Energy Efficient Framework to Find Optimized Route for EVs Movement

A Thesis

submitted in partial fulfilment of the requirements for the award of the degree of

Doctor of Philosophy

in

Computer Science and Engineering

Submitted by:

Ashwani Kumar
(Registration No: 901803007)

Under the guidance of

Dr. Ravinder Kumar
Associate Professor, CSED

Dr. Ashutosh Aggarwal
Assistant Professor, CSED

THAPAR INSTITUTE
OF ENGINEERING & TECHNOLOGY
(Deemed to be University)

Thapar Institute of Engineering and Technology
Patiala-147004, Punjab, India

January 2023

Certificate

I, Ashwani Kumar, Regn. No. 901803007, hereby certify that the work, which is being presented in the thesis, entitled **Energy Efficient Framework to Find Optimized Route for EVs Movement**, in partial fulfillment of the requirements for the award of the degree of Doctor of Philosophy submitted to the Computer Science and Engineering Department at Thapar Institute of Engineering and Technology, Patiala, Punjab, India is an authentic record of my own work carried out under the guidance of Dr. Ravinder Kumar and Dr. Ashutosh Aggarwal. The matter presented in this thesis has not been submitted to any other institute for the award of any other degree.

Place: Patiala

Date: 09/01/2023

Ashwani Kumar

Ashwani Kumar

Regn. No. 901803007

This is to certify that the statement made above by the candidate is correct to the best of my knowledge.

(Dr. Ravinder Kumar)
Associate Professor
CSED, TIET

(Dr. Ashutosh Aggarwal)
Assistant Professor
CSED, TIET

Abstract

There has been tremendous increase in the use of renewable resources in 21st century which is essential to save the environment from the hazardous impact of non-renewable resources. It is projected that India emits approximately three gigatonnes of greenhouse gases (GHGs) per year, accounting for around 7% of global emissions [1]. It is also pertinent to note that road vehicles are responsible for 76% of the total CO_2 emitted by the transportation sector [2]. Therefore, the governments are taking new initiatives all over the world to reduce GHGs production and cut down their reliance on fossil fuels. The evolution of non-fossil fuel-based vehicles or alternative fuel vehicles (AFVs) became a prominent choice for ensuring environment-friendly and long-term transportation sustainability. Thus, AFVs, especially electric vehicles (EVs), are now widely recognized as one of the most effective ways to alleviate GHG emissions, technological developments, and world-wide government incentives. Despite the profound significance of employing EVs, the factors such as limited range of these vehicles, underdeveloped charging infrastructure, and ease of charging services pose a barrier to the mass adoption of EVs. Indeed, the EVs' charging times are substantially large due to CSs' equipment and the composition of the batteries, resulting in increased wait times in CSs. Therefore, we need to have a system that can efficiently manage all the available resources of EV, transportation network, EV and CS. Another challenge lies in the fact that EVs are likely to meet a large number of transportation demands in the near future, complicating the decision-making process due to the coupling of routing and charging simultaneously, which makes it harder to solve such problems. Recent scientific contributions in joint routing and charging have been mainly classified into four domains: i) heuristic approaches; ii) commercial solvers like CPLEX, Gurobi, etc.; iii) machine learning-based approaches; and iv) problem-tailored based on particular structural information. However, each of them has its own set of constraints in terms of computation resources and computation time. None of them can guarantee the solution's optimality. The problem based on structured information of combined routing and charging of EVs has not been thoroughly explored and needs further exploration with some real-time metrics such as battery SoC, traffic condition, state of charging station, ToU energy pricing, etc.

In this research work, a modest attempt has been made to find the much-needed solution to the problem of energy-efficient EV routing. Firstly, the introduced problem has been addressed by inculcating the effect of various road surface conditions (icy, dry, wet, and snowy) and providing the solution by incorporating the principles of Artificial Bee Colony (ABC). Secondly, this problem has been extended by identifying the suitable charging station (CS), keeping in mind the objectives of minimal waiting time and charging cost at the

CS. The K-shortest path (KSP) algorithm has been used to make the route and charging planning more effective. Lastly, this dissertation extends the mathematical model of vehicle's energy consumption estimation with the features of vehicle's start/stop energy expenditure and recapturing energy effect and it also introduces an Amplified-ACO ($\boldsymbol{A^2CO}$)(Amplified-Ant Colony Optimization), routing algorithm based on ACO principles that makes use of the probabilistic selection model, to efficiently solve the underlined problem.

Keywords: Energy-efficient EV routing, CS identification, Regenerative braking, Heuristic approaches, Non-identical road surfaces, Improvised distributed system

Acknowledgements

First and foremost, I would like to thank the Almighty who gave me enough strength and courage to overcome all the obstacles arsing during the period of this research work. I shall be lacking in sincerity and regard, if I do not acknowledge with thanks the sincere efforts of all those people who helped me to complete this work successfully.

I want to express my deep gratitude to my supervisors, **Dr. Ravinder Kumar**, Associate Professor, and **Dr. Ashutosh Aggarwal**, Assistant Professor, Computer Science and Engineering Department, Thapar Institute of Engineering and Technology, Patiala (India), for their erudite guidance, constant advice, and encouragement at every step of my Ph.D. program. Without their unfailing support, this thesis would not have been possible. The contribution to this thesis goes well beyond their role as an academic supervisor and includes regular support on a personal level, without which this journey may never have been completed. And for this, I am truly grateful and will always remain indebted to them.

I am also grateful to **Dr. Shalini Batra**, Professor and Head, Computer Science and Engineering Department, Thapar Institute of Engineering and Technology, Patiala (India), for providing me the necessary administrative assistance in the completion of this research work. I also wish to thank all the members of the doctoral committee, viz. **Dr. Neeraj Kumar**, **Dr. Anil Kumar Verma**, and **Dr. Sunjay Jain** for their valuable inputs during my research work. I am also thankful to my Ph.D. Coordinator **Dr. Sushma Jain** and **Dr. Vinay Arora**, for their kind co-operation and support during the entire period of this study. I sincerely thank all the faculty members and the supporting staff of Computer Science and Engineering Department for their constant help whenever required. I am also obliged to the Director, **Prof. Prakash Gopalan**, Dean (RSP), **Prof. Rafat Siddique**, and the management of Thapar Institute of Engineering and Technology, who provided me all the necessary resources and facilities to complete my work.

I am highly indebted to my parents, **Mr. Surendra Pal Singh** and **Smt. Suman Devi**, for their exceptional support that paved the way for a privileged education for me. They always stood beside me and encouraged me constantly throughout my life. I may not have been able to complete my research work without their cooperation and good wishes.

I would also like to thank all of my friends and colleagues, especially, **Niyaz Ahmad Wani**, **Dr. Shubham Goel**, **Vijay Soni**, **Sandeep Saharan**, **Mohd Abuzar Sayeed**, **Sukhandeep Kaur Shergill** , **Pragya Mishra**, **Nisha Thakur** who always lent me the necessary support to face all oddities of life. Their nice co-operation and encour-

agement would always be remembered.

