to select a charging location based on which the energy consumption load profiles are collected. The charging location and duration plays a crucial factor in load profile generation as EV users might choose to charge at Home or public charging stations. Finally load flow calculations are performed in MATPOWER for power flow analysis. The results observed showcase the energy impact on the power grid as EV users move in their charging behavior.

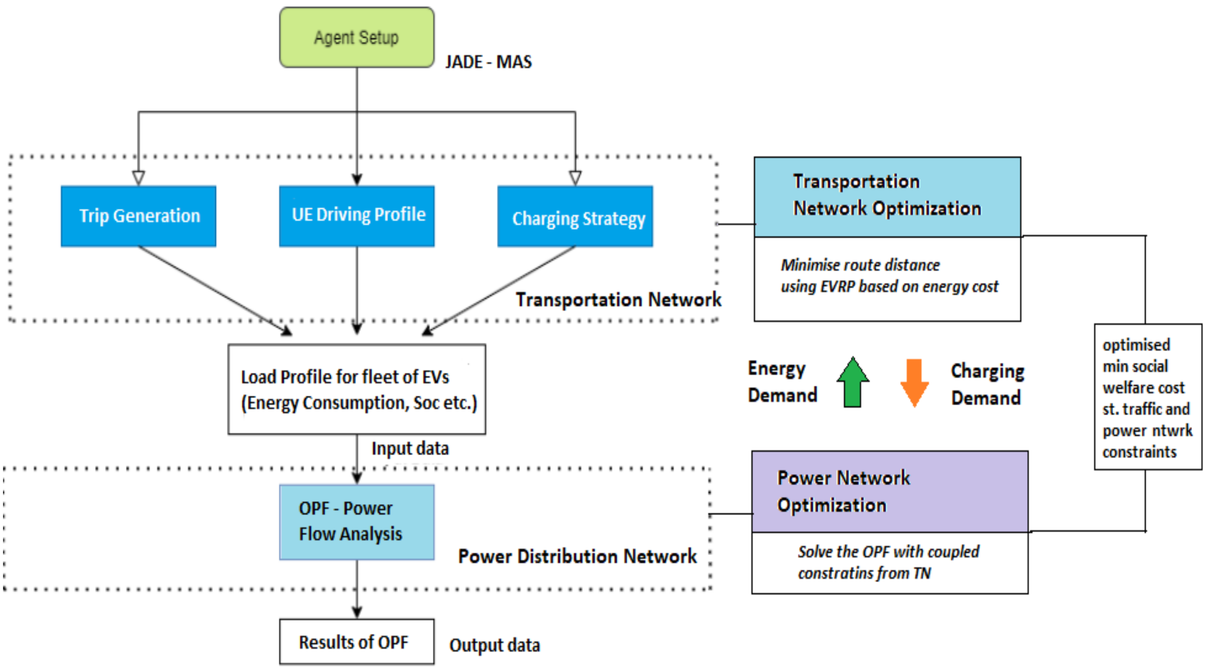

Figure 1.2: Overview of our proposed model with stochastic agent platform integrated with optimized transportation and power network model.

Four types of agents have been modeled in our simulation study. **1) EV agent:** The individual car agents are modeled each having its own characteristics, namely, model type, charging rate, maximum battery capacity, discharge rate, speed, initial battery SoC. **2) Navigation Traffic Route Agent:** This agent is responsible for allocating the routes between travel destinations based on longitude and latitude values and calculates the approximate distance. A Route, having two or more directions (often represented by intersections), is a class representation of the direction information of EV agents traveling from A to B. If there is a traffic jam situation, EV users are redirected to another route. 3) **Charging Utility Agent:** This agent is responsible for collecting the charging information from agents when they arrive at charging stations to recharge depleted EV batteries.

It also decides the charging strategy defined by the users preferences. **4) Scheduling Utilities**: This agent is responsible for other scheduling activities and simulation synchronization along with variable initialization and direction API.

The integrated transportation network and power distribution network model adds driving behavioral patterns with microscopic characteristics with the objective of collecting charging load from EVs at charging stations. Loads at charging stations are connected to network of nodes in a radial distribution system and the voltage profiles are analysed in MATPOWER using power flow. The indicators we have considered for measuring the impact on power grid are: 1) Peak Load Demand, 2) Energy Consumption Profile, 3) Traffic Congestion Factor (with respect to traffic flow) 4) Voltage profiles, 5) Cost associated with EV charging loads and power generation costs.

A bi-level optimization problem is formulated which takes into account the charging cost of connected EVs at charging stations and the power generation cost of power network in multi-agent iterative simulation based approach. We call it iterative simulation because for time dependent user equilibrium solutions, the travel times are updated for every iteration step of the simulation. For each of the coupled networks, its individual network constraints are formulated. To reach a social optimum value, a trade-off between network losses and costs are considered. We analyze the voltage magnitude at each bus node since EVs charging at a particular node has a cascading impact on the other nodes in PDN. Linear approximations to the original power flow problem are relatively easier to solve however they can pose a problem to scale up to larger networks. Solving the OPF problem with the convex relaxation technique of power flow equations have been adopted which overcomes the issue of scaling to bigger network systems. Details of the modeling technique is discussed in *Chapter 4*.

1.6 Thesis Outline - Preview of Chapters

The contribution of this thesis work from initial research to result analysis is highlighted below.

Chapter 1 (Introduction)
The first chapter gives an introduction to the thesis work with its related problem statement and research questions.

Chapter 2 (Background and Motivation)
This section presents the contextual information along with historical developments of impact of EV integration in power systems. An overview and rationale of our study objectives are highlighted along with the methodology aiming at bridging current research gaps. Also, why particularly EVs are subject to energy impact is also discussed in this section.

Chapter 3 (Related work)
We describe the related work of the energy impact of EV integration. The literature review is synthesized in this chapter. The methods and relevant formulations are cited.

Chapter 4 (Modeling Techniques)
The impact of spatio-temporal EV charging behavior and its subsequent energy consumption model under variable load conditions is presented. We define the Multi-agent based mobility framework which can be scaled to larger networks and dynamic EV dispatch use-cases. We also present detailed models of the TN and PDN linking them together via constraints of both networks. An optimization problem is formulated which ultimately saves cost of travel distance, energy consumption and charging load from charging stations in OTPNF model.

Chapter 5 (Implementation)
In this chapter we present the implementation of the proposed model by using JADE - a JAVA Agent based framework and simulation using power flow package MATPOWER in MATLAB. Power flow analysis is done using Backward-forward sweep method.

Chapter 6 (Results and Observations)
The simulation results and observations are presented in this chapter.

Chapter 7 (Conclusion and Future Work)
We communicate some possible future extensions to this work and conclude the thesis.

Chapter 2: Background and Motivation

The current bottleneck for large scale EV introduction and adoption is the battery power capacity and lack of EV charging infrastructure [73]. Due to the limited battery capacity with inadequate charging stations, drivers have *range anxiety* (phenomenon where EV users cannot determine if they can make it to their destination with the stipulated range) which ultimately results in charging the vehicles more than once before reaching their destination. Vehicle manufacturers tend to focus on Plug-in Electric Vehicles (PEVs) and plug-in hybrid vehicles (PHEVs) which includes Electric Vehicles (EVs) as well. The rising trend of EV and PHEV market share as well as charging infrastructure from data gathered from NPE **(Nationale-Plattform-Elektromobilitaet**) [52] demonstrates that more than 1 Million EVs will be deployed by 2022 and atleast 70,000 AC charging points with over 8000 DC points will be installed. Additional charging infrastructure is needed to support the rising trend of global EV sales. The European Commission aims to cut harmful emissions by at least 55% by 2030 and also aspires to be the world's first climate neutral continent by 2050 [60]. This will facilitate the integration of EVs into the smart grid and make the energy ecosystem sustainable. EVs play a crucial role in welcoming the paradigm shift of automobile landscape. When large EV penetration occurs within the transportation network, it will have an impact on the charging infrastructure in the power distribution system.

The below Fig. 2.1 shows the adoption of pure battery EVs by each country from 2005-2019. China and USA are global leaders in EV adoption and Europe has ambitious plans to be carbon-neutral by 2050.

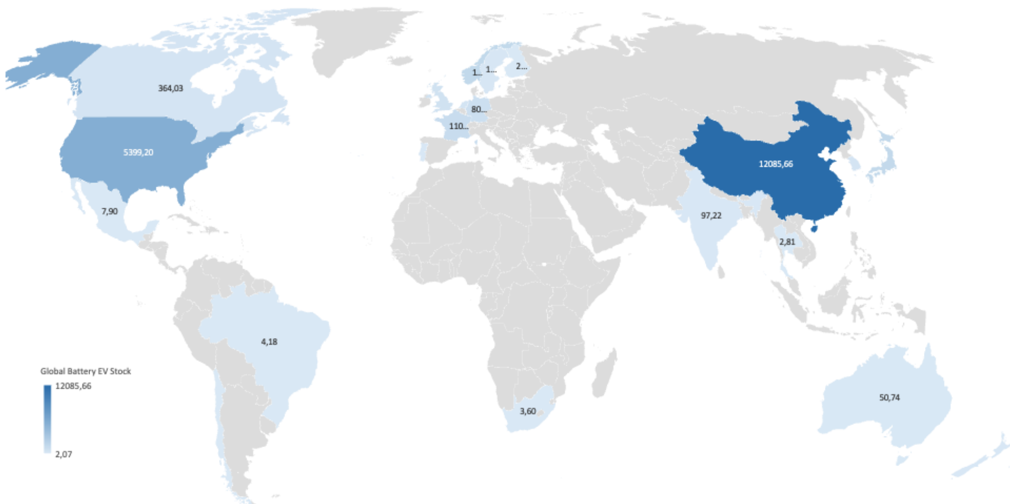

Figure 2.1: Global Battery E-Vehicle Stock by country from 2005-2019 (in thousands) [34]. As more EVs are deployed, the need for optimized operational planning of both TN and PDN becomes necessary to run the power grid smoothly.

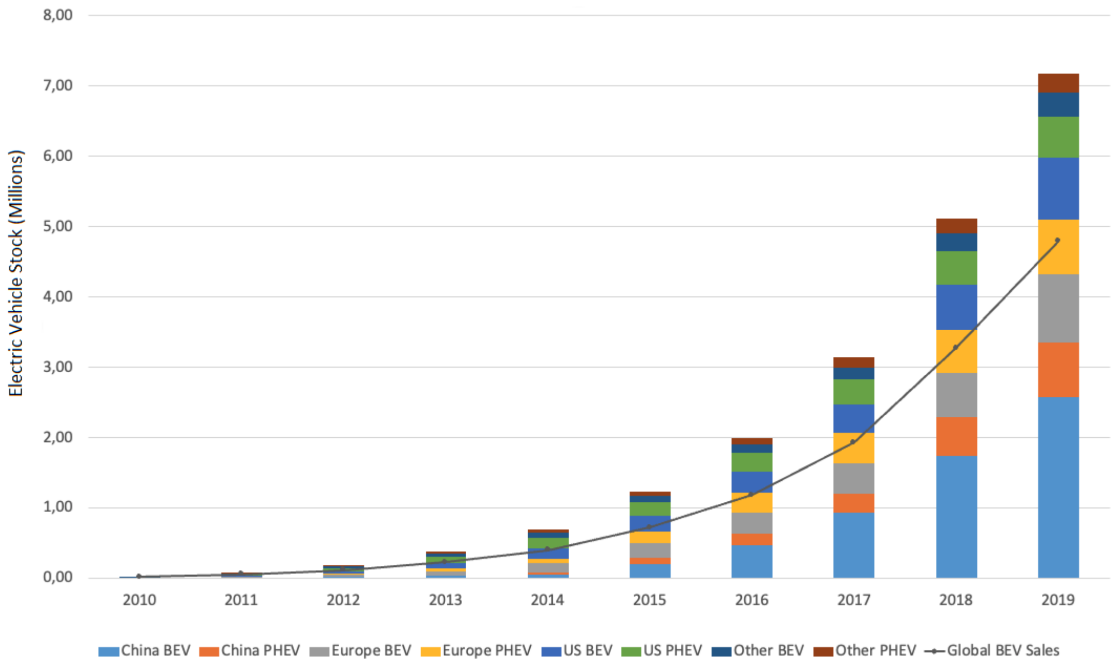

Figure 2.2: IEA Analysis on electric vehicle stock for different markets. The annual average expansion of EVs is 60% from 2014-2019, to a total of 7.2 Million Electric Vehicles in 2019 [34]. This could lead to additional stress on transportation network.

Driver behavior is a key factor which determines the energy usage of an EV which is elemental on weather conditions, traffic density, acceleration rate and maintaining minimum safe distance between following vehicles. When several EVs charge simultaneously, there might be severe consequences on the power grid as huge load is drawn from fast charging stations. The likelihood of rapid EV adoption and potential shift to electric transportation system is a major concern for power systems. Mitigating the peak demand through optimized charging strategies is a key solution to not overload the power grid.

The impact on the distribution systems accounts for 90% of outages and with the introduction EV charging load, it will likely increase the energy impact [51]. A typical LV distribution grid along with interaction of EV fleet is simulated considering various scenarios. The LV residential distribution network where most people charge their EVs at home is a candidate for energy-based impact proposition analysis. The potential risks with uncontrolled EV charging will have the following impacts [58]:

- **Voltage deviations, power fluctuation and quality issues.**
- **Transformer losses.**
- **Increased investment cost in reinforcing grid due to peak demand.**
- **Thermal overloading of LV distribution transformers.**

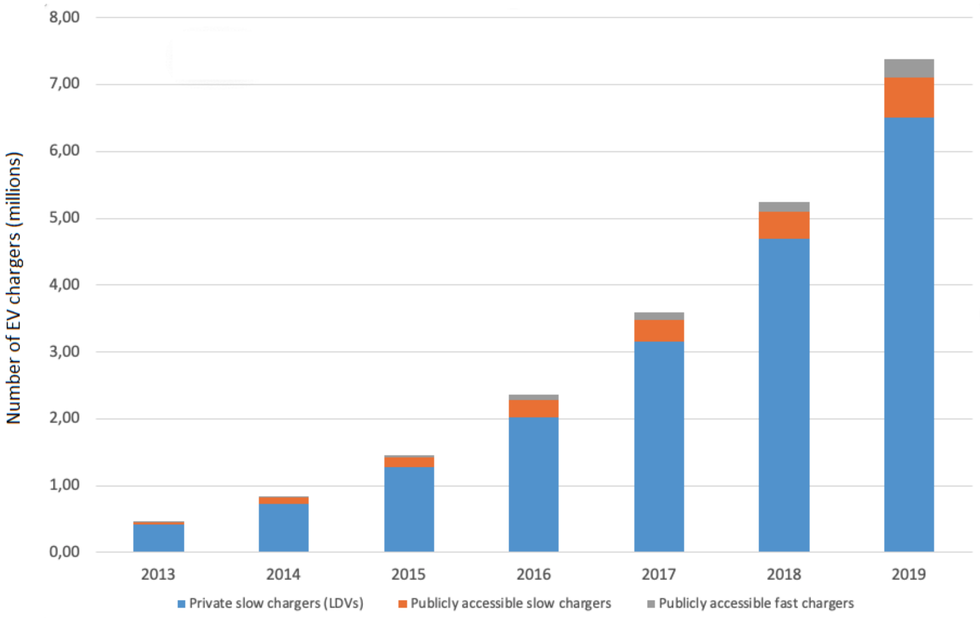

Figure 2.3: IEA Analysis on electric vehicle charging infrastructure currently in place [34]. Increase in the placement of fast charging stations equipped with more than 22 kW charging power connected to the power grid could pose considerable load on the power distribution network.

The motivation behind our research study lies in the fact that due to rapid development of EV and related charging infrastructure replacing conventional ICE vehicles, we need to realize how changes in traffic distribution within the transportation network might affect the stability of the distribution network. The fundamental realism that EVs have less carbon emissions than conventional ICE vehicles, a higher adoption of EVs will be more likely in the future as battery technologies are improved and rapid charging stations are developed. Given this background, it is important to analyze the impact of the Electric Vehicle on the power system to determine if the electricity generation capacity will be adequate to provision EVs demands during the peak hours, without negatively impacting the grid. Since interactions between *Prosumers* (entities which can produce small portion of energy and consume energy at the same time) are a key constituent for the future Smart Grid EV integration impact, we consider an agent-based system to be better suited for our study [14]. Estimated total energy load on the power network during peak load is around 260 GW for evening charging scenarios in sustainable development scenario 2030 [34], and 25 GW for 1 million EVs [80] assuming battery capacity of 50 kWh and 30 kWh respectively.The increase in energy demand is by 4.6 GWh/day which could pose a threat to the power system. This evaluates the effects of EV integration in LV smart grid topology in European countries.

2.1 EV integration in the Smart Grid

The term *Smart Grid* is sometimes defined as an advanced Power Grid with a high degree of de-localization in the production and market trade of energy [15]. A basic representation of the EV integration in the smart grid with the energy load from distribution network is shown in Fig. 2.4. Due to additional power demand arising from higher levels of EV adoption in society, there are quite a few technical problems like power instability, voltage imbalance which may occur [70]. Mitigating those problems in order to make a smooth transition within the smart electrical grid system is the objective behind our research study.

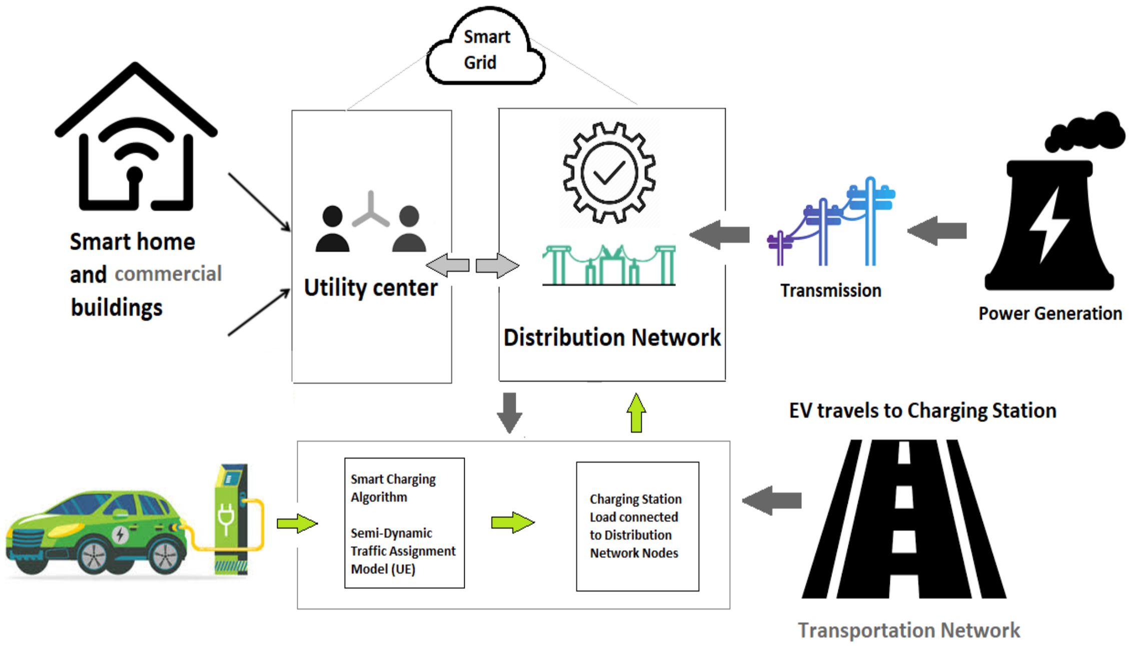

Figure 2.4: The integration of EV in the smart grid

Interaction of EV with Smart Grid Distribution Network

With the increase in level of EV penetration, the interaction between TN and PDN would become prominent due to energy demand from large fleet of EVs and their dynamic charging behavior. EVs are distributed energy sources capable of bidirectional energy transfer [39]. A major challenge is to properly manage and synchronize charging demands for large number of EVs. This is where the smart grid can help optimise both the TN and PDN by economically dispatching loads across the network keeping in mind traffic conditions. A general representation of the EVs interaction in the transportation network with the power distribution network connected to the smart grid is shown in Fig. 2.4. Power is distributed from power generation plants to distribution networks through transmission lines. Typically EVs recharge at home charging sockets or public charging stations having greater efficiency (fast chargers). Typical charging options for EVs are at Home (usually 120V outlet) or at public places such as shopping arenas, offices, highway exits etc. which are usually equipped with DC fast charging options.