Date: (**Ashwani Kumar**)

Thapar Institute of Engineering and Technology
Patiala, 147004
Punjab, India

List of Publications

Journal Publications (SCI/SCIE):

- Ashwani Kumar, Ravinder Kumar, and Ashutosh Aggarwal, "A meta-heuristic-based energy efficient route modeling for EV on nonidentical road surfaces", **Neural Computing and Applications**, pp. 1-14, 2022. **(SCIE Indexed, Impact Factor: 5.130)**
- Ashwani Kumar, Ravinder Kumar, and Ashutosh Aggarwal, "S^2RC: A multi-objective route planning and charging slot reservation approach for electric vehicles considering state of traffic and charging station", **Journal of King Saud University - Computer and Information Sciences**, 34(5), pp. 1319-1578, 2022. **(SCIE Indexed, Impact Factor: 8.839)**
- Shubham Goel, Ravinder Kumar, Ashwani Kumar and Reetu Malhotra, "S^3A: Smart Station Search Assistance for Electric Vehicle—A Step Toward Smart City", **IEEE Consumer Electronics Magazine**, 9(4), pp. 27-33, 2020. **(SCIE Indexed, Impact Factor: 3.789)**
- Ashwani Kumar, Ravinder Kumar, and Ashutosh Aggarwal, "A Meta-heuristic based Energy Efficient Route Modeling for EVs Integrating Start/Stop and Recapturing Energy Effect". **(Communicated)**
- Ashwani Kumar, Ravinder Kumar, and Ashutosh Aggarwal, "A Mat-heuristics Approach for Electric Vehicle Route Optimization under Multiple Recharging Options and Time-of-use Energy Prices". **(Communicated)**
- Ashwani Kumar, Ravinder Kumar, and Ashutosh Aggarwal, "Electric Vehicle Routing Problems: A Review of Emerging Variants and Solutions". **(Communicated)**

Table of Contents

List of Figures

List of Tables

List of Abbreviations

EV	Electric Vehicle
CS	Charging Station
ICE	Internal Combustion Engine
VRP	Vehicle Routing Problem
EVRP	Electric Vehicle Routing Problem
PHEV	Plug-in Hybrid Electric Vehicle
BEV	Battery Electric Vehicle
HEV	Hybrid Electric Vehicle
TSP	Traveling Salesman Problem
S^2RC	Smart Search of Route and Charging
F^2A^2	Firefly with Ant Colony Approach
ABC	Artificial Bee Colony
KSP	K-Shortest Path
ToU	Time-of-Use
EVRPTW	Electric Vehicle Routing Problem with Time Windows
CVRP	Capacitated Vehicle Routing Problem
VRPTW	Vehicle Routing Problem with Time Windows
MDVRP	Multi Depot Vehicle Routing Problem
TDVRP	Time Dependent Vehicle Routing Problem
FAME	Faster Adoption and Manufacturing of EVs
SoC	State of Charge
SRTM	Shuttle Radar Topography Mission
MILP	Mixed Integer Linear Program
LDM	Longitudinal Dynamics Model
EEPP	Energy Efficient Path Problem
PSO	Particle Swarm Optimization
ACO	Ant Colony Optimization
FPTAS	Fully Polynomial Time Approximation Scheme
VAMOS	Traffic Analysis, Management and Optimization System
VNSB	Variable Neighborhood Search Branching
HC	Heuristic Concentration
ALNS	Adaptive Large Neighborhood Search
SA	Simulated Annealing
DCTP	Different Charging Technologies Problem

ILS	Iterative Local Search
SRTM	Shuttle Radar Topography Mission
OSPB	Optimal Splitting Procedure with Backhaul
LNS	Large Neighborhood Search
CAN	Control Area Network
GPS	Global Positioning System
HLNS	Hybrid Large Neighborhood Search
NN	Neural Network
MLR	Multiple Linear Regression
VNS	Variable Neighborhood Search
LSB	Local Search Branching
CWTP	Charging Waiting Time Problem
MDVSP	Multi-depot Vehicle Scheduling Problem
GD	Goods Distribution
L&T	Logistic and Transport
ECV	Electric Commercial Vehicle
FR	Full Recharge
TW	Time Window
EER	Energy Efficient Routing
GVRP	Green Vehicle Routing Problem
FC	Fast Charging
PR	Partial Recharge
NCF	Nonlinear Charging Function
TW	Time Windows
ODCS	Online Deployment of CS
BSS	Battery Swap Station
GLRP	Green Location Routing Problem
IARS	Intention Aware Routing of Electric Vehicle
RTCSRS	Real Time Charging Station Recommendation System
TWQS	Time Windows Considering Queuing System
CTVTT	Charging Time and Variable Travel Time
TDTW	Time-dependent Traffic and Time Windows
ACO	Ant Colony Optimization
EVCNS	Electric Vehicles Charging Navigation System
DP	Dynamic Pricing
CC	Capacitated Charging
ELRP	Electric Location Routing Problem
SD	Stochastic Demand

BSS-LRP	Battery Swapping Station with Location Routing Problem
IRF	Intra Route Facilities
SCS	Smart Charging Strategy
WBA	Web Based Application
DN	Distributed Network
FCFS	First Come First Serve
TDTSP	Time-dependent Traffic State Problem
TMACO	Temporal Multi-objective Ant Colony Optimization
DEVRP	Dynamic Electric Vehicle Routing Problem
RR	Ruin and Recreate
D-ToU-EPP	Dynamic and Time-of-Use based Energy Pricing Problem
MINLP	Mixed Integer Non Linear Programming
SCC	Simplified Charging Control
OSR	Online State Recursion
OPL	Optimization Programming Language
LRP	Location Routing problem
BDA	Benders Decomposition Algorithm
TS	Tabu Search
GA	Genetic Algorithm
DE	Differential Evolution
TD	Time Dependent
TS-MCWS	Tabu Search along with Modified Clarke and Wright Savings
MSBRH	Multi-Start Biased-Randomized Heuristic
BR-VNS	Biased Randomized Variable Neighborhood Search
SCMA	Smart Charging Management Algorithm
DLMP	Distribution Locational Marginal Pricing
OPF	Optimal Power Flow
MPC	Model Predictive Control
CSP	Charging Scheduling Problem
EVRP-MPQ	Electric vehicle routing problem with Multi Priority-Queuing
SCS	Smart Charging Strategy
EVPSS	Electric Vehicle Public Supply Station
ABS	Agent-based Simulation
TDWTRS	Time-dependent Waiting Times at Recharging Station
ISP	Intermediate Stop Problem
ICP	Industry Constraints Problem
HEVRP	Hybrid Electric Vehicle Routing Problem
NCFP	Non-linear Charging Function Problem

CSMWN	Charging Scheduling with Minimum Waiting Time in Network
SIGALNS	Modified Sweep Algorithm, Iterative Greedy Method, Adaptive Large Neighborhood Search
ABSCEV	Agent-based Simulation Framework Reducing Waiting Times in Charging EVs
EVRP-ToU	Electric Vehicle Routing Problem with Time-of-Use Pricing with Partial Recharge

Chapter 1

Introduction

Today, urban areas hold approximately 54% of the world's inhabitants; and in the midst of this living century, this proportion is expected to increase to 67% of the world's population, i.e., by the end of 2050, around 2.5 billion more individuals could be added to the urban inhabitants [3]. This surge in urbanization will eventually necessitate a rapid expansion of the transportation sector. Transportation is the backbone of any developing nation. It is responsible for delivering goods for the construction of day-to-day livelihood. Without the support of transport, the dream of urbanization and development is not achievable. But traditional transportation systems make use of internal combustion engines (ICEs) that emit several harmful and toxicant gases like benzene, nitrogen oxide, sulphur dioxide, etc., and become the primary cause of many respiratory and chronic diseases. Moreover, it is also worth noticing that CO_2 level can surpass 800 ppm by the end of 2100 [4] which would be quite hazardous for humans. Further, the constituent greenhouse gases released by ICEs are the prime reason behind the rise of the earth's temperature that ultimately leads to global warming.

Thus, the governments across the globe are taking appropriate steps and imposing regulations to encourage the use of alternate fuel vehicles. Consequently, we are witnessing the rapid adoption of EVs because they are revolutionizing the transportation sector across the globe, varying from light weight to heavy weight vehicles. Many commercial companies such as La Poste Operators and ENEDIS (a French electricity distribution company) are using EVs as a part of their vehicle fleets for the purpose of distribution [5]. Moreover, the following factors have also influenced this study to undertake the EV technology that has the potential to overcome the hazardous problem of environment as well as provides economic stability to the users.

- From the Indian perspective, there is a massive scope of growth in EVs market. The EV industry in India is far behind with less than 1% of the total vehicle sales. The Government of India has taken multiple initiatives such as subsidies under FAME (Faster adoption and manufacturing of EVs) scheme, Make in India initiative, providing subsidies to EV buyers to boost the manufacturing and sale of EVs [6]. Moreover, the arrival of Tesla in India would further boost the EV growth and attract the potential buyers towards the use of EVs. So, all this growth demands more research in the field of EV routing, battery technology, charging infrastructure, etc.

- Undoubtedly, the use of EV penetration would be quite beneficial to the environment. Unlike the traditional vehicles, EVs cause no emission and noise. In the near future, EVs might replace ICE-based vehicles world-wide in the distribution process. It has been projected that Europe itself would be having approximately 6.5 million EVs on road by the end of 2025 [7].

However, certain technological constraints such as limited cruising range, long recharging time, limited battery capacity, etc. slow down the adoption process of EV operations. Therefore, the scientific community responds to address the challenges introduced by EV technology. The study has identified the prominent issue of EV routing, so-called electric vehicle routing problems (EVRPs) because it has a broad range of potential and is less investigated in comparison to the classical vehicle routing problems (VRPs) that originated in the year 1959, while EVRP has been under evaluation since 2011 [8].

The routing algorithms used for the fossil fuel-based vehicles only targeted to produce the shortest distance between the source and destination or least time consumable route. This is directly proportional to the vehicle's fuel efficiency because the least distance route will directly replicate to less running time of the engine. Hence, the consumption of fuel is also less. But this scenario may not be possible in the case of EVs as they can produce regenerating energy. It is generated when kinetic energy is produced by the brakes while driving the vehicle. Moreover, due to the dual directional energy flow of the electric motor, it is converted into another form of energy which is known as regenerating braking energy. Furthermore, there may be a scenario where, in the route segment, the negative edge weight between the adjacent node occurs. Such a condition is well-allowed by the regenerating braking. Thus, the traditional routing algorithm like Dijkstra's can't handle such a negative edge cost problem.

The research on EV routing is still in its early stage; the problem did not exist a few years ago since EVs were not mass-produced. EV users keep on looking the optimal route, but the criteria may vary from one person to another and the time of the day. Most of the transportation researchers have concentrated on identifying the most reliable paths for travellers who avoid to be late when travelling in a transportation network with uncertainties. Traffic uncertainties can be caused by various factors, such as adverse weather conditions, traffic accidents, vehicle malfunctions, demand variations, etc. Moreover, the limited cruising range of EVs, which requires frequent charging events, is one of the major issues. The underdeveloped charging infrastructure and limited driving range have made EV routing challenging. So, the current work is focused on finding the energy-efficient route and navigate to the charging station, whenever required.

1.1 History and Overview of EV Technology

The first practical EV was built by William Morrison of Des Moines, Iowa in the year 1891 in USA [9]. It had four horsepower electric motor and a 24-cell battery weighing 768 pounds, which was more than half of the EV's total weight. The maximum speed of the car was 14 mph. In 1899, Whitney and the Pope Manufacturing Company jointly formed a new automobile company called Columbia Automobile. The main objective of the company was to build and sell electric cars. In 1912, Charles Kettering invented the first functional electric starter for automobiles.

EVs are propelled by a combination of electric motor and transmission systems. It withdraws power from a pack of batteries or a fuel cell mounted in the vehicle. Conventional vehicles are pretty different from EVs as they run on petrol/diesel, while EVs run on electric power.The EVs' motor is less prone to failure than conventional engines because it has fewer-moving parts than an ICE. Moreover, they are speedier than traditional vehicles. This is due to their ability to generate a high amount of torque from starting an electric motor, but conventional vehicles reach that amount of torque after gaining speed. It offers the EV an edge in starting speed and allows it to accelerate from 0 to 60km/h in a matter of seconds. Furthermore, due to the lack of kilos worth of metal beneath the hood, the lightweight feature of EVs plays an essential role. Based on the discussed abilities, the EVs are primarily classified into the following three categories:

- *Battery Electric Vehicle (BEV)*: In these types of EVs, an electric motor is used to propel the vehicle powered by rechargeable batteries. BEV has a battery pack consisting of multiple small-size batteries and does not have any ICE like conventional vehicles. Batteries are recharged from an external source of electricity, but they can also be charged at run time using a regenerative braking system.

- *Plug-in Hybrid Electric Vehicle (PHEV)*: It has a similar combination of electric motor and batteries like BEV. However, it also features an ICE that runs on fuel available in the fuel tank, whereas an electric motor is powered from a pack of batteries whenever required. Moreover, ICE is used to charge the batteries and propels the vehicle when batteries run low. These vehicles, like BEVs, can be recharged at home or any public charging station (CS). The major advantages of PHEVs are that they have a more extended driving range than BEVs, consume less fuel, and emit less pollution than conventional vehicles.

- *Hybrid Electric Vehicle (HEV)*: These vehicles have both an electric motor and an ICE. Rechargeable batteries power the electric motor, while the ICE uses a petrol tank, and transmission systems employ both to move the vehicle simultaneously. The electric motor works in tandem with the ICE to propel the car. The design of

HEV is very complex due to the integration of both the electric motor and the ICE. The HEV battery pack is very small and can't be charged by an external electricity source. They can only be recharged by ICE or a regenerative braking system. The major advantage of such vehicles is their long driving range with high fuel efficiency.

1.2 Charging Types of EVs

EVs require frequent recharging during the itinerary planning to function properly. Each CS is equipped with a battery charger device, which processes and regulates the electric current passing through it to transfer energy to an EV battery. As an EV supports only direct current, the charger has an inbuilt rectifier that converts AC to DC to recharge an EV battery [10]. Based on the charging technologies, the charging types can be mainly classified as follows:

- *Conductive charging* technique transfers power through direct contact between charger inlet and EV connector. This arrangement uses a cable to connect the CS or standard electrical outlet to the extent of energy transfer. Moreover, it is simple and highly efficient with an on-board or off-board charging facility. On-board charging is considered slow since charging activity is performed inside the EV, whereas off-board charging is deployed at a fixed place to offer a quick charging facility [10].

- *Inductive charging*, also known as wireless charging, is a technique of transferring energy between two objects that employs an electromagnetic (EM) field and ensures electrical safety in all weather situations. However, it has a significant drawback of high energy loss and low efficiency [10].

- *Battery swapping* is a system that allows consumers to exchange an empty battery for a fully charged one at battery swapping stations (BSSs). It offers various advantages, including extended battery life, low time consumption (as low as to exchange the batteries), and relatively minimal management costs, subject to BSS location where the batteries are gathered and managed [11].

- *Charging with different power levels* is regarded as a critical factor in the infrastructural development of EVs. According to the Department of Energy, US., there are currently three levels of charging technologies available: Level 1, less than 5 kw power; Level 2, between 5 to 50 kw; and Level 3, greater than 50 kw, which is super fast charging [12]. Level 1 and 2 chargers consist of on-board AC to DC electronic converter, while Level 3 has an off-board electric converter that makes Level 3 charging a little infeasible because a piece of extra charging equipment needs to be carried alongside.

- *Partial recharge*, wherein batteries are recharged up to the specified charging level.