Chapter 3: Related Work

3.1 Multi-agent Systems Modeling in Transportation Network studies

The use of multi-agent systems to model driving behavior of users on the transportation network have been discussed in Balmer et al. [7], Doniec et al. [22], Hatziargyriou [38] and Bazzan [9]. A stochastic mixed-integer model using AC power flow constraints to assess planning of fast-charging stations within the transportation network and power system network is studied in [85]. No routing algorithm for efficient route choice for traffic elements are considered. Previous literature in [25], have considered fixed charging location and time which mostly occurs at home in the evening or night. Authors in [6] have proposed a mathematical model of EVs charging demand at a charging station based on fluid dynamic model and M/M/s queuing theory. This model represents the spatial and temporal dynamics of EV charging demand at a highway charging station. Rahman et al. [59] studied the impact of EV charging on distribution systems and concluded that charging load must be distributed through the off-peak hours even though EV penetration level is low. Addressing the pessimistic problem due to fixed charging times from critical or completely discharged battery levels, Qian et al. [57] proposed a method modeling the stochastic nature of EV charge time considering the initial state-of-charge (SoC) of battery. Based on Probabilistic Power Flow calculations, Li et al. [42] proposed a method to model the PHEV charging demand employing queuing theory which simulates multiple PHEV behavior. Authors in [53] have developed an agent-based model including temporal distribution and energy consumption during each trip. However it doesn't include impact on low voltage grids and Tariff Controlled dynamic behavior of system considering traffic flow.

The concept of EV users' trip chain is rarely used in power system load modeling [72]. However authors in [72] have integrated STM of EV charging load based on Markov properties and trip chain. Authors have also used SUMO, Markov chain properties and traditional methods described in [62], [17] to model vehicle traffic. A state of the art in vehicular traffic flow models is given in [31]. A cellular-automata based integrated traffic-power simulation framework is developed in [82]. A probabilistic model in an unified power and traffic network to analyze EV charging demand has been developed. Driving behavior is modeled using random trip chains without accounting for driving speed and bidirectional traffic routes taken by EV users. We address this gap by using two-way traffic of EV load in a hybrid simulation setup using power flow analysis.

3.2 Traffic Network Modeling

An early study on macroscopic simulation model for highway traffic jams and stop-start behavior of vehicles was introduced in [40]. Research made on EV traffic simulations on highway networks such as in [16] and [6] ignored the electrical grid of EV charging impact. Authors in [71] have discussed spatial-temporal impacts of EVs on traffic system using probabilistic model of expected nodal EV charging demand based on parking events. Graph theory along with Dijkstra's algorithm is employed in the paper to calculate energy consumption based on trip distance. However the model is generic with macroscopic characteristics taken into account without any coordinated charging events between EV users. A study made in [27] presents a rapid-charging navigation strategy using both traffic data and power system data. However detailed modeling of traffic flow with individual driving behaviors which impacts the power grid is missing in this study. A charging demand forecasting model of EVs based on a data-driven approach is presented in [83]. An integrated traffic and power system model with state transition algorithm has been discussed in [64] to analyze nodal EV charging loads for a transmission network. The EV modeling is done using The National Household Travel Survey (NHTS) data-set in context of travel information. A mathematical model to predict the EV charging load at a charging station is developed in [68] using Poisson arrival location model (PALM) for traffic modeling, Dijkstra algorithm for shortest route planning and Monte Carlo sampling to capture the spatial/temporal charging demand. Luo et al. [46] and Shao et al. [63] have developed an integrated system of ''vehicle-traffic-distribution'' and solved the spatial-temporal distribution of EV charging load by origin-destination(OD) matrix. Most of the work presented in [3-9] have been developed based on spatial-temporal characteristic models, optimizing the route traversed by EVs without detailed modeling of traffic conditions. To alleviate this problem, stochastic trip chain theory with Markov Decision Processes and Monte Carlo simulations have been performed in [71], [87], [65], [74] and [88]. However, the authors haven't investigated into macroscopic factors such as temperature, humidity and microscopic individual EV factors such as traffic congestion and charging willingness to predict the charging load with its subsequent impact on power system grid.

3.3 Power Systems Network overlaid with Transportation Network

A multi-agent system approach is adopted in [32] to study the integration of EV impact on distribution network. A conceptual framework for integrating EVs into the power systems network through medium voltage distribution system operator is presented in [44]. Results show that the use of centralized charging scheme will allow larger EV integration without grid reinforcements. Extensive studies have been made on impact of EV charging on power networks especially on Medium Votage and High Voltage Networks PDN [51],[28],[57], [28], [84], [56]. Authors in [86] have proposed a joint EV charging station planning with distributed photovoltaic (PV) stations incorporated in the territorial transportation and power distribution system. However, the relation between the inter-dependencies of TN and PDN taking into account stochastic spatial temporal user driving behavior with traffic elements has not been extensively studied. Authors in [54] have proposed a planning framework for the coupled network which optimizes the deployment of EV charging stations. Another approach taken [82] utilizes cellular automata theory in an integrated traffic-power simulation framework for EV charging stations but it evaluates the feasibility of EV charging stations deployments without actually quantifying the impact on coupled TN and PDN. Most existing studies have not considered spatial temporal behavior of electricity and vehicle traffic demands with dynamic charging loads. A summary of the state-of-art on studies made on coupled TN and PDN is given in Table 3.1.

Author Reference	Power System Model	Traffic Model	Research Objective
Alizadeh et al. [3]	DCOPF	STA	**min** gen cost & travel time
Manshadi et al. [48]	DCOPF	STA	Equilibrium study
He et al. [29]	DCOPF	STA	**min** TN time & power loss
Jiang et al. [37]	ACOPF	STA	**min** social cost
Sun et al. [69]	SCUC	STA	**min** total operational cost
Wei et al. [76]	ACOPF	STA	**min** total travel & gen cost

Table 3.1: Research study on the relations between coupled TN and PDN. DC/AC OPF: Direct Current/Alternating Currrent Optimal Power Flow, SCUC: Security-constrained unit commitment. STA: Static Traffic Assignment.

According to our review, there has been very little or no study done on dynamic traffic assignment model in spatial temporal variations applied to the coupled TN and PDN networks. The research on the interconnection between TN and PDN is still in its evolving phase. We try to advance the research gaps from previous papers by formulating an optimization problem with added constraints for the transportation network considering EVs charging cost under traffic influence and achieve cost minimal global solution.

The research on impact of EV integration with coupled TN and PDN is relatively new as found from the research work done in past years. Only few interdisciplinary studies have been made on the stochastic spatial-temporal electrical energy and mobility behavior of electric vehicles considering the dynamic activity of both networks. The studies made in [[76],[3], [37]] aimed at minimizing the total cost of both PDN and TN, but without considering the time-varying dynamics of transportation traffic network. The Static Traffic Assignment model has been used which gives a coarse overview of traffic flows through the network. Also, the constraints associated with EVs charging load at charging station are not explicitly modeled.

Chapter 4: Modeling Techniques

4.1 A Stochastic Approach to Electric Vehicle Mobility Model

4.1.1 Multi-agent systems

Multi-agent systems (MAS) comprises of several agents which interact with each other to achieve their goals. They are powerful objects because of their autonomy, social ability and reactivity. To support the energy consumption load in our simulation framework, we have developed a pure electric vehicle with different parameters. Agent-based modeling paradigm has been chosen as our preferred method due to its complex behavioral traits and decision-making heuristics by perceiving the environment. Each vehicle is an autonomous entity capable of interacting with other vehicles in the road network. We consider four EVs each having its own individual characteristics namely Nissan Leaf, Tesla S, Renault Zoe, Kia e-Niro. However within the transportation network, these EVs would react to other vehicles like trucks, buses, ambulances to simulate a realistic behavior. The model simulates the charging characteristics of each EV, its mobility pattern and reactions to various elements impacting the traffic flow deviations. As a result an interactive environment is created where the decision making process and random events are induced contributing to a realistic model that envisions the charging demand for a fleet of EVs or as individual EVs.

a) EV Agent Model

The attributes of EV agent are primarily the EV model, its mobility behavior and charging preferences. The EV agent behaviors are considered to be the daily trips taken (mobility), their corresponding battery energy consumption, energy requirements from the charging station (distribution network in top hierarchy), and the charging opportunities. Depending on the SoC, energy requirements and charging preferences an EV agent decides to begin the charging process to reach a certain destination. The states with their corresponding variables are: driving, parking and charging. These states have inter-related connection to the mobility pattern where EV agents interact with each other to make autonomous decisions.

b) EV Li-ion Battery Model

In an EV, the key parameter in obtaining the energy discharge of a Li-ion battery is the SoC. It measures the residual capacity of the battery. If we consider a fully discharged battery, then if it is charged with current I_t from time t_0 to t, it will hold a charge of:

$$\int_{t_0}^{t} I_t \partial(t) \tag{4.1}$$

The total charge the battery is capable of holding is:

$$C = \int_{t_0}^{t_{max}} I_t \partial(t), \text{ where } t_{max} \text{ is the time when battery reaches its maximum capacity.} \quad (4.2)$$

Thus, the battery SoC can be estimated by the below equation:

$$SoC = \frac{\int_{t_0}^{t} I_t \partial(t)}{C} * 100\% \quad (4.3)$$

The battery open circuit voltage (OCV) has a strong nonlinear relationship with the SoC [18].There exists a functional relationship between OCV and SoC of lithium-ion batteries. In particular, the OCV-SoC curves are obtained by fitting test points of OCV in SoC interval according to the monotonic increasing relationship between OCV and SoC.

The EV battery charging rate z_0(t) is the average charging capacity P_{ch}(kW) of an EV over its maximum battery capacity Q_{batt}.

$$z_0(t) = \frac{P_{ch}}{Q_{batt} * 60} \quad (4.4)$$

(i) OCV-SoC Relationship: In real-world scenarios, the battery OCV curve will be affected by several factors, such as SoC, ambient temperature etc. Since surrounding temperature significantly affects the qualities of lithium-ion batteries, research needs to depict the impact on the OCV-SoC relationship so as to expand the precision of the model with better estimation of SoC. We consider the simplest possible model of a battery cell by comparing the battery operation to that of an ideal voltage source. In this model, the cell voltage is modeled as an independent voltage source. So voltage is considered to be constant and equal to the cell's OCV. We formulate this below as:

$v(t)$ = OCV

We consider the battery cell's internal charge status by defining a quantity known as SoC $\omega(t)$. The two calibration points for our model taking into consideration the intuitive concept of battery health statistics, we define $\omega(t)$ of a cell to be ω= 100% when the cell is fully charged and ω= 0% when the cell is fully discharged. Also define total capacity Q to be the total charge capacity of the battery cell. Q is usually measured in Ah or mAh. Using an ordinary differential equation, we model the battery state of charge change over time in response to the input current provided.

$$\omega'(t) = \frac{\partial \omega}{\partial t}, \text{ where } \omega'(t) = \text{time derivative of SoC.} \quad (4.5)$$

Re-writing equation (4.5) adopting a sign convention of input current i, we formulate

$$\omega'(t) = \frac{-i(t)\eta(t)}{Q}, \text{ where } \eta\text{= Coulombic efficiency } (0 \ll \eta \lessapprox 1) \quad (4.6)$$

Taking the integral of both sides:

$$\omega(t) = \omega(t_0) - \eta(t)\frac{1}{Q}\int_{t_0}^{t} i(\tau)\partial(\tau) \quad (4.7)$$

So when the sign of input current is positive, that means we are discharging the cell and the state of charge is going down. If the sign of cell current is negative, then we are charging this cell and state of charge is increasing.

(ii) Effect of Temperature on battery capacity: Since our model has to operate over a wide temperature range, then we are probably going to be storing many vectors of OCV versus temperature and SoC. To reduce the memory complexity, we consider at any given SoC, the OCV variation is almost nearly linear as a function of Temperature T. The OCV-SoC relationship corresponding to each temperature point can be obtained by the following exponential model:

$$OCV = \sigma_1 e^{a_1 \omega} + \sigma_2 e^{a_2 \omega} + b\omega^2 \tag{4.8}$$

where σ_1, a1, σ_2, a2, and b are the temperature coefficients, OCV is the battery open circuit voltage under different operating temperatures, and ω is the SoC value. Combining respective approximated single-temperature OCV results, a final model of the form below can be formulated:

$$OCV(\omega(t), T(t)) = OCV_0(\omega(t)) + T(t) * OCV_f(\omega(t)) \tag{4.9}$$

where $OCV_0(\omega$(t)) is the OCV relationship at 0° C and $OCV_f(\omega$(t)) is the linear temperature-correction factor for each SoC value (OCV/0°C).

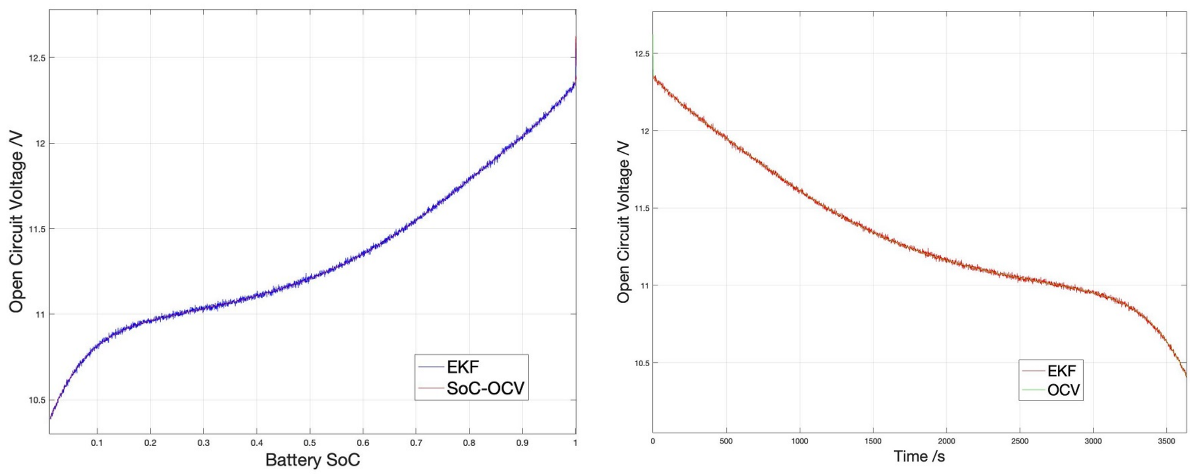

Figure 4.1: Comparison curve of Extended Kalman Filter and SOC-OCV

According to the paper [33] and [24], a comparison between the OCV with respect to SoC change and time using Extended Kalman Filter algorithm applied on Thevenin model and SOC-OCV method is shown in Fig. 4.1. Although the EKF model is accurate in estimating the battery SoC with individual approximated OCV data, due to lack of accurate EV battery modeling data in our study, however we stick to the simpler formulation done in 4.3. The Battery Management System modeling is out of scope in our study. As SoC is a critical component of our study in estimating the charging load and route considerations of EV users, the Extended Kalman Filter algorithm was used as a reference study to gain more insight into the SoC estimation techniques.

4.1.2 Modeling Electric Vehicles in Traffic Flow

With the growth of urban transportation system and population density, traffic congestion is inevitable under many circumstances, especially during rush hours. The impact of traffic flow study is important as it is susceptible to driving/driver behavior, driving strategies and trip planning. The automotive sector is still in a transformative stage to EV adoption, thus the impact of traffic conditions due to large scale EV transition is a great research area. Quantifying the energy implications of the EVs stuck in traffic will help improve the routing algorithms as well as optimal placement of charging stations. Modeling traffic flow is a inductive reasoning process: behavior of individual driving habits and charging options for EVs are developed using traffic observations. The first step is to collect traffic data either physically or from simulations. The observations from these data sources are analyzed and factors that influence traffic flow are acknowledged. In the second step, a theoretical framework is built from the empirical observations performed earlier including behavioral assumptions. Drivers react to environmental changes in road network differently, hence it becomes difficult to predict the exact nature of the behavioral assumptions. In the last step, the traffic flow model is built using the theoretical framework developed earlier. In real-world scenarios, the chosen driving path of an EV user can be altered by traffic jams and deviations due to weather or unexpected events. This becomes a research objective of our study to analyze the impact of EV charging load when EVs deviate from their planned route and considerably reduce their battery SoC, thereby needing to charge at a charging station to reach their destination.

Traffic flow models are mainly categorized into 3 types: Macroscopic, Microscopic and Mesoscopic [31].The basic idea of a Macroscopic traffic model is that it describes the aggregate/bulk quantities of vehicles via some Partial Differential Equations, whereas Microscopic models use Ordinary Differential Equations describing individual vehicle behavior.

A. Fundamental relations of traffic flow

The core relationships of traffic flow behavior is described in terms of three variables: traffic flow, density and speed of vehicles. A traffic flow is a combination of driver and vehicle behavior. Since EV driver or human behavior is discordant, there is a heterogeneity in traffic regulation behavior. This is largely influenced by the individual characteristics of EV agents and their interaction with the environment. Thus traffic flow through a network will vary both both temporally and spatially considering each individual characteristics. We consider the traffic to be a microscopic event affected by the individual movement of each EV. Macroscopic characteristics can be flow m, density d, and speed s whereas microscopic characteristics include gap between two successive vehicles in spatial-temporal headway. The temporal headway is the difference between the time two vehicles, one travelling ahead of the other, arrive at the same point. Spatial headway is the distance between corresponding frontal points of two successive vehicles traveling at certain time. The traffic flow model is especially an important aspect in our study because we need to analyse the impact of EV energy impact as drivers move through congested traffic situations. The impact due to route deviations in temporal and spatial dimension needs to be modeled which can accurately define our goals.

Traffic variables: Car velocity, Traffic flow and density: The car velocity is usually recorded using $v_i = \frac{du_i}{dt}$ for each car $i = 1, \ldots n$. Traffic flow is a function of the average number of vehicles passing per unit time through a road network, viz. $T_f = f(n,t)$. When a large fleet of vehicles are in a closed range with each other with minimized safe distance between two successive vehicles, then congestion might occur. The fraction of cars in close proximity thus can be measured with the **density** - ϕ of vehicles in a certain region. According to the basic law of traffic flow theory [47], traffic flow, $T_f = \phi(n,t)v(n,t)$ is the traffic density multiplied by mean velocity of cars per unit time. As traffic density increases, velocity of each car is reduced.

Speed: It is defined as the rate of motion in distance per unit of time. Speed or velocity s is given by $s = d/t$, where, s is the speed of the vehicle in m/s, d is distance traveled in time t seconds.

The fundamental relation of traffic flow theory provides a close relation between the three macroscopic characteristics described mathematically as: $m = d\ \vec{v_s}$, where $\vec{v_s}$ is the space-mean speed defined as harmonic mean of the instantaneous speed a vehicle passing through a unit time.