EV charging is a highly exhausting and time-consuming process because charging time varies depending on the type of charger available and battery properties such as SoC, health, and capacity. Although we have two options to recharge either full or partial, earlier, full recharge was approached in most EVRP variants. However, the technological benefit of partial recharge over full recharge incurred several advantages such as financial benefits, reduction in charging time consumption, etc. [13–15] .

1.3 General Overview of the Research Problem

The vehicle routing problem, an extension of the well-known travelling salesman problem (TSP), is an optimization problem that asks an optimal set of paths for vehicle fleets to traverse from source to destination for serving a set of customers. Recently, it has emerged as EVRP when EVs penetrate the process of the logistic distribution. It facilitates the formation of an optimal EV route while serving different customers, bearing in mind the various constraints of network, user, EV, and CS. It is more challenging than traditional vehicle routing since the limited cruising range of EV correlates directly to frequent recharge events and demands a significant amount of time. Moreover, the time required to reach a CS and recharge the vehicle is critical for routing because it directly influences route economics. As a result, addressing these challenges is the foundation of our effort.

Let's briefly take a glance at the routing problem from EV users' perspective. It's natural to conclude that EV users are opportunistic in the sense that they generally wish to spend the least amount of energy during the routing. However, the goal of energy-efficient driving of EVs creates novel algorithmic challenges for navigation systems and route planners. Traditionally, routing has focused on finding the shortest paths in networks with positive, static arc costs representing the distance between two nodes. But, by taking into account the recuperated energy of EV, some arc weights could have a negative value, which makes most of the shortest path algorithms like Dijkstra, A*, etc., inapplicable. The most significant task is to locate energy-efficient routes rather than the routes that are short or fast. At first glance, it seems that if EV driver takes the shortest route, the energy consumption will be minimum. However, it is evident that as long as an EV driver demands an optimum energy route that is restricted to the various constraints of vehicle, user preferences, and transportation network, but road surface conditions can also create a potential impact on the vehicle's energy consumption. So, several new challenges have emerged, requiring the divergent approach in designing the models that can be expanded to make more realistic models to overcome the energy-efficient routing problem of EVs [16, 17, 30].

Another observation to highlight at this point is the charging station. The charging of EVs is a significant source of concern due to the underdeveloped charging station infrastructure and limited driving range that lead to inconvenience and generate operational challenges for EV users. For instance, identifying the constraint satisfied CS itself is a challenging task. Moreover, connecting to an outlet or charging device generally takes several hours to recharge an EV fully. As the charging process for EVs is more time-consuming, therefore, EV travellers have to ponder energy efficiency when making path choice decisions to enhance the driving range. However, finding the energy-optimal route doesn't mean that the necessity of identifying the CS is overlooked. However, the selection of the suitable CS is not only limited to the potential decision of EV users and EV constraints, but it can also be influenced by realistic constraints such as waiting time at CS, energy pricing, quality of service, location of CS, charging output, and charging heap availability. As a result, the problem of constraints trade-off arises among the EV, EV user, CS, and transportation network in identifying suitable CS by taking care of the energy-optimal route and dynamic demand changes [18–20].

The focus of this study also lies in the context of the routing cost of EVs, which is highly contingent on reducing the cost of travelled distance and recharging at the CS. Different charging technologies, such as battery swapping, different power levels, partial recharging, and time-of-use (ToU) energy pricing, each is associated with its respective recharging cost, allowing a wide range of charging flexibility. Therefore, the strategy is to carry out a systematic investigation how charging technologies could be leveraged to open innovative possibilities for enabling the broad spectrum acceptance of EVs in road transportation.

1.4 Research Objectives

This dissertation aims to dive into the different perspectives of the EV route planning problem. The prime activities performed in this work are tactical designing of the energy-efficient routing models, identification of potential charging stations, and utilizing an efficient algorithmic approach to address the complex problem. The following are the primary objectives of this research study:

1. To study and analyze the existing methods available for optimized route planning and identify different parameters influencing energy consumption of EVs.

2. To propose a framework consisting of following modules:

    i) An energy efficient routing approach for electric vehicles.

    ii) Identification of optimal charging station subject to vehicle and user constraints.

3. To validate the proposed framework using various performance metrics in different scenarios.

The notions mentioned above, integrated with the problem discussed in Section 1.4, lead to the research questions of determining the optimum energy route, identification of charging station, charging cost with diverse charging technologies, and identifying the most cost (in terms of prices) effective route. Therefore, after attaining these research questions, the solution presented by this study extends the EV range by minimizing the energy consumption, and at the same time, the drivers also minimize their travel costs. As a result, the objectives include determining a final solution to the research problem and analyzing the complex behaviour of the vehicle, charging station, and road transportation system while designing a solution.

1.5 Research Methodology

The methodology invoked in this dissertation delves into how major enabling technologies may be leveraged to unlock the hurdles to widespread adoption of EVs. Each transportation operation is furnished with a presented framework that explores existing and potential futuristic technologies to support the transition to EVs. The following sub-sections describe the methodology for solving the category of problems similar to the objectives discussed in Section 1.4:

- *To attain the first objective*: An exhaustive survey of the current models and frameworks has been conducted to describe the challenges associated with using electric vehicle routing and their proposed solutions. Existing applications, models, and research depicting the EVs transport sector have been explored thoroughly. New advancements in electric vehicle routing, charging infrastructure, and charging methodologies have been investigated.

- *To achieve the second objective*:

  First sub-objective: In this objective, a mathematical model has been presented that characterizes the energy consumption of an electric vehicle during the routing by paying special attention to the road surface conditions (dry, wet, snow, and icy). Moreover, the model considers several passive and active factors, including road elevation, various vehicle resistances, vehicle mass, SoC, and vehicle speed. A meta-heuristic solution approach has been applied to find the most energy-efficient route between the two points and the proposed approach has been tested over the available real time dataset of Warrigal project [21]. A comparative analysis is also presented against some of the available solutions.

  Second sub-objective: The model developed in the first sub-objective has been further extended, adding the functionality to suggest suitable charging stations which are optimally best as per the requirements of a prospective user that includes distance and traffic state between the current location and CS, recharging waiting time, energy pricing, and charging facility at the CS while keeping in mind EVs' constraints. To solve the problem efficiently, a KSP algorithm has been applied and tested over the real transportation network of Chandigarh, India. All scripts related to the KSP algorithm have been written in MATLAB R2021b, whereas CPLEX Optimization Studio has been used to solve the identified problem.

- *To accomplish the third objective*: The supremacy of the proposed framework has been validated using several performance metrics, such as energy consumption at the different route, optimality of the CS, the number of speed changes, journey duration, the real-time traffic condition, the total number of optimal solutions, average computing time, different speed patterns during the day by imposing the different vehicles' parameters on available real-time datasets and case studies.

1.6 Research Contribution

This dissertation enriches the literature significantly in the following manner:

- This work expands the present literature in firm competitiveness by highlighting theoretically and empirically intriguing characteristics of electric vehicle routing. Various issues related to the deterioration of existing electric vehicle routing support applications, models, and frameworks; and research depicts have also been addressed. Moreover, recent technological developments in electric vehicle routing, charging infrastructure, and charging methodologies have also been investigated with special emphasis paid to the selection of specific effective parameters in order to undertake a comparative study of different methodologies.

- A mathematical model for energy efficiency has been proposed which gives special attention to different road surface conditions such as dry, wet, snow, and icy. Moreover, various factors that affect energy consumption like speed, battery health, and road elevation have also been embedded into the design of EV route modeling.

- This dissertation also extends the literature with meta-heuristic-based solution based on the principles of ABC (Artificial Bee Colony) algorithm to assure energy optimality during the EV routing.