Space-mean speed: If there are n vehicles in the road with s_i being the instantaneous (spot speed) of the i_{th} vehicles, then space-mean speed can be formulated as:

$$\vec{v_s} = \frac{n}{\sum_{i=1}^{n} \frac{1}{s_i}} \tag{4.10}$$

B. EV Traffic Model

EV drivers are mostly concerned with the amount of charge its vehicle battery can hold to successfully complete a trip. To overcome the problems associated with modeling an EV traffic model which includes a high degree of granularity and detailing, we propose a hybrid model with Microscopic and Macroscopic characteristics. This model comprises of the extended Optimal Velocity car-following model amalgamated with the Stochastic Intelligent Driver Model. This model aggressively anticipates EV energy usage based on spatial-temporal distribution, travel behaviors, driver routines and scenario-based assumptions based on traffic conditions and weather inputs. The spatial constraints of EV vehicle usage is defined by the amount of energy stored in the battery. The temporal dimension is also a crucial factor as it determines when EV users can reach their destinations. The components which constitute our proposed traffic model include the traffic network and EV mobility behavior.

Macroscopic Model
LWR model: The LWR model (Lighthill and Whitham, 1955; Richards, 1956), is a fundamental model to evaluate the uncertainty of traffic disruption propagation which has shortcomings due to its assumptions of single lane homogeneous traffic flow of vehicles. Vehicles adjust their velocity instantaneously to the density however, traffic flow congestion is caused by vehicular inertia and latitudinal driving behavior.

Microscopic Model
Enhanced Car–following Model: Assuming single-lane roadway, the car following model considers dynamics of individual vehicle subject to its position and velocity of the vehicle ahead. Based on the Intelligent Driver Model (IDM) where each vehicle is aware of its surrounding vehicles and maintains minimum safe distance, desired velocity, acceleration or deceleration. Fig. 4.2 shows the fundamental diagram of the IDM with relation to speed, density and flow.

Headway Vehicle model: Accelerate or decelerate based on the velocity of the vehicle in front.

$$a_i = \frac{v_{i+1} - v_i}{p_{i+1} - p_i} \tag{4.11}$$

where position of the i-th vehicle is p_i and velocity is v_i, acceleration is a_i.

Optimal velocity model: Accelerate or decelerate to an optimal velocity depending on the distance of the vehicle in front.

$$a_i = V(x_{i+1} - x_i) - v_i \tag{4.12}$$

where V is the optimal velocity.

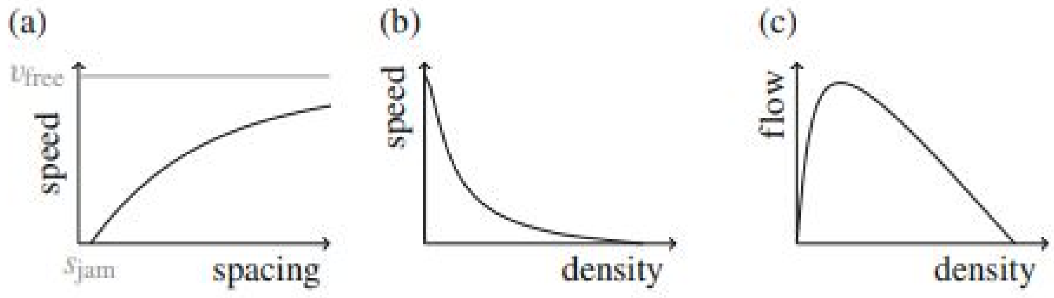

Figure 4.2: Fundamental diagram of IDM: a) spacing-speed, b)Density-speed, c)Density-flow

User Equilibrium Model

Wardrops Principle: According to Wardrop's principle [75], every chosen path in the OD pair *s-d* should have minimum travel cost. Wardrop's first principle is a physics way of perceiving the world which encompasses the most fundamental truths. Hence we adopted this model to our traffic assignment problem to minimize social cost. Travel times on used paths in the same OD pair are equal. We extend this principle to include the total travel cost incurred by an EV user which includes travel time due to traffic flow and monetary cost associated with energy consumption of EV battery, parking at charging stations etc. The Dynamic User Equilibrium route choice principle is adopted in our work to solve traffic assignment problem. Traffic assignment type can be either deterministic or stochastic for which the algorithms used are Frank–Wolfe (FW) or Method of Successive Averages (MSA) respectively. To compute the traffic flows in our optimization problem, we use the Frank–Wolfe (FW) algorithm to find user optimal flow solutions through the chosen OD link pair. Our agents file in the JADE simulation provides the network demand and trip data which must be used to find optimal traffic flows in the Dynamic User Equilibrium framework developed. Once we get the optimal flows including charging costs of EVs at charging stations, we write that to a csv or .dat file for loading into our main optimisation problem OTPNF solvable by COUENNE using AMPL.

Formally UE condition can be written as:

$$f_p^{sd}(C_p^{sd} - u) = 0 : \forall p \tag{4.13}$$

where u is the minimum travel cost, f_p^{sd} is traffic flow on path p between O-D pair s,d and C_p^{sd} is associated cost.

$$C_p^{sd} - u \geq 0 : \forall p \tag{4.14}$$

The following two states are possible for the 4.14 equation:

1. If $C_p^{sd} - u = 0$ then it follows that $f_p^{sd} \geq 0$ from 4.13, suggesting all used paths p have same travel time.
2. If $C_p^{sd} - u \geq 0$, $f_p^{sd} = 0$ from 4.13. All paths which have not been chosen will bear a higher travel time than the minimum cost path p.

The solution to the above UE condition is discussed in Optimization Model of Transportation Network.

System Optimal State:

According to Wardrop's second principle [75], an optimal social equilibrium state is reached when total system travel time is minimized. Ideally the System Optimum (SO) should serve as the main goal of the TN planning operators. The solution to the SO state is mathematically defined as a nonlinear optimization problem which is used for capturing the traffic flow in our user equilibrium study.

$$min \sum_{e \in E} \vartheta_e \tau_e(\vartheta_e) \tag{4.15}$$

subject to the following constraints:

$$\sum_p f_p^{sd} = \eta_{sd} : \quad \forall s,d \tag{1.01}$$

$$\vartheta_e = \sum_s \sum_d \sum_p \psi_{e,p} f_p^{sd}, \quad \forall e \tag{1.02}$$

$$f_p^{sd} \geq 0, : \quad \forall s,d,p \tag{1.03}$$

$$\vartheta_e \geq 0 : e \in E \tag{1.04}$$

where ϑ_e is the equilibrium traffic flow on link e, travel time on link e is τ_e, η_{sd} is the traffic demand or trip rate between s,d origin destination pair, $\psi_{e,p}$ is the decision variable which states if link e belongs to path p or not. τ_e and t_e have been used interchangeably to denote travel time on link e. Eq. 4.15 is strictly convex if $\tau_e(\vartheta_e)$ is monotonic increasing function of travel time on traffic flow, assuming cost on each link is independent of flow.

The travel time τ_e between each link e is computed by a function D of trip distance, energy consumption and other road conditions δ (speed, weather, road gradient, temperature). c_e denotes trip distance and ψ_e energy consumption cost of EVs traveling through each link e.

$$\tau_e = D\left(c_e, \psi_e, \delta\right), \quad \forall e \in E, \tag{4.16}$$

Considering traffic jam situations and density of vehicles, we compute the updated trip time as:

$$\tau_e = \tau_e^F \left(1 + \alpha \left(\frac{\vartheta_e}{Q}\right)^\beta\right), \quad \forall e \in E \tag{4.17}$$

where τ_e^F is the time spent in free flow traffic, ϑ_e is the traffic flow in the road network and Q is the practical link capacity that can handle certain influx of vehicles. α and β are coefficients which can be gathered from realistic traffic observation data.

The below assumptions are considered for adopting the above model:

1. The travel time on link e is a function of traffic flow for that particular link only.
2. Travel time function is strictly increasing and positive.
3. The path cost is known to the user.

These assumptions are modeled in our simulation framework where users choose the least path cost following a shortest path algorithm.One important observation to note is that, to obtain SO state working for large networks, in the UE algorithm, travel time on a given link should be changed with marginal aggregate travel time. This implies as more number of EVs enter a traffic stream, travel times of all EV agents are elevated, which ultimately produces traffic jam and time delay to every other agent.

Marginal aggregate travel time = t(d) + d δt(d), where t is travel time and d is traffic density measured in vehicles/hr.

Beckmann Model:

Beckmann et al (1956) formulated a convex optimisation problem following Wardrop's first principle user equilibrium. Equilbrium solutions can be computed using link flows or path flows. A set of link flows are feasible if they satisfy flow conservation and set of feasible path flows exist if those are chosen within the OD pair which minimizes travel time. In Beckmann model, travel time is assumed to be a increasing function of traffic flow. The German Department of Transportation [1] or BPR [49] function of link cost is referenced to follow this assumption.

$$t_e(x_e) = t_e^0 \left[1 + \alpha \left(\frac{x_e}{cap_e}\right)^\beta\right] \tag{1.06}$$

where t_e is the travel time, x_e traffic flow on link e, cap_e is the capacity of maximum vehicle throughput. Link travel time functions are also known as latency functions used later in our optimization problem.

Frank Wolfe Algorithm (FW) - Link based linear formulation: Beckmann's User Equilibrium program

$$\begin{aligned} min \quad & \sum_{e \in E} \int_0^{x_e} t_e(\theta) d(\theta) \\ s.t. & \sum_p f_p^{sd} = \eta_{sd} : \quad \forall s,d \\ & f_p^{sd} \geq 0, : \quad \forall s,d,p \end{aligned} \tag{4.18}$$

Semi-Dynamic Traffic Assignment System Optimal Model:

To find traffic flows in a given network in a realistic scenario, we use the SDTA model following Wardrop's second principle which states that average travel time is at a minimum during system equilibrium. In our agent based framework, EV drivers cooperate with one another in order to achieve system optimal state which follows the Wardrop principle. The first step is to find the travel time on a given path for SDTA model. The travel time on path p linking O-D pair s,d is formulated as:

$$t_{p,s,d}(t) = \sum_{e \in p : p \in \mathbb{R}_{s,d}} t_e(t) \ \ \forall p,s,d \tag{4.19}$$

where $\mathbb{R}_{s,d}$ is a set of OD pair. Based on our previous formulation for Beckmann Model, we add further constraints to this model discussed in the Optimization Model of Transportation Network.

The steps of the FW algorithm are as follows:

- **Step** 1: Initialization, set counter to 1; all-or-nothing assignment based on $t_e = t_e^0$
- **Step** 2: Update travel time as a function of traffic flow: Set $t_e = t_e(x_e)$
- **Step** 3: Direction finding, yield a set of auxiliary flows.
- **Step** 4: Line search
- **Step** 5: Move next
- **Step** 6: Convergence test: If convergence criterion is satisfied, stop (solution = set of equilibrium link flows); else iterate over + 1 & go to step 1.

Solve the Beckmann Model using FW algorithm for our simulation framework:

The steps on how an integrated shortest path algorithm namely Dijkstra's algorithm is used to integrate the Beckmann User Equilibrium Model FW algorithm is given below.

Given: Input demand and network files for the sample network. The files contain OD trip data.

- **Step** 1: Employ Dijsktra's algorithm to compute the shortest path for each EV agent trip based on free flow travel time t_e^0 through each link e. Calculate the traffic flow x_e for each chosen path on link e. Set counter = 1.
- **Step** 2: Update travel time as a function of traffic flow, $t_e = t_e(x_e)$ using BPR function.
- **Step** 3: Again use Dijsktra's algorithm to compute the shortest path for each EV agent trip based on the updated travel times $t_e = t_e(x_e)$. Calculate traffic flow x_e for each chosen path segment. Formally, having found the shortest path $p_{s,d} \in P$ for the corresponding source, destination *s,d* on the edges included in the shortest path $p_{s,d}$, set the traffic flow corresponding to the pair *s,d.*
- **Step** 4: Produce auxiliary flows for all or nothing loading. unconstrained optimization to calculate the optimal step size.
- **Step** 5: Update traffic assignment parameter by flow conservation constraints.

- **Step** 6: Convergence test: If convergence criterion is satisfied, stop (solution = set of equilibrium link flows); else iterate over + 1 & go to step 2.

Traffic Simulation:

Assuming the road network to be a graph with nodes and links wherein EV agents are moving in the network, the following characteristic properties are considered.

- a free flow travel time
- length of the road and number of lanes in the road network
- link flow capacity which denotes maximum vehicles/hr the road can handle.
- number of agents currently on the road network, ie. link.

Solving the Dynamic User Equilibrium Traffic Assignment problem, the output we get is traffic flow and travel time given the road capacity and agents moving in the road network. This information shall be used in our optimization problem later on.

Methods for traffic assignment in transportation network.

The method we employed for the traffic assignment which calculates load on a given network is assignment with traffic congestion based on Wardrop Equilibrium. The steps needed to assign traffic is as follows:

- Region selection and construction of road network through Graph theory. The entire transportation network can be represented as a graph, with nodes denoting the origin-destination points and edges denoting the paths chosen by individual EV agent.
- Construct Origin/destination (OD) matrix: The movements of each origin-destination pair within the transportation network is captured in a OD Matrix.
- Calculate travel costs and travel times: Different factors (e.g., travel time, distance, monetary cost, toll etc.) are grouped into a single entity called generalized cost incurred during a trip. The cost is calculated based on the traffic congestion on each link. Based on various traffic levels (determined by the traffic congestion index factor), costs are updated on every iteration.
- Traffic Assignment: This is the final step of the process. Utilizing the Origin-Destination data simulation can be carried out on a transportation network given the network and demand data, to output the traffic flow. Also, travel times on the given road network links can be computed.

4.1.3 EV Routing and Charging Characteristics

Electric vehicle routing and state transitions

The path chosen by EVs in the transportation network is dependent on many factors such as traffic flow, road congestion level, battery SoC, time constraints etc. Usually drivers tend to choose the shortest path which meets their travel demands avoiding any congestion in traffic flow. We take a simple example where EVs start from their home and make subsequent trips during the day. Based on this trip request made, the estimated travel time is used for the user equilibrium traffic flow study. Let us consider this using a graph network shown in below Fig. 4.3.

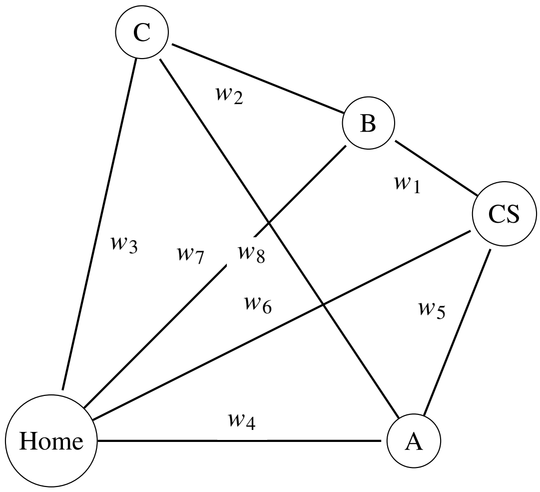

Figure 4.3: Connected Weighted Graph Network of EV travel route showing Origin as Home and trip locations A, B, C with a charging station CS within the network vicinity.

Let a connected Graph be defined as $G = (V \cup \{ C, E \})$ where $\{ V = 1, . . . , n \}$ is the set of nodes (n number of EV agents), $C = \{ n, n+1, ... , n+k \}$ is a set of j charging locations assuming a central point from where EVs originate - Home as a charging location too. E = { (s, d); (s, d) ∈V; s ≠ d } is the set of edges connecting each agent to their respective locations in the origin-destination pair s, d. Each edge $(s, d) \in E$ has some non-negative value which is assigned to trip distance c_{ij}, energy consumption or cost $\psi_{s,d}$ and speed s_{sd} associated with the agents. For each EV agent v ∈V = 1, . . . , n, we define the following set of decision variables:

$$x^v_{sd} := \begin{cases} 1 & \text{if vehicle } v \text{ makes a trip from source } s \text{ to destination } d \\ 0 & \text{else.} \end{cases}$$

$$rc^v_{it} := \begin{cases} 1 & \text{if vehicle } v \text{ has recharged at node } i \text{ for a certain time period } t \\ 0 & \text{else.} \end{cases}$$

$$w^v_j := \begin{cases} \text{Non-negative waiting time of vehicle } v \text{ at charging station } j \end{cases}$$

Dynamic EV Charging Model - M/M/s Queuing Theory Analysis

The arrival time, service time, queue length and charging duration is a part of the service delivery process with multi-objective optimization. Since EVs arrival and charging behavior are independent of each other, we deduce the following assumption for arrival and service rate of EVs at a charging station. The assumption is that the link e is considered as a queuing arrangement with M/M/s queue with Markovian properties [62]. Using this assumption we adopt the Davidson link cost function [19]. In this function, the dependent variable is travel time t which is a function of independent variable traffic flow x with some other parameters such as t_e^0, cap_e and α which is proportionality coefficient for the travel-time cost function.

$$t_e(\vartheta_e) = t_e^0\left[1 + \alpha\left(\frac{\vartheta_e}{cap_e - \vartheta_e}\right)\right] \tag{4.20}$$

The charging completion rate z_0(t) in one minute is the average charging capacity P_{ch}(kW) over battery capacity Q_{batt} of the EV. It can also be defined as the charging ratio based on traffic flow.

$$z_0(t) = \frac{P_{ch}}{Q_{batt} * 60} \tag{4.21}$$

Thus, we can formulate the average number of EVs arriving at a charging station with respect to traffic flow in the network, during a certain time window:

$$\lambda(x_e, t) = z_0(t)T_{ch}\ \frac{\vartheta_{e,t}}{\vartheta_{e,t} * j_{ch}} \bigg/ \Delta_t \tag{4.22}$$

where $\vartheta_{e,t}$ is the captured traffic flow at link e during time t. j_{ch} is the possible number of charging stations in the transportation network. Δ_t is the predicted time interval during subsequent charging activities. T_{ch} is the total charging time for the EVs.

If the number of EVs arriving at a charging facility exceeds the charging pile capacity of a charging station, they need to wait for a certain period of time to get service. This increases the overall travel time which has been formulated above in the Davidson function 4.20.

The probability of EVs charging at a charging station j with k charging piles concurrently using queuing theory can be formulated as:

$$P_j(n) = (\frac{p^n}{n!}) * P_j(0), n = 1, 2..k, \forall j \tag{4.23}$$

$$P_j(0) = \left[\sum_{n=1}^{k-1}(\frac{p^n}{n!}) + (\frac{p^k}{k!(1-\alpha)})\right]^{-1}, n = 1, 2..k, \forall j \tag{4.24}$$

where p is the queue utilization factor related to x_e/Cap_e. The cost function defined by German Department of Transportation [1] is a piecewise linear relation of mean velocity wrt. traffic flow. Being strictly convex, the solution to the User Equilibrium and System Optimal states are unique in nature.

Based on the formulations above, the mobility behavior from JADE simulation data and traffic flow data is shown below in Fig. 4.5 and 4.4. The queuing model based on equations 4.24 and 4.23 are iterated over 24 hours.