- An improvised distributed system, namely, S^2RC (Smart Search of Route and Charging) has been proposed that plans an energy-efficient EV route and utmost user convenience (identification of CS with minimal waiting time and recharging cost at CS), regardless of the several passive and active parameters of transportation network, user, vehicle.

- An agile charging station identification approach based on the theories of KSP (K-shortest Path) algorithm, implicitly employed by S^2RC system, has also been presented.
- Though there has been a large amount of research into the territorial characteristics of vehicles, this study considers the effect of EVs ' start and stop on energy consumption.
- EV recharging is usually a tedious and time-consuming process. Therefore, this study includes the effect of regenerating braking that produces the recuperation energy when traveling downhill or during the braking operation. This waste energy can be used to replenish the vehicle's battery.
- This dissertation also proposes an Amplified Ant Colony Algorithm (A^2CO) embedded with a probabilistic selection model that amplify the search efficiency of the proposed algorithm.

1.7 Outline of the Dissertation

This section lays down the scheme of the current work as follows:

Chapter 1: This chapter introduces us to the various aspects of the study, and explains the motivation, and objectivity behind the work. It illustrates the necessity to address the EV routing problem and the different challenges involved in its development.

Chapter 2: This chapter is focused on reviewing the relevant literature on the subject under investigation. It is a modest attempt to study the detailed modeling approaches of EVRP. However, EVRP modeling is a collaborative effort, not a single standalone entity of numerous interrelated supporting modules such as force modeling, transmission modeling, battery modeling, CS modeling, route modeling, load modeling, etc. Thus, the main objective of this chapter is to find the gaps in the research area by reviewing the various modeling techniques, solution approaches, tools, and evaluation measures.

Chapter 3: This chapter describes the two-fold contribution of the current research work. Firstly, a novel ABC-based algorithm has been developed to achieve EVs' energy optimum routing problem. The algorithm can produce the route between source and destination, but it can also identify which route is most energy economical out of all the possibilities. Moreover, the modelling of energy-efficient routing considers the road surface condition and the impact of dynamic and static parameters of EVs on energy consumption. Secondly, different road surface conditions have been included in the problem formulation and its solution. Later, the algorithm is out to test in a case study, followed by a comparison of various generated routes.

Chapter 4: This chapter proposes a distributed architecture, named S^2RC, where EVs wirelessly exchange information to assist EV users during the route selection and recharging decision. It is supposed that two-way communication of sensitive information (e.g., SoC level, current and destination location, EV's SoC, and user preferences) occurs between EVs and the distributed framework. At the same time, S^2RC provides the details about third parties such as transportation networks, traffic regulators, and CSs. S^2RC makes use of developed optimization model to find the optimal route and recharging station, as per the users' preferences. The top two variables that influenced the users' preferences are EV's energy efficiency and user convenience. These provide optimal choice to the EV user.

For instance, an EV user willing to travel from a specific source to a fixed destination raises a recharging concern. The user is enabled to find a suitable CS through an EV's agile charging slot reservation process accounting an optimization model with three objectives including minimum energy consumption, minimal waiting time at CS, and minimum charging cost. This model is employed by the S^2RC distributed framework to achieve an optimum route going through a CS, keeping in mind the global occupancy of on-road charging resources, the road network, traffic conditions, and EV characteristics. The k-shortest path (KSP) algorithm has been used to integrate the transport network with a scaled directed graph and obtain the several route plans having different parameters such as energy, distance, cost, and time. Regardless of varying parameters in the optical mesh network, the KSP algorithms yield the most optimum solutions that satisfy nearly all user requests, whereas such problems are more complex to address using an ordinary shortest path algorithm [22, 23].

Chapter 5: This chapter extends the mathematical model presented in chapter 3 by accounting the effect of vehicle's start/stop and recuperation energy on the EV's energy expenditure during routing. To achieve the objective of maximizing the energy-efficiency, it also introduces Amplified-ACO (A^2CO), a routing algorithm based on Ant Colony Optimization (ACO) principles that makes use of the probabilistic selection model (DS^2 relies on Distance, Speed, and State-of-Charge). This study simulates the proposed model over the real-time map of Chandigarh (India) and provides a comparative study against some of the nature-inspired meta-heuristic approaches such as classical ACO and Particle Swarm Optimization (PSO). The proposed model justifies its significance under various parameters, viz. energy consumption, travel time, total travel distance, and remaining SoC.

Chapter 6: This chapter concludes the work by highlighting its contribution made toward energy-efficient EV routing. It presents the key findings of this work. Further, it also explains the scope for future research in the field under investigation.

Chapter 2

Literature Review

The previous chapter offered an overview of this thesis. It covered the fundamental idea related to energy-efficient routing problems of EVs, unfolded its close alliance with other underpinning technologies, and introduced to the various issues of the study area which included the problem statement, and objectives. It also provided a brief description about the contributions and organization of this research work.

This chapter presents an extensive literature review on the development and operational challenges in EVRPs. It helps in finding a new path in the development of EV routing. It provides the latest information about the EVRP variants, methods, energy models, available tools, other vital parameters, etc. used in the study area. Related taxonomies of differently introduced problems, solution methods, evaluation of problems, etc. have also been presented to overcome with the routing challenges of EV.

In order to a systematic review of the previous studies, the chapter has been structured as follows. Section 2.1 outlines the basic EV routing model. Section 2.2 illustrates the various allied EVRP variants. Section 2.3 is focused on reviewing the various problem-solving approaches to EVRP. Section 2.4 addresses the literature analysis. Lastly, Section 2.5 concludes the chapter by providing the research directions.

2.1 Basic EV Routing Model

The distribution process of logistic firms was the reason behind the inception of VRPs which aimed to reduce transportation cost of vehicles while serving different set of customers. However, in order to reduce the negative impact on the environment and meet the emission standards, less polluting means of transport vehicles such as EVs are essential. However, EVs need to manage certain additional constraints of vehicle, transportation network, and CS. The limited cruising range of EVs directly corresponds to frequent charging. But the identification of the CS itself is a highly computational task because the CS may be available at some diversely scattered geographical region. Therefore, to overcome such sort of complexity, the existence of EVRP is badly required.

M. Schneider et al. [24] were the first to deal with the routing of EVs while considering the possible visits to CS and time windows. In their research work, they formulated the objectives in such a way that not only the fewer number of vehicles were required in the operation, but also minimized the total travelled distance. The problem was expressed as a MILP model on a complete directed graph G, where customers and path between customers were represented as vertices, and arcs of the graph respectively. Let $V = \{1, 2, ..., K\}$ be a set of customers, and R be a set of CS. A virtual collection, R', of charging stations was defined for more than one visit to the same CS. The depot was indicated by vertices 0 and $K + 1$, while each route started and ended with vertex 0 and $K + 1$ ($V_{0,K+1} = V \cup \{0\} \cup \{K + 1\}$) respectively. Graph G was defined as ($V_{0,K+1} \cup R', A$), where A was set of arcs and defined as $\{(i, j)|i, j \in V_{0,K+1} \cup R', i \neq j\}$. Based on the real-life parameters of EV, different arc (i, j) values were defined as cost (c_{ij}), distance (d_{ij}), energy consumption (e_{ij}), regenerating braking (rb_{ij}), travel time (t_{ij}), and speed (v_{ij}). Moreover, where an arc (i, j) was traversed in the graph, the binary variable x_{ij} was equal to 1, otherwise it was 0.