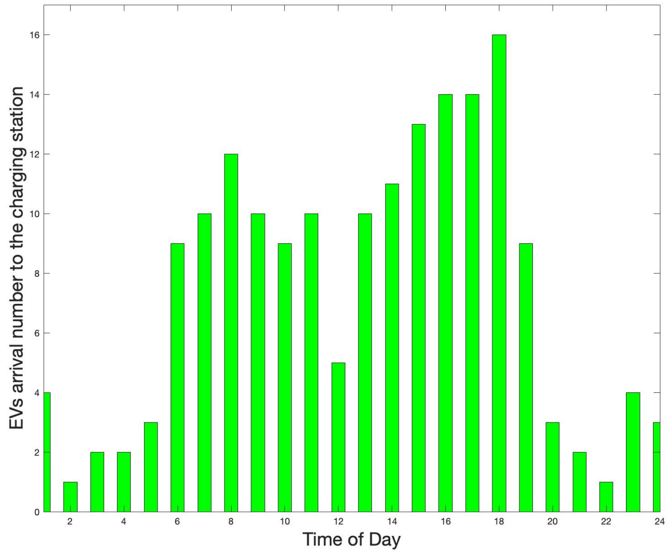

Figure 4.4: Number of EVs arriving at a charging station

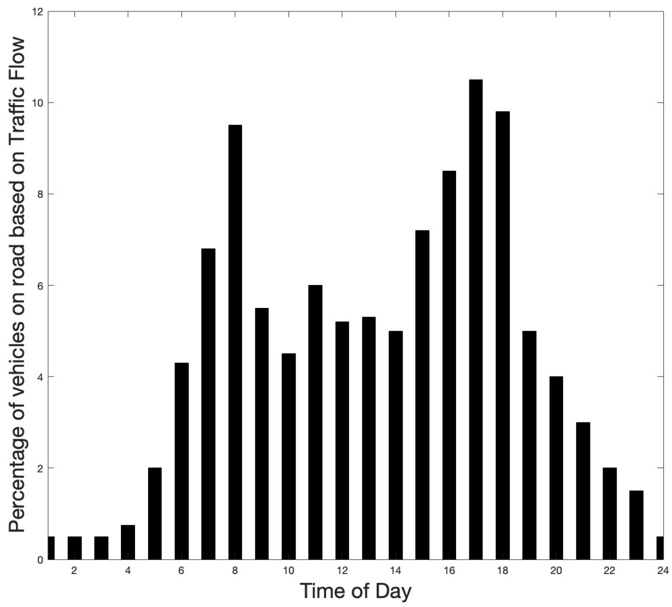

Figure 4.5: Percentage of EVs on road based on JADE simulation and traffic flow data

Dijkstra's shortest path algorithm

To find the shortest path between Origin-Destination (OD-Pair) in the transportation network, the popular Dijkstra's algorithm [20] is used. The nodes represent the location or points where EV users wish to travel and the weights correspond to the distance (in km). The objective is to find the optimal route between two points which minimizes the distance, thereby reducing the need to recharge EV batteries frequently or to find charging spots faster. We modify the algorithm to use multiple weights, one denoting distance and another energy requirements to chose that path or the speed at which a vehicle can travel (low speed in freeway would indicate traffic jam). Ultimately, the energy minimal path shall be chosen for efficient EV routing. The pseudocode of the Dijkstra's algorithm is given below 4.1.

Algorithm 4.1: Dijkstra's Shortest Path Algorithm

```
                                  // Input: Graph G=(V,E) using positive weight function l.
function DIJKSTRAS(Graph, source)
    dist[source] := 0                      // distance from source: Initialization array
    for each vertex v in Graph: do                         // Initialization sequence
        if v ≠ source then
            distance[v] := ∞        // Initially distance from s to v is infinite (unknown)
            previous[v] := NaN // Previous optimal path node from source which is undefined
        end if
        add v to X                              // All unvisited nodes initialized to X
    end for

    while X is not empty: do                                              // Main loop
        u := vertex in X with min distance [u]     // Source node with minimum distance
        remove u from X
        for each neighbor v of u: do
            alt := distance [u] + length(u, v)
            if alt < distance [v]: then                       // Shorter path to v is found
                distance[v] := alt
                previous[v] := u
            end if
        end for
    end while
    return distance[], previous[]
                      // Output: List containing distances - distance(v[1],v[j]) = d(v[j]).
end function
```

Assuming we create a sample network ***M*** (matrix of n x n elements), the assignment rules of element l_{ij} in ***M*** are shown below. Each cell in the matrix contains a positive value which denotes the weight (distance) between links. ***ndl*** indicates that there is no direct link between two nodes. After the matrix ***M*** is developed, the shortest path algorithm can be used to obtain each shortest travel route between a source node to all other nodes in the network.

$$l_{ij} = l_{ji} := \begin{cases} \mathrm{d}_{ij} & \textit{(i, j)} \text{ is an accessible edge in } \boldsymbol{E} \\ 0 & \mathrm{i = j} \\ ndl & \textit{(i, j)} \text{ is not an accessible edge in } \boldsymbol{E} \end{cases}$$

$$\mathrm{M} = \begin{bmatrix} 0 & d_{12} & ndl \\ d_{21} & 0 & d_{23} \\ ndl & d_{32} & 0 \end{bmatrix}$$

EV charging characteristics

Since the power demand due to EV charging depends on the charge pattern, preferences, battery capacity, SoC, time of arrival, route deviations due to traffic congestion etc., these factors are crucial for the determination of overall charging demand at charging stations. The available battery SoC when EVs arrive at charging stations is a random variable with Gaussian distribution model as in [4]. The pdf is described in equation 4.25 with $\mu = 0.5$ (average remaining SoC) and $\sigma = 0.3$ (standard deviation) and $SoC_{available}$ is the remaining SoC of battery. The available SoC is calculated from the JADE simulation data.

$$f(SoC_{available}) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(SoC_{available}-\mu)^2/2\sigma^2} \tag{4.25}$$

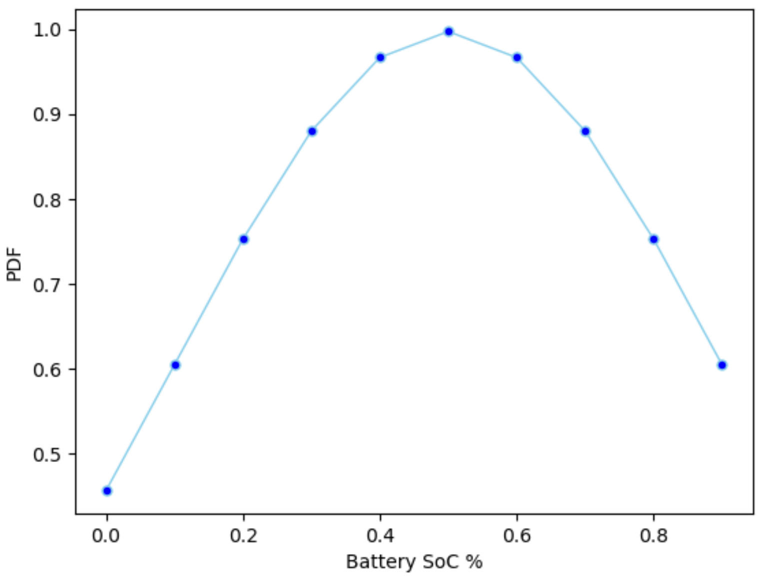

Figure 4.6: Graph showing the probability distribution of discharged EVs battery SoC taking into account the available remaining battery SoC, calculated from trip simulation in JADE.

C. Methods for modeling EV travel behavior pattern

Spatial-Temporal characteristics of EV travel:

The stochastic movement and charging events of EV users have contingent impacts on the spatial-temporal EV charging load characteristics. We introduce a series of variables which define the mobility model of EV travel behavior stochastically assigned to each EV agent. These variables alter the trip time and mileage of a certain EV agent arriving at its next destination. Due to this, the battery SoC and power consumption is changed which in turn affects the duration, location, charging preference and time of EV charging load in the grid.

The ***temporal*** variable denotes the vehicle traveling and parking time - duration. The Initial start time t_0, arrival time a_i, travel time t_i and the parking duration p_i. The spatial variable is defined as the energy consumption rate (mileage) and location of the vehicle during each trip. These are the destination point D_{ij}, mileage m_{ij} and trip distance t_{ij}. The route chosen by the vehicle has certain influence on the variables considered. The ***spatial*** transition probability is defined as a matrix. During a time interval t_i, the probability sum of EV agent driving from point *i* to point *j* is exactly 1. $\sum_{j=1}^{S_t} p_{\rho_{ij},t_i} = 1$, where S_t = state space of location types. The variables are as follows:

Initial start time (t_0): The EV starts the trip at this time of the day. We take the start times of every trip in the morning between 7-8 am and while returning back 5-7 pm.

Travel Time(t_i): The travel time is related to the velocity s_i and distance between *i* and *j* t_{ij}. The mobility data is stored in a 2D matrix from the simulation.

Traffic Flow ($\vartheta_{e,j,t}$): Traffic flow captured by the charging station *j* in time period *t*, in link *e* of the transportation network.

Mileage (m_{ij}): Calculated based on a normal distribution between points *i* and *j* for each vehicle considering their trip distance.

Parking Time (p_i): The parking time for Residential area is a function of the Weibull distribution. For the other areas, we consider the generalized extreme value distribution function. The parking time depends on the location and anticipation for next trip of the user. Assuming a normal distribution for parking duration $p_i \sim N(\mu_i, \sigma_i^2)$, the Probability distribution of parking time can be formulated as

$$f(p_i, \mu_i, \sigma_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-(p_i-\mu_i)^2/2\sigma_i^2} \tag{4.26}$$

Arrival Time (a_i): The arrival time is updated after every step from the initial start time of trip to its final destination including the parking time.

Total Trips per day (K_i): The total trips made in a day are determined using a probabilistic variable generated through a Poisson distribution function which is a discrete distribution,with a Poisson paramter λ.

$$P(k) = \frac{e^{-\lambda}\lambda^k}{k!} \tag{4.27}$$

The arrival of EVs at a charging station is also determined by the Poisson distribution function, where $P(k)$ is the probability of *k* vehicles arriving at a charging station and λ being the average arrival rate. Fig.4.7 shows the Poisson distribution for EVs arriving at a charging station.

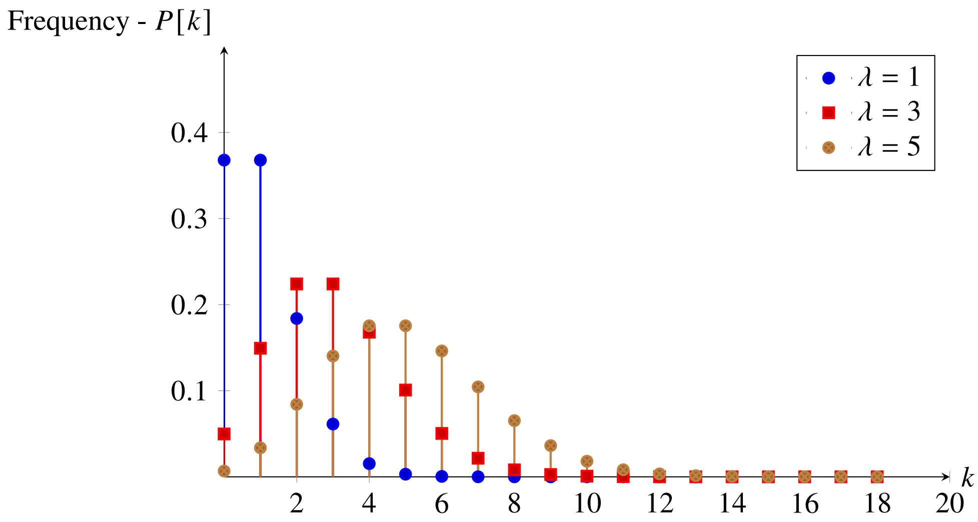

Figure 4.7: Probability of arrival rate of EVs at a charging station

Destination Point (D_{ij}): The destination is modeled according to a Probability Distribution Function based on the transportation network topology. Each destination point is randomly allocated to each EV.

Velocity of Vehicle (s_i): To keep the model simple, velocity of EV agents are modeled as constant values. However, due to traffic consideration, there is a deceleration factor where negative velocity induces slow moving vehicles or braking scenarios. Deceleration factor (d_i) = - s_i.

SOC(SoC_i): assigns the initial state of charge of the vehicle. It can be formulated mathematically using the probability distribution model as:

$$f(SoC_0, \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(SoC_0-\mu)^2/2\sigma_i^2} \tag{4.28}$$

where SoC_0 is the initial SoC of battery usually between 0.2 and 0.8. μ is the average SoC value and σ the standard deviation of the model.

Total distance $(T_i)$and **trip distance** (t_{ij}). The total distance covered by the vehicle in a week is the cumulative exponential distribution function of the trips made per day expressed as:

$$T_i = \sum_{j=1}^{K_i} t_{ij} \tag{4.29}$$

Simulation was performed to evaluate the charging demand in the power network for various scenarios of spatial-temporal features.The methodology includes stochastic variables as defined above and for individual charging preference of EV users, battery capacity, operational facilities at charging stations which ultimately affects the charging load. In the simulation, defining the number of iterations and EV agents is deemed necessary. The time step for every iteration is set at 30 minutes interval.

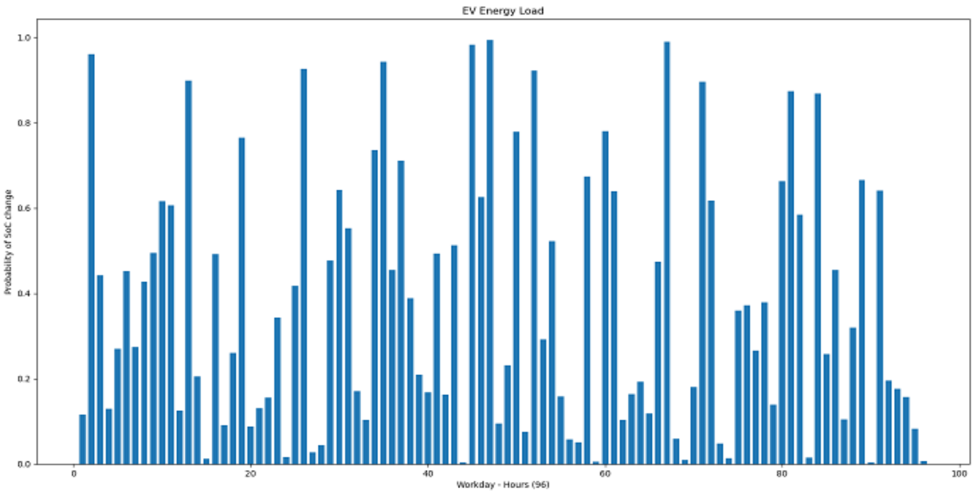

Figure 4.8: Relative change in SoC due to driving patterns

Fig.4.8 shows the relative change in SoC profile computed from an Agent-based modeling framework JADE over a period of 96 hours. The peaks indicate a change in battery SoC due to charging activities and travel patterns. There is a considerable variation in SoC percentage during the day especially between peak hours and off-load hours. The ideal scenario would be to flat the peak curves to bring a more stable impact towards the power grid. The model estimates the SoC changes based on trips made during each day considering minimum and maximum energy preferences, number of EVs, the trip duration on a typical workday, number of hours to simulate etc.

Traffic Data and EV Driving Pattern

EV users' driving pattern provides an insight into the daily distance traveled and charging times which ensures that the drivers' trip requirements are satisfied. Due to the low public availability of EV users data, a survey made in [5] from northern Europe and Danish National Transport Survey [81] shows the data about some key variables including driving range, charging behavior with the location, time and charging method. The battery SoC, destination for each trip, energy consumption of car per km and charging load from charging stations are important factors for EV integration research. The key parameters needed for this are defined in the below table 4.1

Description	Value / Parameter
Initial SoC	75-85%
Average Energy Usage	150-180 Wh/km
Workday Trip Start Time	7-8 am
Workday Trip End Time	5-6 pm
Parking Duration	P_t
Charging Duration	C_t

Table 4.1: Parameters for EV charging

4.1.4 Electric Vehicle Energy Consumption Model

4.1.4.1 EV Charging Mathematical Model

When considering the load impact of an EV charging scenario based on the placement of charging stations, the important players are charging power, duration of charge, battery SoC and charging moment. So to develop a mathematical model of the EV energy consumption, we must quantify the charging heuristics. Depending on the type of charging facility available at a charging station (AC slow charge or DC fast charge), the charging power and duration will vary considerably. Subsequently the energy load will be dependent on number of EVs simultaneously charging at a specific station during a certain time period. Thus, EV charging power can be considered as a discrete random variable. EV plug-in time and charging moment is important for stochastic modeling, as it might portray an instantaneous increase in load depending on the charging characteristics. Since the start time of charging and duration dependent on the battery SoC is purely stochastic a probability distribution function modeling approach is well suited to estimate the charging needs. According to [57], most EV users charge their EV batteries at 6 pm and more than 90% of them charge between 1 pm and 23 pm. The Gaussian distribution for these charging events in discrete time windows i can be modeled as:

$$f(c_i, \mu_i, \sigma_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-(c_i-\mu_i)^2/2\sigma_i^2} \tag{4.30}$$

where c_i is the time when EV starts to charge, μ is the mean for maximum probability density location and σ is the standard deviation of charging time. The probability distribution of EV charging start time is shown in Fig. 4.9.

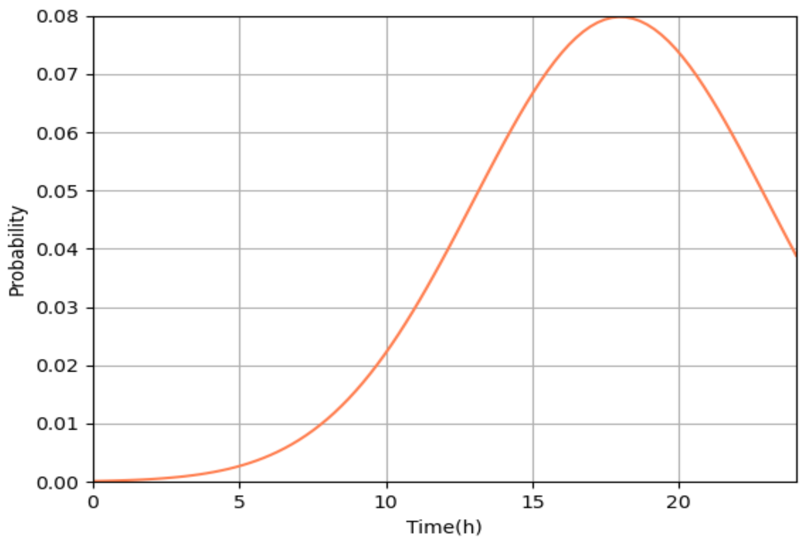

Figure 4.9: Probability distribution of EV charging time initiation. Most EV owners usually tend to charge their EVs after coming back from work during evening hours.

4.1.4.2 Factors affecting EV charging load

The EV charging load is affected by the charging characteristics, behavior, location, battery State of Charge (SoC) and number of EVs charging simultaneously. The charging behavior comprises of the start time of charging, daily trip mileage and SoC. The different charging modes are shown in 4.2. Charge-characteristics are the rated battery capacity, charge per km (mileage), rated power, charging power etc. The charging operation for a fleet of EVs at the charging station varies with the amount of energy estimated as a function of time and is dependent on the EV users individual preference. The need to recharge at a charging station is dependent on a certain opportunity during a trip. Based on the SoC and several other factors pertaining to traffic flow and EV characteristics, multiple charging opportunities might be presented at different locations which have been summarized in 4.3.

Vehicle Charging Modes

Typically EV users charge at residential complexes with slow Level 1 charger with rated power of 1.2 kW. In public places where fast charging options are available, such as in office or dedicated charging stations near highway or city node points, level 2 and level 3 chargers are employed whose power rating are 7kW and greater than 20 kW. We define the different charging modes as follows:

Charging Mode	Rated Power
Level 1 - Home	1.2 kW
Level 2 - Office	7 kW
Level 3 - Public Fast Charging	> 20 kW

Table 4.2: Different Charging Modes

Vehicle Parameters

The different stochastic vehicle parameters that are used to model the simulation is given in the below table 4.3. These parameters are mostly related to the trip behavior of EV agents.

Description	Value / Parameter
Initial SoC	75-85%
Average Parking Time	P_t
Workday Trip Start Time	7-8 am
Workday Trip End Time	5-6 pm
Traffic Jam Waiting	T_{jam}
Charging Duration	C_t
Charging Efficiency	95-99%
Battery Capacity	Q_{batt}
Charging Power	P_{ch}

Table 4.3: Parameters for Vehicle Trip - OD pair

4.1.4.3 Charging Power Consumption

When we have the initial data of EV charge location, start-end times of charging, initial SoC of battery etc., we can model the power consumption based on [12].

$$P = \int_{ch_0}^{ch_0+T} P_{ch}(t)dt = (1 - SoC_i)Q_{batt} \tag{4.31}$$

where P is the power consumption at time T, SoC_i and Q_{batt} is the initial SoC and rated capacity of EV battery, ch_0 the start time of charging through duration T, $P_{ch}(t)$ denotes the maximum charging power at time t. Here T can be used to denote the duration of charging time when EVs are parked at a charging station. The total electrical consumption from the power grid will be the energy required for the charging station to bring SoC to 100% or up to the desired power level to reach a certain destination determined by the user.

4.1.4.4 Relative change in Battery SoC due to travel behavior.

As EVs move in their daily travel behavior, the SoC changes relative to the traffic conditions and other behavioral factors. The initial battery SoC follows a gaussian distribution. The change in battery SoC for an EV influenced by traffic and other activities during a typical workday commute is shown below in Fig. 4.10

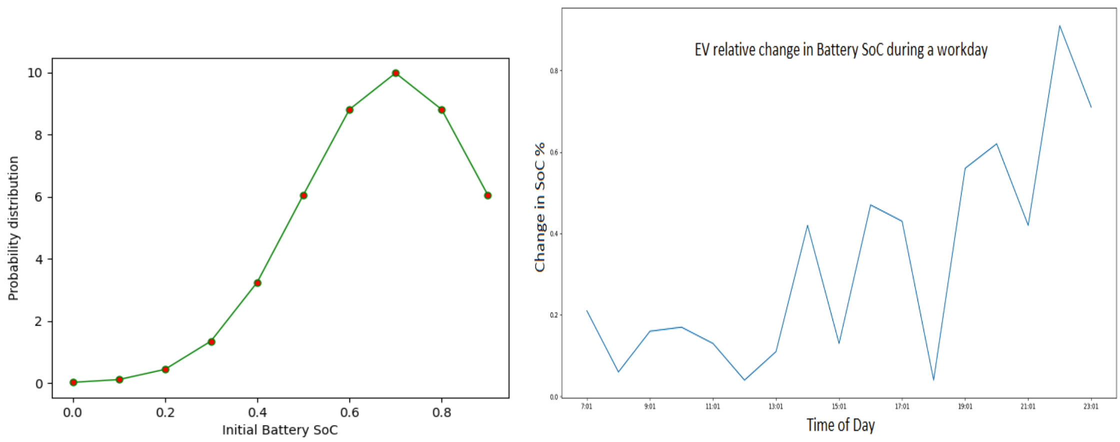

Figure 4.10: Probability distribution of initial battery SoC which shows the percentage of battery EVs account for while starting a trip. The relative change in battery SoC for trips made during the day is shown in the right figure. For this paper we consider the initial SoC to be between 60% to 80%.

4.1.4.5 Optimized EV charging schedule using *Smart Charging* technique

To determine the most profitable start time for charging an EV battery, the mathematical modeling of *smart charging* is an optimization problem which aims to minimize the EV charging cost at a domestic or public charging station.

$$min\left(\sum_{t=1}^{n} R_t^k * L_t^k\right) \tag{4.32}$$

Equation 4.32 defines the Objective Function, where R_t and L_t^k represent the charging rate in unit price and charging load at station k during time t respectively. The constraints for the objective function in (4.32) are as follows:

$$\sum_{t=1}^{n} L_t^k = (1 - SoC_i)Q_{batt} \tag{4.33}$$

Equation 4.33 is the constraint for EV energy demand with initial SoC, where SoC_i and Q_{batt} is the initial SoC and capacity of EV battery. From the expression P = VI, the charging power must not exceed a certain threshold value.

$$0 \leq P \leq P_{ch}(t) \tag{4.34}$$

Equation 4.34 is the constraint for EV Charging Power where $P_{ch}(t)$ denotes the maximum charging power at time t dependent on SoC and temperature. Hence, $P_{ch}(t)$ can be expressed as a function of SoC (ω) and temperature (T) $P_{ch}(t) = f(\omega$(t)), T(t)). Please note that ω(t) is the SoC of EV battery at time t.

If the total EV batteries being charged at time t = 1,2,..,n and their fractions be c_1, c_2,..,c_n, then the total charging fractions must be $\sum_{t=1}^{n} c_t = 100\%$. Also if n_t is the total percentage of EVs charging then $0 < n_t < 1$.

Let V_i be the voltage magnitude at bus i, V_i^{min} and V_i^{max} are the minimum and maximum voltage magnitudes at bus node i, then the constraint for Voltage Magnitude is satisfied by the following equation:

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{4.35}$$

1. Proposed EV Charging Load and Optimal Power Flow Model.

A high level model of the proposed charging demand and optimal power flow is shown in Fig. 4.11. Traffic assignment problem has been integrated with JADE simulation to gather EV mobility behavior. The charging load is aggregated based on the energy required from the power grid when EVs are connected to a charging pile.

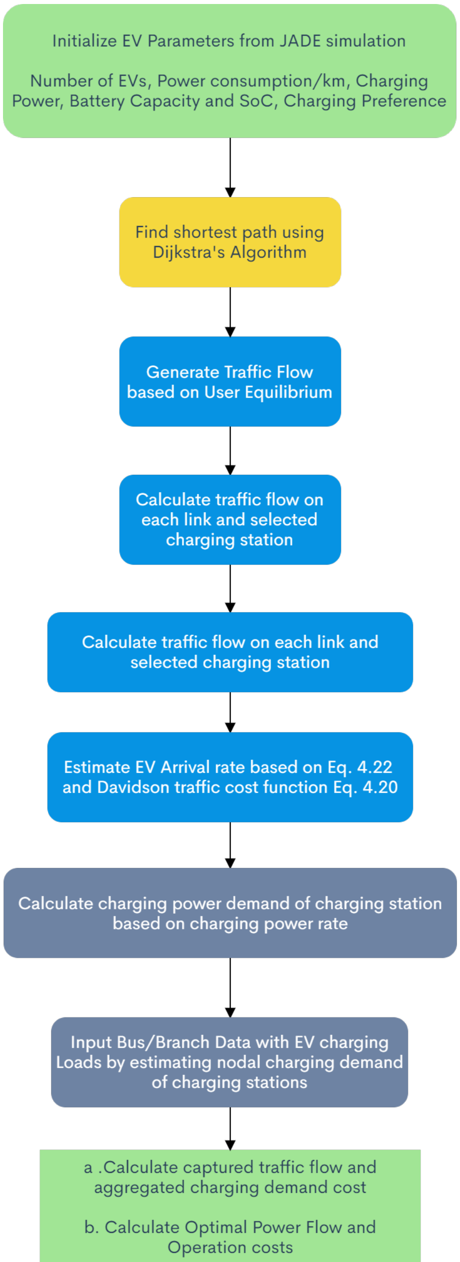

Figure 4.11: A high level representation of the EV charging demand and Optimal Power Flow of considering Power Distribution Network and Transportation Network.

2. EV charging load estimation

The EV charging load at each charging station throughout the day is formulated below. The depleted energy *E (kWh)* of an EV *v* battery at time period *t* can be defined as:

$$E_t^v = \begin{cases} E_t - 1^v + E_{ch}^j * \delta t & \text{if charging the EV at station j,} \\ E_t - 1^v - \psi * d & \text{if EV is driving,} \\ E_t - 1^v, & \text{else} \end{cases} \tag{4.36}$$

where the E_{ch}^j is the charging power (kW) at station *j*. d is the driving distance (km), and ψ is the specific energy consumption of an EV expressed in (kWh/km). Power relates to the transmission rate of energy. It is the average power output, measured in watts (W) whereas Energy is expressed in KWh.

Hence, the total charging load L (kW) at each station *j* at time *t* is:

$$L_t^k = E_{ch}^j * V_t^j \tag{4.37}$$

where V_t^j is the number of EVs charging in station *j* at time *t*. The energy consumption of an EV will be the total power required to bring the SoC to 100% or depending on the user's charging preference. By summing up the traffic flow at links connected to each charging station *j*, the total number of EVs being charged at time *t* can be calculated.

The below table 4.4 shows the energy requirement due to change in SoC % for a single EV during a weekday. From our JADE simulation, initially considering the SoC to be 90%, the energy requirement and charging time based on 3 charger types can be evaluated from the below table.

Initial SoC %	90%	80%	75%
Final SoC %	79%	39%	13%
ΔEnergy (kWh)	1.1	3	5.8
Δt 3 (kWh)	0.36	1.0	1.9
Δt 7 (kWh)	0.15	0.42	0.82
Δt >22 (kWh)	0.05	0.13	0.26

Table 4.4: Energy requirement wrt change in SoC %

From the above table, it is quite clear that an average EV user would require about 3.3 hours of wait time at a slow charging pile to recover upto 80% battery SoC. Similarly if a fast charger of 22 kwH is used, the same person would require 0.13 hours to recharge its EV battery to 80% SoC. Assuming there are several EVs at a charging station, the energy usage and charging time increases significantly posing a threat to the distribution network.

Given the charging power rating of each EV and the energy required to complete a trip, the amount of energy required from the power grid A_{ch}^{ev} for each EV can be calculated. To calculate the cost of charging in order to bring the battery SoC to 100%, we must multiply the EV battery capacity (kWh) with the charging cost per kWh, determined by the network operators.

4.2 Power Flow Model Basics

4.2.1 Basic Problem Framework

The power flow problem is a fundamental problem of calculating the bus voltages (magnitude and angle) of a distribution network at steady state under given conditions of load, generation and network statistics. Taking concepts from Power flow analysis from [89] which is fundamental to our power system optimization, we formulate our model. A power flow model is built using relevant load, generation and network data. The input/outputs are shown in 4.12. By solving nodal power flow equations the output of the optimal power flow problem is generated. The inception point of determining power flow problems is to associate the known and unknown variables. The list of known and unknown variables for 3 bus types are summarized in Table.4.5. Based on these variables, the buses are categorized into three types: Slack (Reference), Load/Generation (PV), and Load(PQ) buses [2].

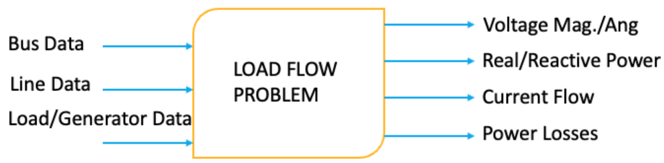

Figure 4.12: Input/outputs to calculate steady state operating features of a power network from given line and bus data.

Bus Type	Voltage (|Vi|, Angle)		Real Power			Reactive Power		
	Mag	*Angle*	*Gen*	*Load*	*Net Pi*	*Gen*	*Load*	*Net Pi*
Slack/Swing	S	S	U	S	U	U	S	U
Generator/PV	S	U	S	S	S	U	S	U
Load/PQ	U	U	S	S	S	S	S	S

Table 4.5: ***S=Specified, U=Unknown***, Description of 3 Bus Types with Real and Reactive Power specifications. The known and unknown variables are also specified.

The loads are connected to the PQ Bus and based on Optimal Power flow calculations, Power generation cost, Voltage Magnitude, Voltage Angles, Power Losses etc. are calculated. This helps us to determine any imbalances and vulnerability of the PDN. Details of the power flow problem has been discussed in our Optimization Problem formulation.

Since the R/X ratio (Reactance to resistance of power line) of transmission line will be less than Distribution line because of shortness in line length and the low voltage level, conventional power flow method such as Newton-Raphson is not suited for radial distribution network. Reason being divergence criterion of the algorithm. Hence we use the Backward-Forward Sweep method [61] for power flow analysis. MATPOWER is the choice for power flow analysis using power system simulation and optimization which is a free and open-source tool used in MATLAB. The IEEE 30 test node radial distribution system was used for analyzing the voltage deviations and power losses due to EV loads.

4.2.2 Load flow problem formulation

The operating conditions of the radial distribution network under steady states for a given set of input like EV load demand, we define the radial power flow analysis network as follows:

1. There is a network of nodes (Buses) and Branches (Lines or Transformers)
2. Consumers (EV users denoted as loads) withdraw power at nodes.
3. Suppliers/Generators inject power at nodes to balance the overall demand supply, ie. Branch flows out of a node (supplier) = net nodal injection (generation demand).

Each node is described by 4 main variables:

- μ_i = Voltage magnitude
- δ_i = Voltage angle
- P_i = Real power
- Q_i = Reactive Power

For each bus i, the steady state equations for Real and Reactive Power can be written as:

$$\begin{aligned} P_i &= |\mu_i| \sum_{k=1}^{n} |\mu_k||Y_{ik}| \cos(\Delta_{ik} + \delta_k - \delta_i) \\ Q_i &= -|\mu_i| \sum_{k=1}^{n} |\mu_k||Y_{ik}| \sin(\Delta_{ik} + \delta_k - \delta_i) \end{aligned} \tag{4.38}$$

Backward-Forward Sweep Method using Kirchhoff's Law:

The backward-forward Sweep method [61] utilizes the radial bus network topology of distribution systems. There are three 3 main steps. The first step is the calculation of nodal current injection in each node. Next is the backward sweep process where branch line-currents in child lines are first computed and then subsequently the branch current on the main line is computed using Kirchhoff's law. The initial starting point is the branch last in the order. The last step is the forward sweep where the bus node voltages are updated initiating from the root bus. The three steps are iteratively run until the voltage magnitude values at each node in the current and former iteration is less than a specified tolerance factor.

4.3 Optimization Model of Transportation and Power Networks

We present refined optimization models of the coupled transportation and distribution networks subject to specific constraints related to our study. The interactions between EVs charging impact on the PDN are captured. The idea is to make a conjunction between the two generally independent networks and formulate an optimal operation which aims at minimizing the social welfare cost associated within them.

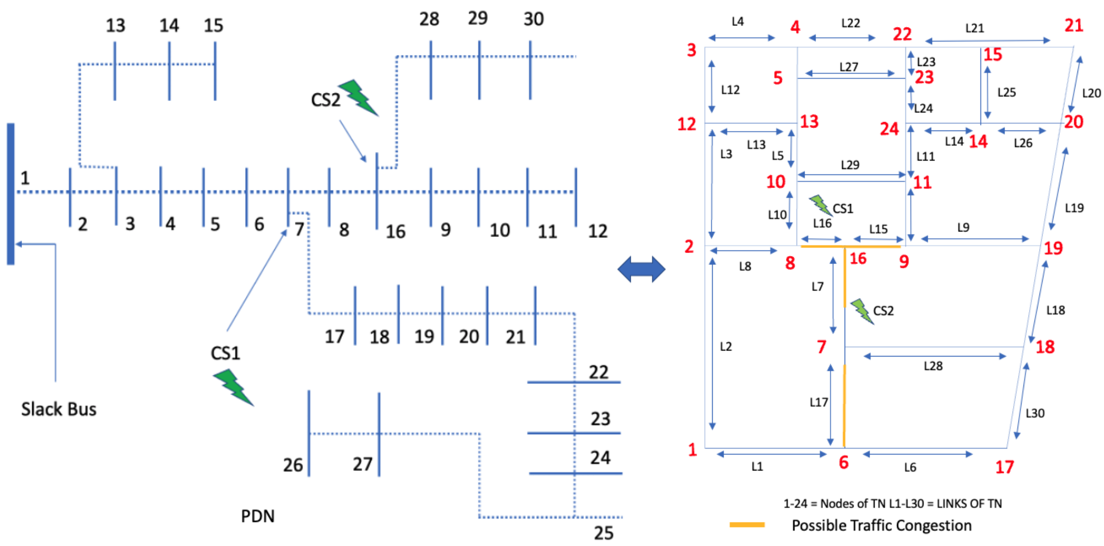

Figure 4.13: Schematic representation of modified IEEE-30-Bus test radial network (line diagram) with connected charging stations and the sample snapshot of transportation network with 24 nodes. We assume each node is connected bidirectionally in the TN.

The IEEE 30–bus power system test case with two connected charging stations CS1 & CS2 is shown in Fig. 4.13. The radial power system topology allows to evaluate multiple EV fleets power demand load discharge scenarios where links are serviced by an electrical bus. Links between nodes 7 and 16 serve as the main conjunction for the PDN. The charging station CS1 is placed at the conjunction of main road connecting to bus node 7 in distribution network and CS2 is placed at the branch node of Bus 16 which is located within the OD pair of the given transportation network.

4.3.1 Transportation Network Model

We design the topological structure of the transportation traffic network using a connected Graph ***G(V,E)***. Its a simplified diagram representing the road network having ***V*** as the set of nodes and ***E*** as the links between nodes with its corresponding distance (in kms). $v \in V$ is the set of end points or intersection of multiple road sections inside the transportation region. These end-points can be origin or destination nodes and its links have associated costs which is the travel time for EV users. Within the Transportation Network (TN), each EV leaves from its origin ***s*** and travels to ***d*** which can be considered as source and sink. Let $\vartheta_{e,t}$ denote the traffic flow on link $e \in E$, which is generated by traffic demand of Origin-Destination pair (s,d) connected by subset of paths in V. A latency function $\tau_{e,t}$ represents time to travel on link e, as a function of aggregated traffic flow on link e. Each EV user tries to minimize its shortest path travel time in traffic roadways.

We formulate the optimization of TN as travel time cost and associated cost of energy during a charging event for aggregated EVs at the charging station, subject to some constraints. The objective function C_{TN} is defined as follows:

$$C_{TN} \quad := min \sum_{t \in T(T)} \sum_{e \in T(E)} \left([w * \tau_e(t)] + X_{e,t}^{Cg} \right) \vartheta_{e,t} + G_{ch}^{ev} \tag{4.39}$$

subject to the following constraints:

$$\tau_e(\vartheta_{e,t}) = \tau_e^0 \left[1 + \alpha \left(\frac{\vartheta_e}{cap_e - \vartheta_e} \right) \right] \tag{1.1}$$

$$C_j^{ev}[\pi_0(t)] = w + P_{ch}^{ev} \pi_0(t) \tag{1.2}$$

$$C_{p,t}^{sd} = \sum_e \left(C_j^{ev} \tau_{e,t} + X_{e,t}^{Cg} \right) \psi_p \tag{1.3}$$

$$T_{p,t}^{sd} = \sum_e \tau_{e,t} \left(\vartheta_{e,t} \right) \psi_{e,p} \tag{1.4}$$

$$\sum_{p \in P_{sd}} f_{p,t}^{sd} = \eta_{sd}(t) + X_{e,t}^{Cg} [x_{t-1}^{sd} - x_t^{sd}], \forall s, d \tag{1.5}$$

$$\vartheta_{e,t} = \sum_{p \in P_{sd}} f_{p,t}^{sd} \psi_{e,p}, \forall e \in E \tag{1.6}$$

where τ_e^0 parameter is the travel time (free flow) on link e, $\vartheta_{e,t}$ is traffic flow, cap_e is the capacity of link e, α is a parameter for Davidson function in **(1.1)**. We used the Davidson's function because it is linear and easily solvable fitting into actual traffic data. C_j^{ev} is the charging cost of EVs at a charging station *j*. P_{ch}^{ev} is the charging power-rate of unit traffic flow in the network (100 vehicles/h) and π_0 is the location marginal price (LMP) in **(1.2)**. In Eq. **(1.3)**, $C_{p,t}^{sd}$ denotes the travel cost on path *p* in O-D pair *s-d* for departure time *t* and $\psi_{e,p}$ is a decision variable to state if path *p* on link *e* is chosen or not. Also, $C_j^{ev} \tau_{e,t}$ denotes the aggregated link travel-time and charging cost. $X_{e,t}^{Cg}$ denotes the traffic congestion cost index of the selected flow link during time *t* which can be expressed as a ratio between traffic flow and road capacity in **(1.3)**. $T_{p,t}^{sd}$ is the travel time on path *p* between the Origin-Destination pair (s,d) in **(1.4)**. Flow conservation constraint is satisfied in **(1.5)** for all residual traffic flow in origin destination pair from current to previous time period traffic demand wrt. congestion index and added to the current traffic demand $\eta_{sd}(t)$. $f_{p,t}^{sd}$ is the traffic flow on path *p* between source and destination pair. Constraint **(1.6)** denotes traffic flow on link *e* is the sum of all possible taken routes or paths through each link in the time horizon *t*.