To determine the overall driving range of EVs, it was important to know about their energy consumption because of the low energy storage capacity. The simulation model can estimate the energy consumption, but the complexity of EVRP makes it more difficult due to the factors, such as unfamiliar driving cycles in advance, real-time approximation, etc. Energy consumption is normally calculated based on the vehicle's LDM (Longitudinal Dynamic Model). Therefore, actual force (F) is estimated based on different resistances and acceleration, as shown in the Eq. (2.1). R. Abousleiman and O. Rawashded [30] introduced a model which characterized the energy consumption of an EV. The output power (P_{out}) at the battery terminal was represented in Eq. (2.2), where M represented vehicle mass, g tended to gravitational acceleration, ρ_a represented air mass density, f_r represented the tire rolling resistance coefficient, A_f was frontal area of the vehicle, C_D was aerodynamic drag coefficient, V stood for vehicle speed, i was road grade, δ was rotational inertia factor, and a was the vehicle acceleration in m/s^2. Moreover, Eq. (2.3) represented the regenerating power input (P_{in}), where $\alpha = (0 < \alpha < 1)$ was the percentage of the total brake energy that could be regenerated by the electric motor. The Eq. (2.4) represented the total power ($Energy_{Total}$) consumption at the battery terminal. It has been observed throughout the literature that many studies followed the principle of vehicle's LDM to design their energy consumption model [8, 25–27, 39, 55, 61, 147].

$$F = (Grade, Rolling, Air, Acceleration) \tag{2.1}$$

$$P_{out} = V(Mg(f_r + i) + \frac{1}{2}\rho_a C_D A_f V^2 + M\delta a) \tag{2.2}$$

$$P_{in} = -\alpha * (V(Mg(f_r + i) + \frac{1}{2}\rho_a C_D A_f V^2 + M\delta a)) \tag{2.3}$$

$$Energy_{Total} = \int (P_{out} + P_{in})dt \tag{2.4}$$

2.2 Allied EVRP Variants

Numerous vehicle routing variants have been studied over the years. But due to the EVs integration into the logistics, novel routing research challenges have been adopted as EVRPs. So, owing to the specific properties of EVs, some new variants of EVRP have emerged over the time. In this section, some of the prominent variants of EVRP and their related problems have been reviewed.

2.2.1 Energy-Efficient Path Problem (EEPP)

The EEPP is viewed to be the very first originated problem of EVRP. Many algorithms such as Dijkstra, Bellman-Ford, A*, etc. are applied to compute energy-efficient routes between some source and destination [31, 52]. The parameters such as distance to destination, routing cost, travel time, etc. have nearly positive arc values in the graph representations and do not yield any barrier in the energy computation. However, negative edge weight values generated by regenerative braking, energy limits, and other factors that could only be computed at query time make energy computation, as well as EEPP, a challenging assignment. So, the literature related to the field of EEPP has been reviewed as hereunder.

R. Abousleiman and O. Rawashdeh [39] provided solution to the negative weight edge problem. For this purpose, they applied the Bellman-ford search on the proposed electric vehicle model to get the most energy-efficient route. Extensive simulations were done on the Matlab with different size test instances; and it was found that the proposed methodology would not yield optimum solutions, if distance or travel time were taken into consideration. Moreover, the proposed approach became impractical for a large number of edges and vertices. A. Liebscher et al. [62] presented another short revision of the energy-efficient path problem of EVs and addressed it with the help of a modified Bellman-ford algorithm that worked over real-time data, made available by the local traffic management center. R. Abousleiman and O. Rawashdeh [30] introduced an energy-efficient routing model using PSO, and they showed a 9.2% reduction in energy consumption via the route suggested by the proposed algorithm over the route recommended by Google Maps and MapQuest. This novelty was further enhanced by R. Abousleiman et al. [61] to minimize the total energy consumption and proposed the use of ACO. Simulations were carried out over the real-time data from Fiat 500e 2013 EV, and results revealed that the best four routes generated by the proposed model proved to be 9% more energy-efficient than the routes suggested by MapQuest and Google Maps. A. M. Bozorgi et al. [69] presented a data mining-based model to address the problem of energy and time-efficient routing of EVs. The techniques were applied to trace down the speed profile from the historical driving data of the Warrigal project [21]. Their results showed that optimal solutions would yield by continuous observation of the real-time data. More recently, M. Strehler [53] have proposed an energy-efficient walk model for hybrid EVs named FPTAS based on binary search. The authors introduced two-cycle prevention approaches called restricted charging function and resource conversion. Simulations were performed to check the applicability with four randomly generated test cases and avoided almost every cycle caused by charging properties. Similarly, C. De. Cauwer et al. [56] introduced a multiple linear regression model to suggest the minimum energy consumption route. Moreover, a geographic information system tool was used to create the link between road segments and real-time driving data from GPS and CAN networks. At the same time, the neural network was applied to predict the unknown driving parameters before the vehicle's departure. Prediction results revealed that their model would predict energy consumption on any road segment before the departure of the vehicle with an overall error prediction of approximately 12% to 14% of the total energy consumption. More recently, A. G. Garcia et al. [58] modified the PSO intending to improve computing time and to reduce the energy consumption of EVs. The simulation results revealed no significant difference in the energy consumption compared with the Bellman-ford approach, even in the traffic changing environment, but PSO outperformed the computation time for the larger-sized map. In their work [67], G. Macrina et al. addressed a mixed fleet GVRP involving partial recharging and time windows with aim to minimize the total energy consumption.

Table 2.1: Key Findings and Outcomes of Different EEPP-based Approaches

References	Problem Name	Key Findings	Outcomes and Remarks
[39]	EER	•Objective is to identify energy-efficient route. •Bellman-ford based solution approach. •Considered negative edge weights. •Energy consumption model based on LDM model. •Extensive simulations over Matlab optimizer. •Tested over different map sizes.	•Energy-efficient path is generated in reasonable time. •Optimal solutions would not be produced if it was applied on distance or travel time. •Im-practical for higher number of vertices and edges.
[30]	EER	•Objective is to minimize the energy consumption. •PSO based solution model. •Single constraint optimization problem. •Matlab simulations. •Real-time dataset of 2013 Fiat 500e EV. •Comparative analysis with Google Maps and MapQuest.	•9.2 % less energy consumption route suggestion while compared with Google Maps and MapQuest. •Improved processing speed over large data sets when compared with Bellman-ford.
[56]	EER	•Utilizes the MLR model. •Based upon neural network. •Energy estimation and speed profile prediction model. •Data-Driven approach. •Based on real world conditions.	•Predicted energy consumption before departure precisely. •Energy-efficient routing. •Distinguishes various power consumption influencing factors.
[53]	EER	•Novel FPTAS model. •Constrained shortest path problem. •Based on the principles of binary search. •Matlab optimizer. •Randomly generated test cases.	•Computed energy-efficient path. •Avoid cycle in the journey. •Need heuristics approach.
[62]	EER	•Based on vehicle's LDM model. •Utilized modified Bellman-ford approach. •Data from OpenStreetMap and OpenDEM Map. •VAMOS traffic management system.	•Shortest route considered to be the most energy-efficient route.
[69]	EER	•Time and energy-efficient model based on historical data. •Data-driven approach. •Data Mining techniques were utilized using Weka tool. •Warrigal project's data [21].	•Reduced the travel time and energy consumption during the routing. •Shortest route does not employ minimum energy consumption route. •Continuous observation of the real-time data.