The first term of the objective function $\left([w * \tau_e(t)] + X_{e,t}^{Cg} \right) \vartheta_{e,t}$ in **4.39** refers to the travel cost associated with traffic flow for all EVs including traffic congestion cost index. The second term of the objective function G_{ch}^{ev} denotes the aggregated charging cost of all EVs at charging stations referred to in equation **4.43**. As the number of EVs grows, the charging demand grows significantly which changes our objective function value.

The constraints associated with charging of EVs at charging station are:

$$0 \leq P_{ch}^{ev} \leq P_{rmax}^{ev} \tag{1.7}$$

$$P_{ch}^{ev} + SoC_{\min}Q \leq SoC_{\max}Q \tag{1.8}$$

$$\sum_{j=1}^{Cap_j} \sum_{k=1}^{Cap_k} P_{j,k}^{ev} \leq Cap_j * l_j(Cap_j)N_j \tag{1.9}$$

$$\sum_{j=1}^{Cap_j} \sum_{k=1}^{Cap_k} H_{j,k} = N_{ch}^{ev} \tag{2.0}$$

- Constraint (1.7) states that charging rate must be within the maximum charging rate of EV.
- Constraint (1.8) denotes the charged quantity (kWh) must be less than the maximum vehicle battery capacity Q.
- Constraint (1.9) states that sum of all EV charging instances $P_{j,k}^{ev}$ should be less than or equal to the total charging capacity of the charging station. Cap_j stands for charging station capacity, l_j the load it can handle and N_j is the power efficiency factor.
- Constraint (2.0) restricts the maximum number of charging piles k which could be installed at charging station j is N_{ch}^{ev}, where $H_{k,j}$ is a decision variable to state a node has been assigned to a charging pile in the charging station. Station j have at most Cap_k charging piles.

4.3.2 Power Distribution Network Model

A PDN is operational based on radial or mesh network. In our study, we consider the radial distribution network installed in urban areas, represented by a directed Graph $\mathcal{G}$ ***(M,B)*** in a tree topology. The set of buses is denoted by $\boldsymbol{M}$ and the set of branches or power distribution lines are denoted by $\boldsymbol{B}$. The slack bus is indexed as O and a pair {i, j} is used to denote a link between bus i to j. If a load or generator is connected to each bus node $i \in M$, then its corresponding electric power demand or bus injection power is set to 1 deterministically. Voltage profile and power losses are contributing factors which can determine the security of safe operation of distribution networks in Direct Current Optimal Power Flow (DCOPF) [23] model. However, using DCOPF power flow equations are not suited for distribution systems because of high voltage fluctuations and power losses are higher than transmission systems. To stabilize the voltage magnitudes, reactive power must be injected into the system. DCOPF power flow solutions may not be feasible because they might not satisfy all non-linear power equations. Tightening those relaxations might become difficult to scale to bigger networks in future. Owing to these issues, convex relaxations of AC power flow equations have been adopted through second-order cone [8] method. Generally, solving AC-OPF problems through convex relaxations provides a feasibility check on global optimal solution. If the solution is not feasible, a lower bound on the objective function is provided by solving the OPF. Relaxations on AC-OPF can lead to convex optimization problem which are easy to compute providing bounds. AC-OPF problems are generally assumed to be NP-Hard [41], [10], however for optimisation in distribution networks, AC Power flow equations are typically more important.

4.3.2.1 Optimal Power Flow

An OPF problem is defined as: power flow analysis when combined with economic dispath (ED) problem gives us an optimal power flow solution. Since the standard power flow doesn't consider generation costs, the economic dispatch problem is used to minimize the operating cost (generally fuel costs) of a power distribution network with some constraints.

Let V_i, I_i, p_i, denote the voltage, current and power injection for each bus $i \in M$ respectively and χ_{ij} denote the bus admittance, I_{ij} current flow from bus i to j for each line pair in { i, j }. The summary of used notations which are standard in power flow studies are shown in Fig. 4.14.

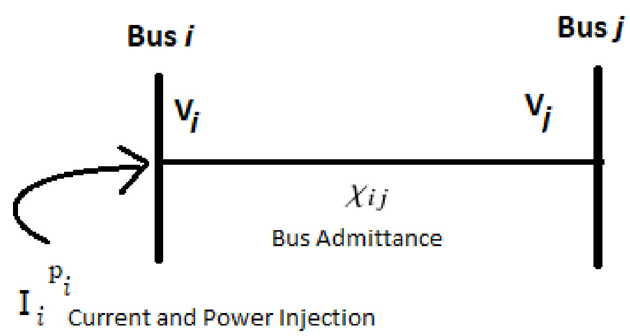

Figure 4.14: DC network model notations

During each time period t, branch flow equations are iterated to calculate power flow. We employ the seconder order cone programming technique [8] for optimal power flow (SOC-OPF) to solve the optimization problem due to some non-linearity in our constraints which must be relaxed and transform into a convex-optimization problem. This ensures that the problem can be solved in polynomial time and make it tractable. The power flow equations and relaxations are adopted from [26], [45], [23]. Assuming there exists a Power Network System Operator in Smart Grid managing the operations in PDN whose objective is to minimize the power generation cost based on EV charging demand. The objective is to lower the power generation and power purchase cost from the grid, maximizing social benefits. Hence, the operational cost of PDN (C_{PDN}) is formulated as:

$$C_{PDN} \;:=\; \sum_{j \in M} \Phi_j [(p_j^{gen}(t))] + \pi_0(t) \sum_{c \in \lambda_0} \Gamma_{0c}(t) \tag{4.40}$$

where λ_j is the set of child end buses in the distribution line starting from bus j.

The first part of the equation states cost for loads connected at bus j during time period t and the second part is the energy purchase price from power grid. $\Phi_j [(p_j^{gen}(t))$ is the convex cost function which denotes the cost of generating power from bus j at time t. $\pi_0(t) \sum_{c \in \lambda_0} \Gamma_{0c}(t)$ is the purchase cost of energy from main grid where $\pi_0(t)$ is the co-efficient of energy production cost during time period t. We assume that energy consumption is charged by the operator using LMP (Location Marginal Price) which is usually a fixed contract price in a region. Power generated at bus i during time t is denoted by $p_{i,t}^{gen}$, demand by $p_{i,t}^{dem}$, and voltage angle on bus i is denoted by θ_i. Power flow from node i to j is denoted by P_{ij}.

The constraints for the power flow equations in PDN are:

$$P_{ij,t} + p_{j,t}^{gen} - r_{ij} I_{ij,t} = \sum_{k \in \lambda_j} P_{jk,t} + p_{j,t}^{dem}, \forall l, t \tag{2.1}$$

$$Q_{ij,t} + q_{j,t}^{gen} - x_{ij} I_{ij,t} = \sum_{k \in \lambda_j} Q_{jk,t} + q_{j,t}^{dem}, \forall l, t \tag{2.2}$$

$$U_{j,t} = U_{i,t} - 2\left(r_{ij} P_{ij,t} + x_{ij} Q_{ij,t}\right) + ((r_{ij})^2 + (x_{ij})^2) I_{ij,t} \forall l, t \tag{2.3}$$

$$I_{ij,t} \geq \frac{\left(P_{ij,t}\right)^2 + \left(Q_{ij,t}\right)^2}{U_{i,t}} \tag{2.4}$$

$$I_{ij,t} \leq I_l^r, \forall l, t, U_{i,t}^f \leq U_{i,t} \leq U_{i,t}^r, \forall i, t \tag{2.5}$$

$$p_i^f \leq p_{i,t}^{gen} \leq p_i^r, q_i^f \leq q_{i,t}^{gen} \leq q_i^r, \forall i \tag{2.6}$$

$$\theta_0 = 0 \tag{2.7}$$

- Constraints (2.1) and (2.2) denote the Nodal Active Power Balance and Reactive Power Balance of the network.
- Constraint (2.3) represents Ohm's law formulation of voltage drop on branch i-j.
- Constraint (2.4) denotes the SOCP relaxation applied to nodal active and reactive power.
- Constraints (2.5 - 2.6) puts upper/lower bounds on current/voltage limits as well as generator output.

Next, we discuss the methodology on how to solve the above problem using heuristics.

4.3.2.2 GA-OPF - Optimal Power Flow using Genetic Algorithm Solution

Our objective is to solve the load dispatch problem by minimizing the energy generation cost. We solve the OPF problem using a quadratic cost function to minimize the total power generation cost and power losses wrt. EV charging demand. The flowchart of the solution algorithm is shown in 4.15 The solver we used was the *MATLAB Global Optimization Toolbox* which provides functions to find global solutions to an optimization problem. It is useful because it can handle non-linearity in the power flow equations and solvable by heuristics such as genetic algorithm. The method used is as follows:

- **Step1:** We run optimal power flow analysis in IEEE 30 node test base system using Backward-Forward Sweep method [61] to get the power flow data consisting of bus voltage magnitudes.
- **Step2:** Obtain bus data (voltage magnitudes & power flow), branch data and power generation cost co-efficient values from previous step.
- **Step3:** Convert the constrained optimization equation to unconstrained problem by using a penalty factor method.
- **Step 4:** Run the optimization problem in 4.40 through Genetic Algorithm for x generations and find optimal solution to our load dispatch problem by considering the analysis done on Step 2.

To minimize the total real power generation cost, an OPF objective function is formulated as:

$$min \sum_{i=1}^{x}\left(a_i P_{g,i}^2 + b_i P_{g,i} + c_i\right) + 1000 * abs\left(\sum_{i=1}^{x} P_{g,i} - P_{dem} - P_{loss}\right) \tag{4.41}$$

$$\text{s.t:} \sum_{i=1}^{x} P_{g,i} = P_{dem} + P_{loss}$$

$$P_{loss} = active(\sum_{j=1}^{x} V_i Y_{ij} V_j)$$

$$Q_{loss} = reactive(\sum_{j=1}^{x} V_i Y_{ij} V_j)$$

where $P_{g,i}$ is the active power generated at bus i. a_i,c_i, c_i are the cost coefficients at generator i. The equality conditions of power flow are applied here. The inequality constraints are upper and lower bus voltage magnitude/angle limits, boundary conditions on active power generation at generator buses and upper/lower bounds on reactive power generation as well as injection.

Our genetic algorithm iteratively runs on the following steps:

1. Generate a set of populations, generation limits and candidate solutions array.
2. Load Bus and Branch data from case file (added EV charging load)
3. Initialize Y-bus to zero.
4. Form Y bus and diagonal elements of branch admittance values.
5. Initializing Jacobian matrix (Bus data values)
6. Calculate Active/Reactive power
7. Perform iteration and generate offspring from reproduction, crossover, and mutation.
8. Chromosomes of the new offspring are evaluated via fitness value related to cost function.
9. Re-iterate for each offspring for best fitness value.
10. If max generation is reached or search goal is attained, return the best chromosome value as final solution, else go to step 7.

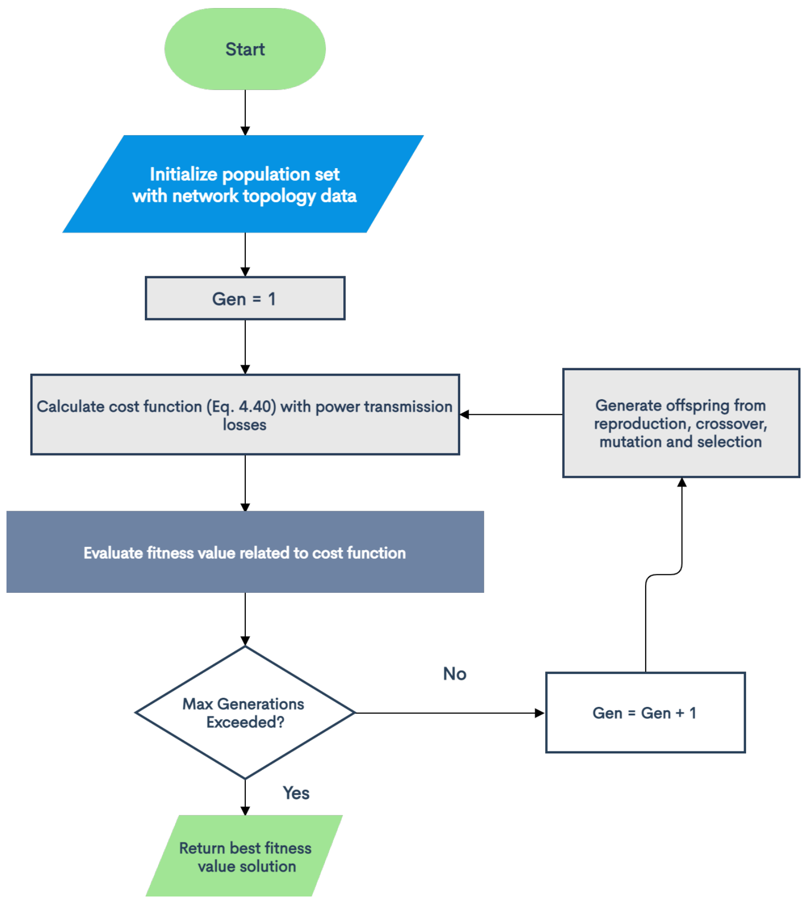

Figure 4.15: Flowchart of the proposed Optimal Power Flow optimization process through Genetic Algorithm. Iterative process of optimal cost solution.

4.3.3 Coupled Distributed and Transportation Network

Fig. 4.16 shows the overlaid layers of Transportation and Distribution Networks. The connected charging stations to the power network are shown in dotted lines. To analyze the impact of EV penetration in the power grid, we consider spatial and temporal EV movement. As EVs move in their daily transport behavior, their battery SoC changes with time. It may happen due to traffic congestion and route deviations, EV might need to charge in the way. This charging scenario impacts the load connecting the TN to the buses of distribution network.

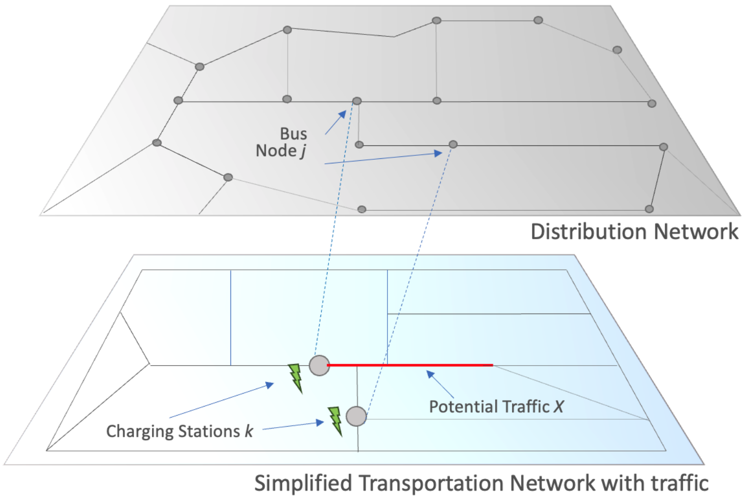

Figure 4.16: Snapshot of the IEEE-30 bus PDN network and hierarchical coupling of the TN, referencing the original Fig.4.13. Two charging stations are connected to PDN nodes.

The coupling constraints that we model in our optimization problem with the TN is the EV charging demand of power balance constraint in the PDN. To achieve feasibility, the target load generator's active power injections can be adjusted to optimality which we aim to do. Thus, the total active power demand at bus i would be the sum of regular power demand at bus i with the summation of aggregated traffic flow of EVs charging at charging station having a charging rate during time period t. The charging stations in TN draw load from the PDN. Assuming one bus is connected to a generator, the total active power demand at bus i is the sum of its regular power demand plus the ev charging demand in unit traffic flow. We assume that energy consumption at link e is a linear function of unit traffic flow [77]. We formulate this link between TN and PDN as in constraint **(2.8)** and other related constraints as follows.

$$p_{i,t}^{dem} = p_{i,t}^{r} + \Psi \sum_{e \in S(i)} z_{e,t}, \quad \forall i \in M \tag{2.8}$$

$$C_{p,t}^{OD} = P_{ch}^{ev} \pi_j(t), \quad \forall p \in E, \quad \forall j \in M \tag{2.9}$$

$$Cap_k = \sum_{e=1}^{Cap_k} \vartheta_{e,j,k} A_{ch}^{ev} \tag{3.0}$$

where $p_{i,t}^{dem}$ is the total active power demand and $p_{i,t}^{r}$ the regular power demand at bus i during time t.

Ψ is the unit traffic flow charging demand rate and $z_{e,t}$ is the traffic flow through link e. $S(i)$ is the set of charging stations on link e that are connected to bus i .The parameter Ψ is important to consider because it follows the modeling approach used in our charging station load. It can be estimated according to EV penetration level or current TN EV charging rate. The higher the level of EV penetration, greater will be the charging rate parameter. For constraint **(2.9)**, the coupled bus $j \in M$ supplies energy to charging station located in the link $p \in E$. In constraint **(3.0)**, Charging capacity Cap_k of a charging pile k is equal to the traffic link e charging demand, connecting charging station pile k with bus node j denoted as $\vartheta_{e,j,k}$, times the amount of energy to be charged by the EV denoted as A^{ev}_{ch}.

Maximising EV penetration level

Assuming a LV power distribution network, the objective is to support the maximum number of EV charging demand without violating grid constraints and operational efficacy. For a single time period, the PDN aims to handle maximum charging requests and we formulate it below:

$$Max \;\; \mathcal{L}_v \;\; \sum_{b \in j}^{Cap_j} N^{ev}_b$$

s.t:

Power Distribution Network Constraints (2.1-2.7)

Coupling Constraint of both networks (2.8-3.0)

(4.42)

where $\mathcal{L}_v$ is the set of variables used in our optimization formulation **2.1 - 3.0**. The binary variable N^{ev}_b is set to 1 if charger b is connected to charging station otherwise *0*. The objective function maximizes the number of EV charging requests, respecting the distribution network constraints. The above problem is a mixed-integer non-linear model which can be solved using COUENNE or CPLEX/IPOPT solvers.

By running the above program, we get a maximum of 45% EV penetration level that can support charging demand without negative impacts on grid. Voltage magnitudes are between 0.1 - 0.3 % deviations which is acceptable for large scale EV penetration scenario without critical power failure issues.

Aggregated Charging Cost

The aggregated charging cost G^{ev}_{ch} for EVs at each charging station j is calculated based on the charging power of each EV and the electric charging cost of charging station connected to a bus in PDN. Given the charging rate and EV charging power, when a charging station is connected to the power network bus, the function $G^{ev}_{ch}(t)$ estimates the charging cost during time period t. Summing up all the charging instances for each vehicle considering traffic flow on link e connected to a charging pile k at a charging station j multiplied by the amount of energy it requires to be recharged, gives us the total aggregated charging cost. Formally, we can describe it as follows:

$$G^{ev}_{ch} = \sum_{j}^{Cap_j} (\pi_j) \left[\sum_{e=1}^{Cap_k} \vartheta_{e,j,k} A^{ev}_{ch} \right] \tag{4.43}$$

4.3.4 Optimal Transportation-Power Network Flow Model

The travel cost of EVs in the TN includes time taken to travel from source to destination in traffic, corresponding to its User Equilibrium condition. We adopt the fundamental Wardrops Principle [75] in generalized format to solve Traffic Assignment problem, essentially finding traffic flow distributions. When EVs recharge at charging stations, the energy required is transmitted via nodes in the PDN to the EV battery. The smart charging technique employed in this paper would determine the optimal charging rate with its objective to minimize the load at the charging station. Assuming there exists an Independent System Operator who manages both the networks, its aim would be to minimize the total cost of both the interdependent systems, thus maximizing the social welfare. The objective function taking into consideration both the networks can be formulated as:

$$OTPNF \;:=\; min[C_{PDN} + C_{TN}] := \sum_{j \in M} \Phi_j [(p_j^g(t))] + \pi_0(t) \sum_{c \in \lambda_0} \Gamma_{0c}(t) \; + \sum_{t \in T(T)} \sum_{e \in T(E)} \left([w * \tau_e(t)] + X_{e,t}^{Cg} \right) \vartheta_{e,t} + G_{ch}^{ev}$$

s.t:

Transportation Network Constraints - (1.1 - 1.8)

Power Distribution Network Constraints (2.1-2.7)

Coupling Constraint of both networks (2.8-3.0)

(4.44)

The OTPNF problem is a mixed integer convex optimization problem which can be solved through commercial solvers like IPOPT, CONOPT, COUENNE etc. Since the constraints have been relaxed and acceptable convexity of the optimization, the program can be solved in polynomial time leading to optimal solutions. The only computational burden is when the number of parameter grows or there is a huge traffic data, the objective function value is evaluated in an iterative manner which might increase the CPU usage for large-scale networks.

After relaxing the non-linearity constraints and convexifying the objective function, we solve the convex mixed integer non-linear program using Couenne solver [67] and AMPL [66], which apart from handling convex MINLPs can also solve non-convex MINLPs. The acceptance of the best solution in certain time threshold can be evaluated based on the optimality gap computed by the individual solver used. Although global optimality is not guaranteed for other solvers, however for Couenne solver, since it implements linearization, bound reduction and branching using branch-bound algorithm, it can find the best solution if interrupted or global optimum solution without interruption.

Chapter 5: Implementation

5.1 Simulation System Design

Agent-Based Modeling (ABM) is a computational modeling paradigm of dynamic agents interacting with the environment. In particular, the detailed heterogeneity of agents in the social system simulation where driver behavior is unpredictable makes it an interesting platform for EV energy consumption study. The computational modeling of systems such as in ABM, the dynamic behavior of the constituent agents comprises of a set of rules which act on data.

A. Multi-Agent Systems (MAS)

Multi-agent systems consist of agents and their environment. In MAS, agents are regarded as entities which is autonomous, viz. it is differentiable from its environment considering spatial, temporal, or operational attributes.The main purpose of MAS is to decompose a large complex task into smaller and simpler ones which would be assigned to each agent to achieve. Agent technology originated from Distributed Artificial Intelligence (DAI) concept [79], [30]. In general, an agent has the following properties:

1. **Reactivity**. Agents are able to perceive their encompassing environment and respond to its changes satisfying their design objectives. This is especially useful in unknown environments where agents updates its actions without having a preconceived notion of what must be learnt. The agents react to its surroundings based on the actions of other agents within the network. Naturally, this immensely helps in our simulation model by adapting to unknown environments or graph networks of larger scale per se.

2. **Proactiveness**. A proactive goal-oriented behavior is undertaken by the agents to fulfill their request for successful trip completion within the transport network. Each agent tries to reach its ultimate destination by proactively judging its path supported by efficient routing algorithms and mapping data. The objective in our case is to create a data-set of complete Origin-Destination trips with realistic environment settings. The data set shall contain information like traveled paths/links, time to travel, traffic flow, energy consumption, battery SoC and related information for analysis later.

3. **Social ability**. Agents form an interactive communication channel with each other to provide some designated service, through FIPA protocol (Foundation for Intelligent Physical Agents) [35], [55]. This property is unique to our study since, imitating social behaviour of EV users is a complex phenomenon and often unpredictable due to stochastic driving elements in the environment. According to our research, this concept of *Consensus Dynamics* found in the social behavior of agents is very crucial in ***Graph Theory*** , which is a huge fundamental backbone of our research. In Complex Network Theory, use of Multi-Agent Systems have been done by [30].

Apart from the core properties mentioned above, an Agents' behavior is determined by a set of rules governed by some algorithm or logic contained within an object-oriented programming paradigm, in our case Java. Also, agents have internal states which are data attributes represented by discrete or continuous variables.

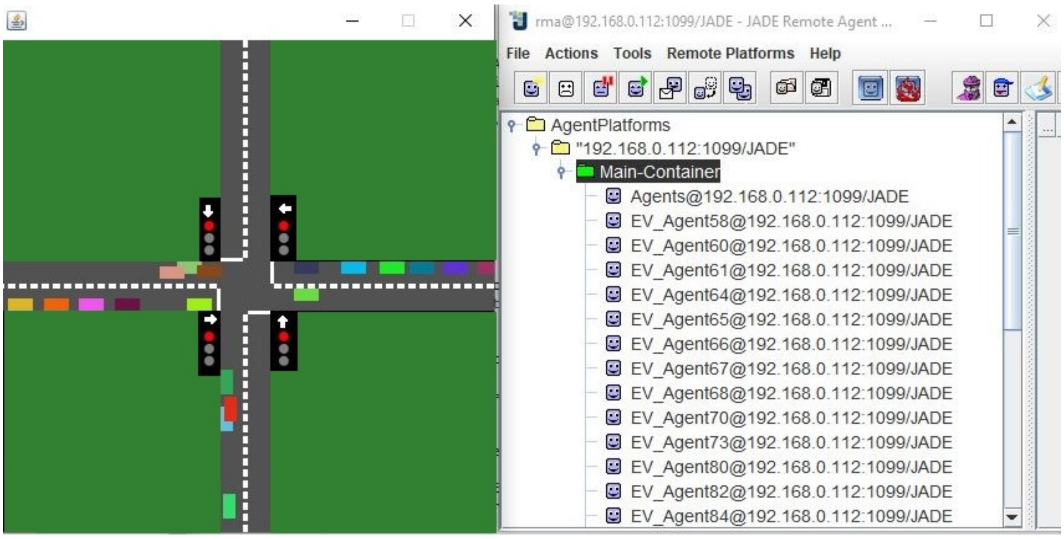

Figure 5.1: JADE GUI with sample traffic scenario

B. JADE Platform

The JADE (Java Agent Development Environment) is a JAVA language based fully FIPA compliant middleware framework with a set of (graphical) development tools. One of the advantages of JADE is the standard compatibility for agent messaging and the compliance with FIPA specifications from a communication perspective [13] and [15]. Also, it has high adaptability to distributed environments for objected oriented development platforms. Fig.5.1 shows the GUI for a road intersection where several cars (agents) are traveling and reacting to traffic lights. When EVs are stuck in a traffic-jam situation, the corresponding energy calculation data is extracted to analyze the impact on load curves. The JADE framework offers a graphical user interface to platform establishment through its RMA agent which shows the attribute of the Agent Platform it belongs to (agents and agent containers). An RMA is a Java object, instance of the class ***jade.tools.rma.rma*** [35].

The action of each agent is operated by a set of rules, principally including EV speed, charging opportunity, charge time, remaining battery SoC, charging power and total charging demand (load). These are updated on every *tick* of recursive aggregations according to the principles designed in the simulation framework.

Matlab Environment for Power Flow Analysis

We used MATPOWER 7.1 in MATLAB R2020a 64bit Windows version to run our Power flow analysis. Additionally we installed the Global optimization toolbox to run our Genetic Algorithm. The IEEE 30 power flow data has 30 bus, 6 generator case and OPF data which we used to test the impact on power distribution network.

Chapter 6: Results and Observations

6.1 Electric Vehicle Charging Load Impact

6.1.1 Charging Load for different scenarios

A semi-realistic program was created to account for the EV charging load under different scenarios. The parameters of the program are stochastic and randomly generated samples of vehicle iterations were developed. Taking into account the variation of charging load data from our JADE simulation, a random distribution of EVs parked in different scenarios such as locations in residential, commercial, leisure or workplace was generated using Monte Carlo simulation. Driving time fitting parameters and standard deviation was calculated using Gaussian distribution. The Transition Probability Matrix of travel purpose was generated randomly from the EV agents data-set. The spatial transition probability was converted into a M x N x N three-dimensional matrix. Travel time, parking time, arrival time, mileage between two destination points, battery SoC, battery capacity, mileage are considered as parameters. The smart charging algorithm is applied to the simulation and final load curves are presented in Fig. 6.1 for 100 EV users. The general assumption is typical day with 24 hours and working time 7-8 hours, rest is leisure time.

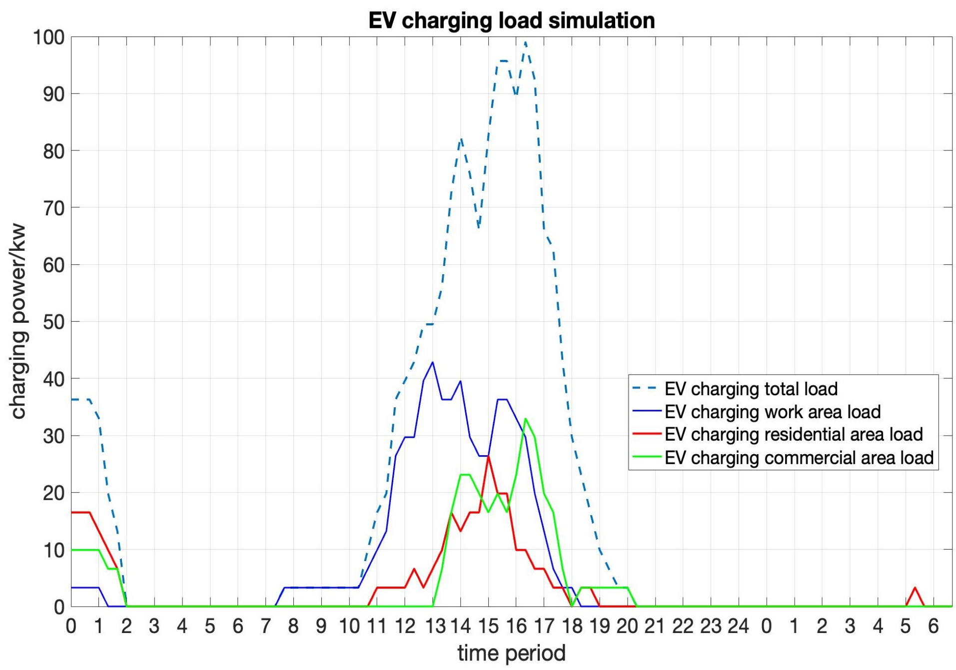

Figure 6.1: EV charging load for different scenarios

6.1.2 Impact of EV charging load on PDN

We solve the OPF problem for PDN using GA-OPF. Fig. 6.2 shows the voltage profiles for scenario when EVs are connected to the grid. Our Optimal Power Flow optimization solved using Genetic Algorithm reduces the load from PDN. It brings the peak voltage due to high EV charging above the lower bound. We demonstrate a better voltage stability which also reduces the power generation cost of the network. Results of our optimal power generation cost are presented below in Table 6.1. Results demonstrate when EV penetration level exceeds 10,000 for a single day period, there is a significant drop in voltage impacting the grid stability. But with optimized charging schedule and combined GA-OPF, the voltage profile could be improved. EV charging load on the bus nodes of PDN caused relatively low voltage magnitude values. Our reference boundaries is however set to 0.91 p.u as voltage lower bound and 1.05 p.u as upper bound.

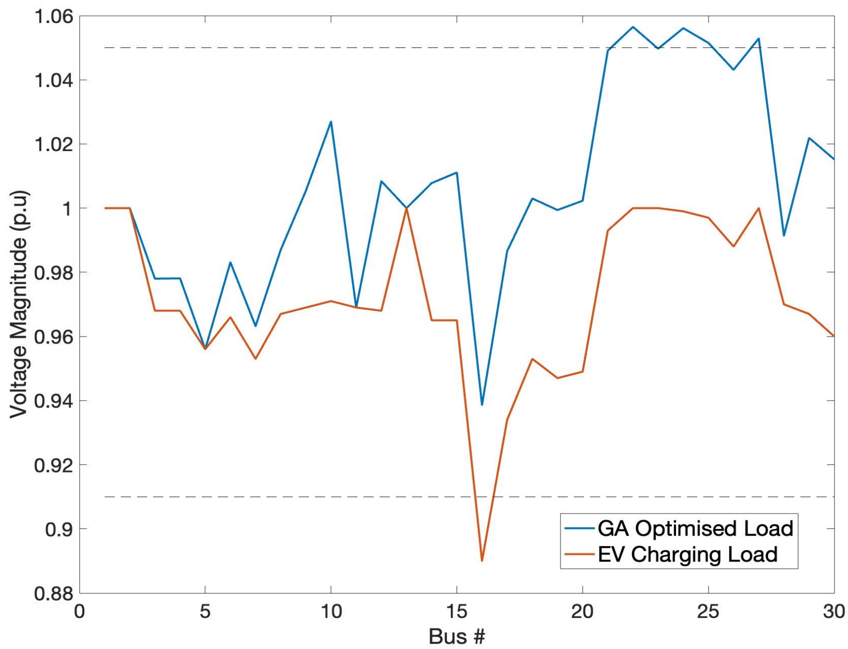

Figure 6.2: Voltage profile for EV charging load and optimized GA OPF

Method	**Bus 1**	**Bus 2**	**Bus 22**	**Bus 27**	**Bus 23**	**Bus 13**	***Total power generation***
NR-LoadFlow	113.06	60.97	37.00	21.59	19.20	26.91	278.73 (MW)
GA-OPF	33.4854	80.00	50.00	35.00	10.00	40.00	248.45 (MW)

Table 6.1: Distribution of power generation for NR method and GA-OPF

Results for the GA Optimized generation costs and power losses are given below in Table 6.2 and 6.3 which demonstrates lowering of power generation cost and power loss for the PDN.

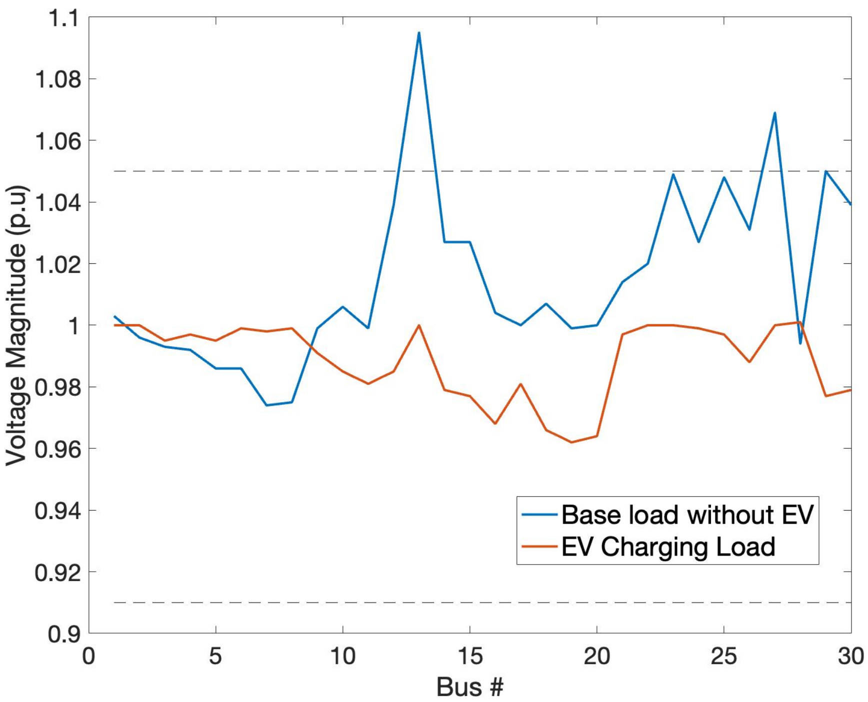

Figure 6.3: Voltage load profile for base case and EV charging scenario.

Method	Total power gen cost (Eur/hr)	Iterations	Power Loss
NR-Load Flow	751.10	-	4.33
GA-OPF	593.79	50	3.31

Table 6.2: Power loss and generation cost in IEEE 30 bus test system

Results of the power losses reported from the load flow analysis and GA-OPF problem is presented below in Table 6.2 and 6.3 for two population sizes 50 and 100 respectively. The parameters used in the Genetic Algorithm to solve the OPF problem is given in table 7.1. The GA-OPF is run only on the PDN but not on the coupled networks. That is discussed later in the results section.

Method	Total power gen cost (Eur/hr)	Iterations	Power Loss
NR-Load Flow	751.10	-	4.33
GA-OPF	592.65	100	3.2

Table 6.3: Power loss and generation cost in IEEE 30 bus test system

The Fig. 6.3 shows the voltage profile for scenarios when no EVs are connected to the grid and case when 5% EVs are connected to the grid. We observe that even for low EV penetration, there is a significant drop in voltage magnitude owing to charging demand of EVs however it doesn't violate the lower bound voltage magnitude of 0.91 p.u.

6.1.3 Network congestion analysis of coupled networks

The cascading effect of transportation traffic flow distribution on the power distribution network are shown in Fig. 6.4 and Fig. 6.5. Possible areas where high traffic flow is expected is shown in the links (OD-Pair). The congestion index of TN is estimated using the data from User Equilibrium traffic flow by dividing link capacity with traffic flow. The effect of traffic flow has impact on the power demand at the power distribution network and loading capacity.

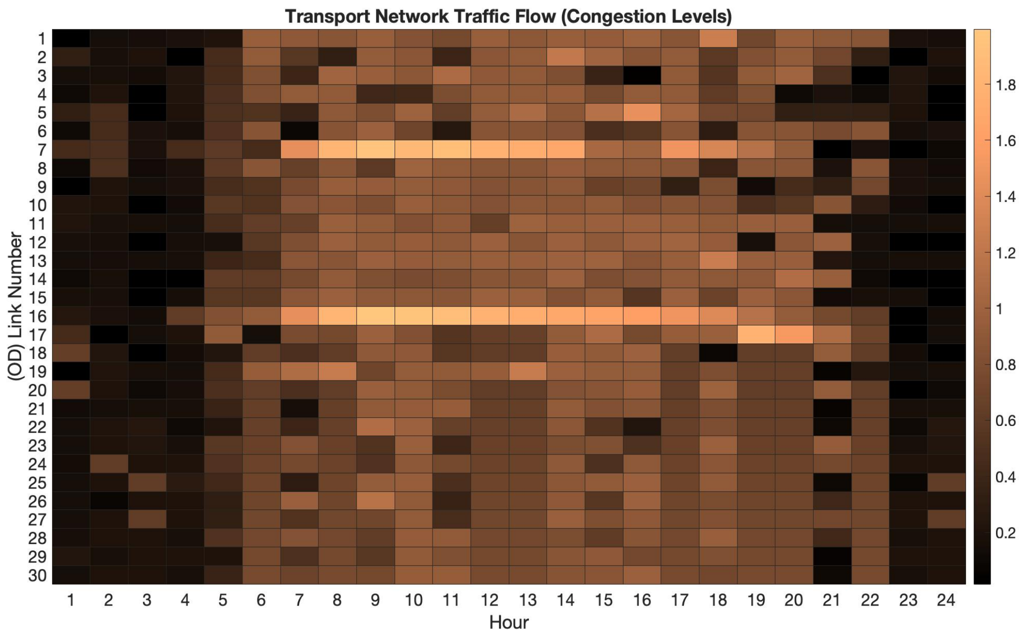

Figure 6.4: TN traffic congested areas (traffic flow)

We consider a sample network with 30 zones and 30 links having 552 OD pairs and 76 path links. Fig. 6.5 shows the voltage magnitude heatmap showing possible areas where nodes suffer from high EV charging demand. The congestion level of PDN is high at bus number 16 and 6 during the morning peak of 7-9 am and evening peak time between 5-7 pm. Bus 16 in our network provides the charging link where charging piles are present to support multiple incoming EVs. The voltage magnitude is low due to high EV charging demand at that node. The peak power demand is at 8 am and 6:30-7pm. We assume the lower bound of voltage magnitude to be 0.91 and 1.05 is the upper bound.