Continued on next page

Table 2.1 – *Continued from previous page*

References	Problem Name	Key Findings	Outcomes and Remarks
[61]	EER	•Objective is to minimize the energy consumption and to maximize the endSoC. •ACO based meta-heuristic model. •Constraints satisfied optimization problem. •Matlab simulations. •Real-time of 2013 Fiat 500e EV. •Make use of Google Maps and MapQuest.	•Best four routes proved to be 9% more energy-efficient as compared to the routes suggested by the MapQuest and Google Maps.
[60]	EER	•Bi-objective optimization model to maximize the reliability of on time arrival and energy-efficiency. •Uses KSP algorithm. •Heuristic approach. •Matlab simulations. •Numerical demonstration. •Real-time traffic conditions.	•Generation of energy-efficient path. •Polynomial computation complexity. •Overcomes the traditional shortest route finding algorithm's (Dijkstra algorithm) in-feasibility.
[67]	GVRP	•Energy-efficient routing of mixed fleets. •MILP model. •HLNS algorithm. •Mat-heuristics approach. •Partial recharging, time windows and braking energy is considered as constraints. •CPLEX simulator. •Test Cases were introduced to check the supremacy.	•HLNS was faster as compared to CPLEX. •Medium types of instances were also solved by the HLNS quickly. •Optimal solutions were found by the CPLEX optimizer only for 10 instances.
[58]	EER	•Objective is to reduce energy consumption and computational speed. •Model based on PSO. •SUMO simulator. •Uses OpenStreetMap, SRTM data. •Comparative study with Bellman-ford approach.	•Improved processing time for larger map size. •No difference in finding energy-efficient route while compared Bellman-ford approaches.

Table 2.2: Key Findings and Outcomes of DCTP based Approach

References	Problem Name	Charging Constraint(s)	Key Findings	Outcomes and Remarks
[95]	GVRP	PR, FR, FC	•Objective is to achieve minimum energy cost. •Constructive and local search heuristics. •K-PseudoGreedy heuristic algorithm. •Mathematical programming model. •SA algorithm. •Instances from S. Erdogon and E. Miller-Hookds, and M. Schneider et al. [24, 97]. •Instances created based on the dataset from E. Labs [98]. •CPLEX solver. •Implementation in Fortran 95.	•None of charging technologies overlook the other. •Partial recharging was proved to be more significant in saving in cost and energy.
[102]	EVRP	TW, PR	•Mathematically formulated as MILP. •VNSB mat-heuristic solutions. •MILP is implemented in AMPL. •CPLEX optimizer. •Uses the instances of M. M. Solomon [59].	•VNSB was computationally faster than MILP. •Total running time outside the depot is improved by 23.02%.
[101]	EVRP	FR, PR, TW	•Objective is to minimize total routing cost. •Exact branch price and cut algorithm. •The exact algorithm relied upon customized mono-directional and bidirectional algorithms. •Set partitioning model. •Different charging variants. •CPLEX optimizer. •Historical benchmark instances from M. Schneider et al. [24].	•Partial recharges have reduced routing cost by 0.97% and total employed vehicles by 2.25%.
[99]	EVRP	TW, PR	•Aim is to minimize the total distance traveled. •0–1 MILP based model. •Uses ALNS algorithm. •Removal and insertion operation are incorporated into the problem. •Uses CPLEX Optimizer. •Java environment implementation. •Historical instances from M. Schneider et al. [24].	•Routing decisions were improved with partial recharging (PR). •PR may save total distance by 10% as compared to full recharge for small instances. •For large size instances, PR is more effective in case of restricted time windows.

Continued on next page

Table 2.2 – *Continued from previous page*

References	Problem Name	Charging Constraint(s)	Key Findings	Outcomes and Remarks
[5]	EVRP	PR, FR, NCF	•To achieve the objective of minimum travel and charging time. •MILP based formulation. •Introduced hybrid meta-heuristic comprises of ILS and HC. •Java environment. •Gurobi optimizer. •Created own set of instances.	•Partial recharges would be exploited by the multiple mid-route recharge.
[96]	EVRP	FC, PR	•Objective is to minimize the total distance as well as to reduce charging costs. •Integer programming model for different charging cases. •CPLEX optimizer. •Uses the instances of M. Schneider et al. [24].	•Reduction in EV fleet with fast charging. •CPLEX was able to produce the optimal solution only for 5 customers instances.
[32]	EVRP	TW, FC, PR	•Objective is to reduce total recharging cost while minimum number of vehicles. •MILP model. •Introduced mat-heuristic algorithm comprises of ALNS and exact procedure. •Destroy and repair algorithms. •CPLEX Optimizer. •Fort instances of A. Felipe et al. [95].	•Fast charger would be suitable for wider time windows. •Fast charging reduces the fleet size and energy consumption.

An energy consumption model was developed that could take into account real-time parameters. In particular, they developed a MILP model to satisfy the user's constraints. Also, a mat-heuristic model was developed based on LNS; and it was revealed that the mat-heuristic was less time-consuming than the exact ones. Later, L. Shen et al. [60] evaluated a bi-objective optimization model intending to maximize the energy-efficiency and on-time arrival reliability in a stochastic traffic network.

This section provided a detailed description of the EEPP. The problem stems from the EV's low cruising range, resulting from limited energy resources. Evaluation of real-time energy consumption with various internal and external factors is challenging. However, the developed model offers large scalability with better control in the restrictive environment. Optimizing EV route and energy consumption strengthens the trust of EV users and provides a decision support tool for the effective operation of EVs [11,68,172,177,200]. Incorporation of artificial intelligence and data-mining technologies into the dynamic energy consumption models further enriches the demand side management, and sustainability of EVs [173–176]. The Table 2.1 summarizes significant findings and results of the above-mentioned EEPP-based approaches, which can be extended for their use in energy-efficient routing in the EV routing environment. The table helps to understand the key features, parameters, and core ideology focused on developing a novel future solution to the problem.

2.2.2 Different Charging Technologies Problem (DCTP)

Charging technology is another field where existing EVRP models remain a step behind, thus, creating the biggest obstacle in establishing EVs. There has been an urgent necessity for smart as well as fast charging technologies (as fast as to refuel a fuel-based vehicle) for the widespread adoption of EVs [41]. The charging time of different charging technologies could be optimized to facilitate the customers' needs. If some of the customers have narrow time windows, they could be provided with a fast-charging facility, but slow charging could be an economical option, if time is not the constraint. Therefore, the recharging station constraints that deal with DCTP, such as type of charging, the number of charging slots, time-dependent charging, etc., may further require more attention. The various state-of-the-art technologies studied over the years to counter the DCTP, have been reviewed as follows:

In this domain, A. Felipe et al. [95] introduced research that studied GVRP together with variants of multiple recharging technologies and partial recharge constraints. They proposed various constructive and deterministic local search algorithms to minimize recharging costs. Moreover, simulated anneal (SA) meta-heuristic was also introduced to overcome the infeasibility achieved due to the local optima problem generated by the deterministic local search algorithms. Further, the authors illustrated the benefits of multiple charging technologies over partial and full recharges. B. Catay and M. Keskin [96] showed the impact of a fast-charging station on route planning with the objective to minimize the total travelled distance. The authors tackled EVRP with time windows and formulated individual mathematical models for single and quick-charge options while utilizing small-size instances from the literature. The results revealed that the quick charging option could decrease energy cost and fleet size reduction. The authors extended their work [32], where they attempted to minimize the total operative vehicle count as well as charging cost by giving the facility to choose one of the charging technologies, viz. normal, fast, and superfast charging. A meta-heuristic combining of ALNS and integer programming was also introduced. It was concluded that fast charger would get minor influence on charging for the more comprehensive-time windows.