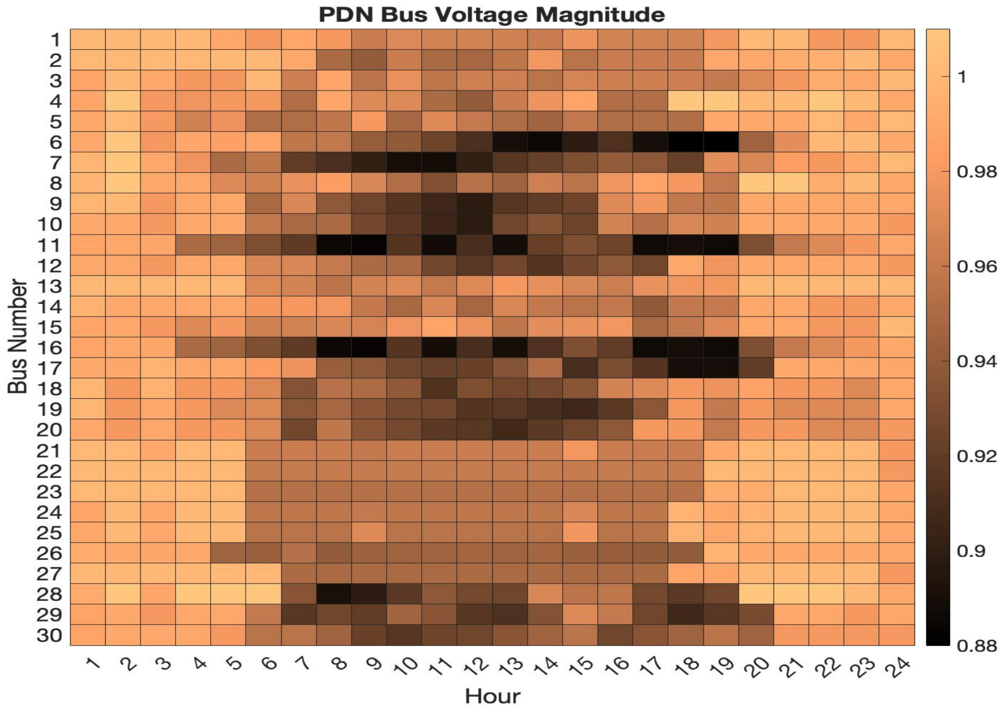

Figure 6.5: PDN Bus Congestion (Voltage Levels)

6.1.4 Optimization results for the coupled TN and PDN

We ran our OTPNF optimization problem using Couenne Solver and AMPL code in an Intel Core(TM) i3-4160T CPU @ 3.10GHz clock speed with 8 Gb RAM but no GPU. The solver has many dependencies which must be pre-installed and configured before running our optimization problem. The following results were extracted after executing the solver. For ACOPF and DCOPF, piece-wise linear generator costs are considered.

Formulation Method	Solver	Iterations	TN Cost	PDN Cost	Optimal Cost
OTPNF	CONOPT	16	3384.28	5220.39	5470.67 Euro/hr
ACOPF	MATPOWER	N/A	-	8812.22	8812.22 Euro/hr
DCOPF	MATPOWER	N/A	-	8372.12	8372.12 Euro/hr
C_{PDN}	IPOPT	19	-	5220.39	5220.39 Euro/hr

Table 6.4: Comparison of costs associated with the TN and PDN in (Euros)

Our OTPNF formulation found a locally feasible optimal solution with an optimal cost (objective function value) of 5470.67 Euros/hr. If coupling constraints were not considered then the aggregated costs of both networks would have been 8.604,67 Euros/hr. A cost savings of 36% was estimated. From the above table, we observe that our Optimal Transportation-Power Network Flow model can lower the operating costs of both the networks when our Stochastic Dynamic User Equilibrium traffic assignment based formulation is used along with Optimal Power Flow.

The heatmap showing possible affected nodes with EV charging load, with cascading effect on subsequent bus nodes depicted in the below Fig. 6.6.

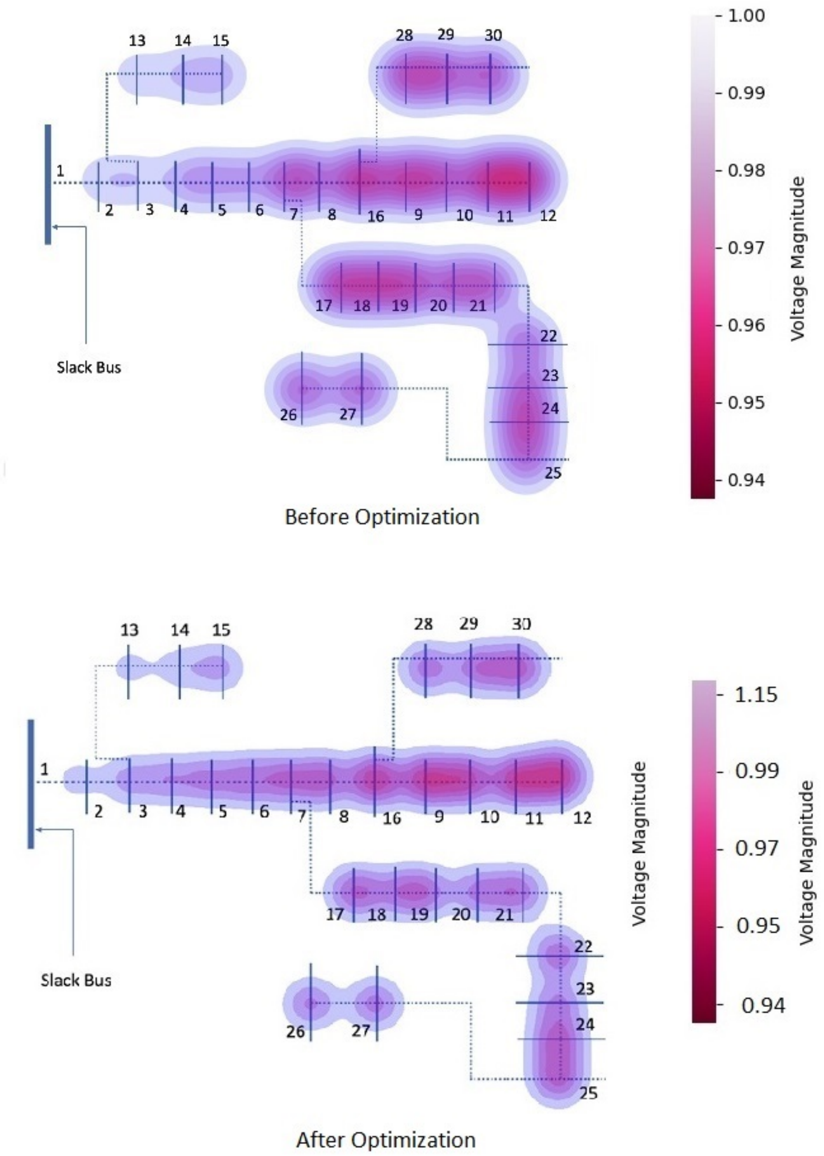

Figure 6.6: Before and after Heatmap observation of drop in voltage magnitude due to EV charging load and its cascading impact on subsequent nodes of the radial network. The figure on the top shows before optimization is done and bottom figure shows optimized voltage profile. We aimed at alleviating the voltage profile of affected nodes, putting less strain on the power grid.

6.1.5 Impact of traffic conditions on Energy consumption

The core relationships of traffic flow behavior is described in terms of three variables: traffic flow, density and speed of vehicles. Since EV user behavior is discordant, there is a heterogeneity in traffic regulation behavior. Influenced by the individual characteristics of EV agents and their interaction with the environment, traffic flow through a network will vary both both temporally and spatially. The distribution of EVs energy consumption in traffic condition and normal free flow urban network along with SoC change comprising of several trips made in a day is shown in Fig. 6.7.

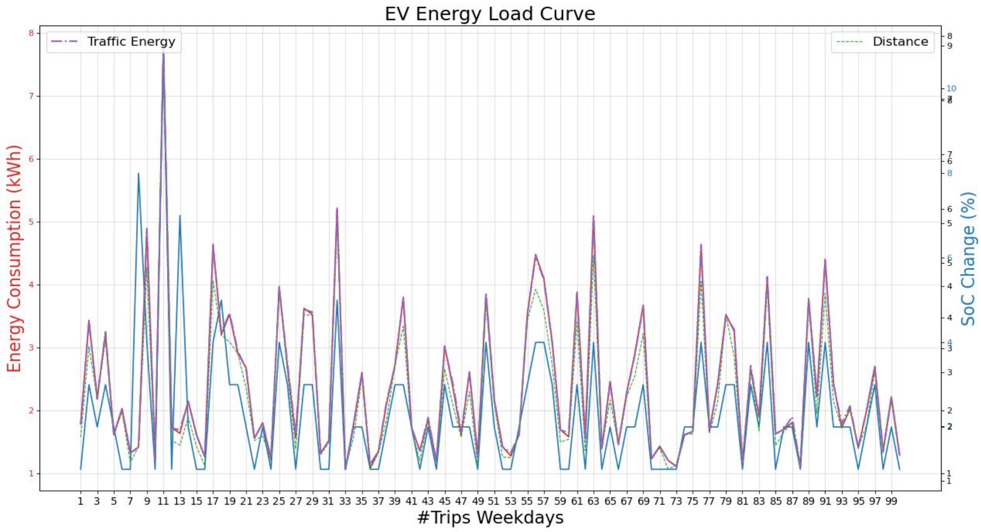

Figure 6.7: Energy Consumption and Battery SoC Change during weekday trips

The daily traffic and power demands of 100 EV users for the analyzed 30 link network is shown in Fig. 6.8. The data is related to the User Equilibrium traffic flow that we calculated earlier using Wardrop's principle [75]. The traffic flow data is measured in 24 hours with hourly intervals and power demand is calculated based on the charging demand of EV users from the PDN. Fig. 6.9 shows the load curve of EVs night time and evening charging scenarios.

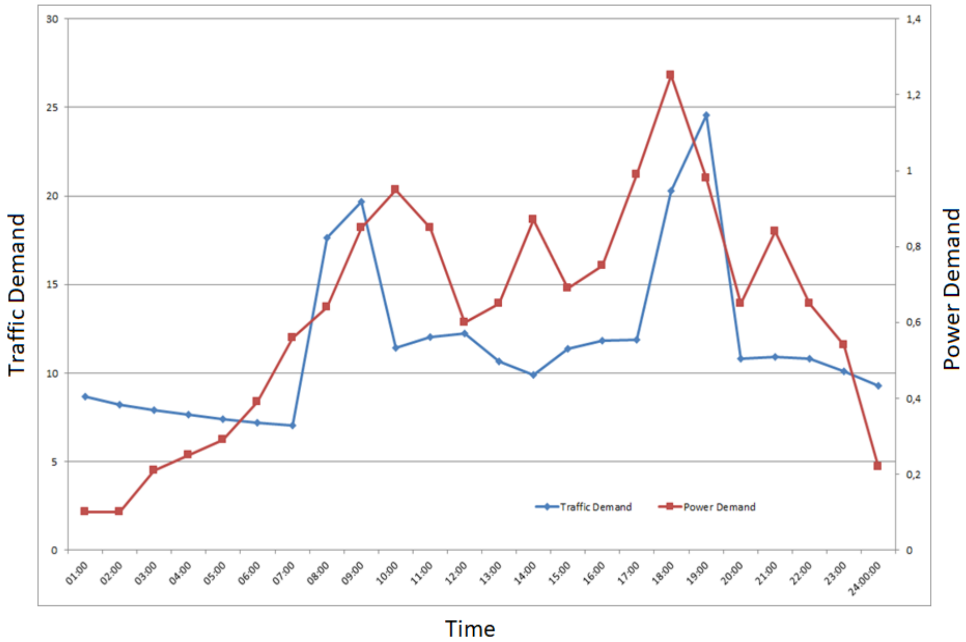

Figure 6.8: Variation in daily traffic and power demands for multiple EVs

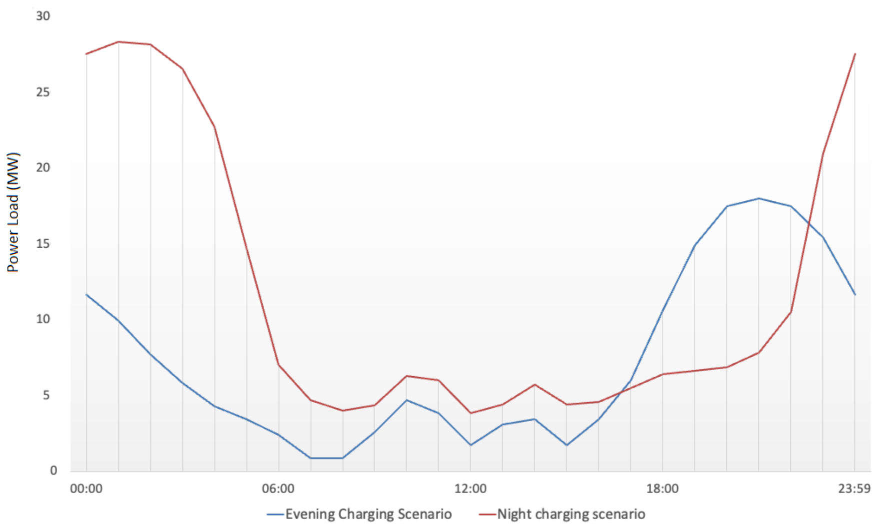

Figure 6.9: Power load profile for evening and night charging scenarios.

Chapter 7: Conclusion and Future Work

7.1 Conclusion

Penetration of multiple EVs in society inevitably brings concern for the optimal operation of transport and power networks. In this thesis project we present an approach to develop an optmization model which minimizes the mutual costs associated with transportation and power distribution networks. By using a Dynamic User Equilibrium model with agent based simulation of EV mobility behavior, we developed an optimisation model for the coupled TN and PDN. The synthesis of JADE - Java Agent DEvelopment framework and Power Flow Analysis in MATLAB to attain user equilibrium solution can help system operators plan and manage their networks more efficiently. The optimal charging cost and power generation cost brings economic benefit to both the networks. The impact of integrating EVs in the smart grid has been evaluated based on two cases; first one being the energy load profile estimated from change in mobility behavior as EV users commute during a day and the second being its impact on the distribution network node voltage profile.

1. The first part focuses on EV mobility based on several elements within a transportation network of a certain geographical region. This includes the battery SoC, travel time, distance, time to recharge EV, traffic density, re-charge options at charging stations etc. Due to the distributed intelligence of the agent-based platform, the decision making perception is influenced by routing algorithms which affects the quality of behavioral data collected. Results show the daily load profile of EV users (ranging from 100 to 10000) considering several scenarios. The spatial temporal variations of EV mobility through Origin-Destination trip data and EV charging data is used to model the User Equilibrium traffic model solving the Traffic Assignment Problem (TAP).

2. In the second part, voltage profiles (phase, angle, magnitude, power loss) is calculated using Backward Forward Sweep algorithm in MATLAB. For the ACOPF problem, the calculation is done on Newton-Raphson load flow method in MATPOWER. The collected power flow data is used to solve the Optimal Power Flow problem using Genetic Algorithm. We reduced the power generation cost due to EV charging demand which maximizes social welfare. We identified hot spots within the distribution network having high voltage magnitude which could cause instability to the power grid. By overlaying the transportation and power system network hot spot, we could easily identify areas where load was more than tolerable limits. Through an optimisation problem formulation, the power losses and power generation costs were minimized.

Our study highlighted the impacts of EV charging load in the transportation network overlaid with the distribution network, providing quantitative and qualitative results for the coupled systems. Future network planners could optimize our model to forecast time varying traffic demands and electricity generation cost considering factors that affect the behavior of each entity within the system. Our results demonstrate the impacts of large scale EV penetration which affects the optimal operation of power distribution network, which was solved using Optimal Transportation Power Network Flow optimization model, reflecting on voltage stability and minimising social welfare cost. This is an interesting area of further research as EV adoption grows higher into society.

7.2 Future Work

Our current work can be extended by developing more efficient algorithms for the EV routing and dynamic traffic assignment using real-time data from multi-modal sources. As the adoption of EVs continue to grow, in the future, the optimal placement of charging stations within the transport and power network would be crucial for sustainable operation. Through better simulation tools, the captured traffic data and charging behavior could be analyzed to perform better optimizations. Our model doesn't consider V2G operations of EVs, so that could be also included in future work. By adding wireless charging solutions and battery swapping stations, a maximum social benefit could be achieved for the coupled networks. The effect of weather conditions as well as Heating, Ventilation, and Air-conditioning (HVAC) systems on battery SoC, energy requirements and traffic flow could also become part of our model. Ofcourse, by utilizing real-time data from EV Information and Communication Technologies and robust in-vehicle bus network such as Controller Area Network (CAN), data could be further analyzed to build a more efficient and realistic model. A multi-objective optimisation problem could be formulated with integrated photovoltaic panel load and EV recuperative energy due to braking could be developed to study impacts on smart microgrid.

Furthermore, the assumptions made in this thesis could be relaxed and ancillary services could be integrated into the smart grid to make the model more realistic. Also, development of a more accurate Dynamic Traffic Assignment model which could establish traffic flow dynamics for large-scale EV swarm could be utilized to study further impacts on the power network. When renewable distributed generators are integrated into the PDN, the impact of random power output and power dispatch from EVs to grid could become an interesting topic.

7.3 Appendix

The parameters used in our Genetic Algorithm is as follows:

Population	Generations	TimeLimit	BaseMva	Accuracy	Pwr Tolerance factor
100	100	300	100	0.0001	0.0001 p.u

Table 7.1: GA OPF Parameter settings

Parameters of the distribution line network

Line #	R (p.u.)	X (p.u.)	Line #	R (p.u.)	X (p.u.)	Line #	R (p.u.)	X (p.u.)
E1-E2	0.0192	0.0575	E5-E7	0.0460	0.1160	E14-E15	.2210	0.1997
E1-E3	0.0452	0.1852	E6-E7	0.0267	0.0820	E16-E17	.0824	.1923
E2-E4	0.0570	0.1737	E6-E8	0.0120	0.0420	E15-E18	.1073	.2185
E3-E4	0.0132	0.0379	E12-E14	.1231	.2559	E18-E19	.0639	0.1292
E2-E6	0.0472	0.1983	E12-E15	.0662	0.1304	E19-E20	.0340	0.0680
E4-E6	0.0119	0.0414	E12-E16	.0945	.1987	E10-E20	.0936	0.2090
E10-E17	0.0324	0.0845	E21-E22	.0116	.0236	E10-E22	.0727	.1499
E10-E21	0.0348	0.0749	E15-E23	.1000	.2020	E22-E24	.1150	.1790
E27-E29	.2198	0.4153	E25-E27	.1093	.2087	E29-E30	.2399	.4533

Table 7.2: IEEE 30 Branch Line Data

Optimal Travel time and traffic flow for the sample network.

Arc	Capacity	UE_travelTime	UE_Flow	Congestion Factor
E1-E2	25900.20	6.0	4127.78	0.1593
E1-E3	23403.47	4.0	7742.51	0.3308
E2-E1	25900.20	6.4	4368.14	0.1686
E2-E6	4958.18	4.0	5857.34	0.9830
E3-E1	23403.47	4.3	7730.01	0.3303
E3-E4	17110.52	2.3	13679.45	0.7794
E3-E12	23403.47	7.8	10086.02	0.4309
E5-E7	11110.52	10.20	17463.84	1.572
E16-E17	8229.91	18.08	15096.87	1.834
E18-E19	23403.47	4.23	18448.87	0.7883
E20-E24	5000.0	3.63	4258.92	0.8517
E28-E30	15078.50	4.25	4908.82	0.3255

Table 7.3: Small Network 24 Links Optimal traffic equilibrium results

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I hereby declare that the work presented in this thesis is entirely my own and that I did not use any other sources and references than the listed ones. I have marked all direct or indirect statements from other sources contained therein as quotations. Neither this work nor significant parts of it were part of another examination procedure. I have not published this work in whole or in part before. The electronic copy is consistent with all submitted copies.

Stuttgart, 31.01.2021 Kaushik Sadhu

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