EV recharging is an extremely tiresome and time-consuming process because charging time varies with the type of charger available and the properties of the battery, such as SoC level, health, capacity, etc. Although two options exist to recharge, either full or partial. However, earlier, full recharge was approached in most EVRP variants, despite, the fact that partial recharge had several advantages such as financial benefits, reduction in charging time consumption, etc over full recharge. To analyze the effect of partial recharge, numerous research studies focusing on the formulation of EVRP with partial recharge have been reviewed. The work of M. Bruglieri et al. [102] addressed a variation of EVRP in which time windows and partial recharging constraints were taken into consideration. They formulated the problem as a 0-1 MILP and aimed to minimize the total duration of running time and the number of EVs. As the problem was determined to be an NP-hard, a mat-heuristic VNS clubbed with LSB was developed to find the optimal solution using different instances from the literature. Similarly, M. Keskin and B. Catay [99] introduced a more realistic scenario of partial recharging in the formulated problem of EVRPTW. The authors introduced an ALNS algorithm-based solution for the developed MILP problem to solve it efficiently. The positive impact of partial recharging was shown on energy-saving and total cost. It was also ensured that EV would charge enough, at previous CS, to finish the remaining segment to the next CS or the destination. Hence, eliminating some of the charging stations in the route and ensuring significant improvement in route decision with partial recharging. Likewise, to reduce the total routing cost and decrease the count of operative vehicles, G. Desaulniers [101] presented a route planning algorithm which took into consideration four types of recharge variants: (i) not more than one recharge per route with fully recharged at the CS; (ii) various recharges per route with fully recharged; (iii) not more than one recharge per route with partially recharged; (iv) various partial recharges. Mono-directional and bi-directional algorithms were introduced for presenting the feasible route plan with each problem variant. Moreover, the proposed algorithm solved all the four variants on the instances having up to 21 CSs and 100 customers. For the increased instances of around 50 and 100 customers, bi-directional labeling outperformed the mono-directional labeling. The results revealed that partial recharges reduced routing cost by 0.97% and the total employed vehicles by 2.25% in the case of single recharge per route, while 1.91% and 3.80% respectively for multiple recharges per route.

EV charging technology not only affects the total journey time, but also the economical interest of the EV user. EV charging is still a subject of great concern because some studies have highlighted the importance of partial recharging, while others have emphasized on the relevance of full recharge. Apart from these, some have addressed the quantity of recharge, while others have examined the different levels and fast charging [14,72,191–194]. The Table 4.3 summarizes some of the major findings and outcomes of DCTP-based approaches as mentioned above. There are plethora of solutions available that have diversified DCTP and offered a diverse range of solutions to address the mentioned problem. Despite this, many of them fall short on account of their performance and the trade-offs among other elements of EV sustainability such as routing, power balancing, user economics, EV constraints, etc. Thus, the discussion as mentioned above can encourages the researchers to find a better solution for EV recharging [100,195,196].

2.2.3 Charging Waiting Time Problem (CWTP)

It can be inferred from the existing EVRP literature that EV recharging would be initiated as soon as it reaches the CS [103]. However, congestion at the CS is a matter of grave concern. There could be the possibility of limited number of charging slots, or it might take a long time to recharge the vehicle fully. So, taking this problem into consideration, the following studies undertaken for review are focused on the "charging waiting time":

H. Qin and W. Zhang [104], in their work on CWTP, targeted to minimize the waiting time of EVs in a large road network. For this purpose, different distributed scheduling protocols were proposed. A. Hess et al. [108] introduced a charging model based on the battery charging cycle of EVs and navigated to the CS on demand. Moreover, on-road traffic density was the prime focus in the proposed queuing network model. Similarly, D. Said et al. [110] presented a multi-queuing model, called EVPSS, to minimize the charging delay at public CS. Further, G. B.Qiu et al. [107] also developed the queuing system model based on queuing theory. Inspired by the real-life scenario of Netherlands, M. M. DeWeerdt et al. [106] proposed a novel IARS system, which scheduled en-route charging of EVs while taking into account the practical assessment of the network. The evaluation involved the real location of CS and time-dependent traffic conditions. The study was able to forecast the congestion at CS and helped to select the route that had minimal travel time. The proposed system reduced 80% waiting time in most of the cases, while the overall journey time decreased by more than 50%. Later, A. Tian [111] proposed a real-time system based on large-scale data mining that suggested an EV taxi driver, a congestion-free CS. The presented methodology worked on the real-time GPS trajectory and historical recharging event of around 800 EV taxis to underline the operational state of each EV taxi. It finally ensured that the proposed system could accurately estimate the waiting time and reduce it by 50%. I. Garcia-Magarino et al. [112] developed an ABS framework for reducing the waiting time at the CS. The presented framework simulated the effects of EV charging plan while routing various coordinating policies. M. Setak and A. Karimpour [109] presented a MILP model for EVRPTW on multi-graph to consider queuing approach at the CS. A simulated annealing meta-heuristic was proposed to enhance the solution and solve the larger instances. Most recently, M. Keskin et al. [103] presented EVRPTW taking into account soft time-dependent queuing time at the CS. They presented the exact solver and ALNS heuristic to minimize the total routing costs. Furthermore, the CS adopted the M/G/1 queueing system model; and a penalty was charged for the latecomers. The waiting time was considered crucial during the routing and should not be overlooked. Z. Moghaddam et al. [211] introduced a meta-heuristic-based solution, and later some more improvements were noticed with different solution approaches and ideologies [209, 210, 212].

This section summarizes some of the most important contributions made in the CWTP of EV routing domain. It is essential to optimize the charging waiting time at the CS in order to take a step toward the creation of a smart city since it provides a hassle-free, less time consuming, economically stable and convenient environment for EV users [103]. Several charging strategies and models such as, partial recharge, fast charging, queuing model, etc. are adopted to mitigate the challenge of prolonged waiting time [111, 209–212]. However, most of the studies found in this domain have performed in the static environment. There is still a lot of space for improvement in terms of providing the real-time exposure to the problem. The Table 2.3 has summarized some of the major findings and outcomes of the above-mentioned CWTP-based approaches.

2.2.4 Time-dependent Traffic State Problem (TDTSP)

In conventional EVRP studies, travel time between source and destination is solely focused on distance travelled, if the traffic environment is considered static. In reality, traffic movement is dynamic due to different factors such as weather fluctuations, road accidents, and traffic jams due to some unforeseen causes. [114, 278]. Moreover, the traffic movement can change recurrently due to some day of the week, time of the day, festival day, etc. So, the studies relating to the TDTSP have been reviewed as follows:

Table 2.3: Key Findings and Outcomes of CWTP-based Approaches

References	Problem Name	Charging Constraint(s)	Key Findings	Outcomes and Remarks
[104]	CSMWN	FC, FR	•Model for minimize waiting time at CS. •Model based on the insight of theoretical study. •Advance charging reservation. •Introduced protocol for charging schedule. •Extensive simulation over 100 nodes.	•Reduced EVs' waiting time and generate charging schedule.
[108]	ODCS	FC	•MILP model for charging station deployment. •Solution given by genetic programming approach. •Queuing network model. •Attraction model for charging station navigation. •SUMO traffic simulator.	•Minimum waiting time at the CS. •Optimal solution with 30 plugs at CS.
[106]	IARS	FC	•Objective is to compute waiting time at CS. •Intention aware routing system. •Model based on probability. •LOGIT algorithm. •Real-time data from M. M. de weerdt [47].	•Improved 80% in waiting time at CS in most of the cases. •The overall journey time reduced by more than 50%.
[111]	RTCSRS	FR	•Charging station recommendation system. •Used data mining approach and historical data information. •Identification of recharging intentions. •Data driven method. •Real-time GPS trajectory.	•Accurately predict the waiting time at the CS. •Observed cost time reduction by 50%.
[112]	ABSCEV	FC	•Objective is to reach the CS with minimal time and manage booking of time slots at CS. •ABS framework. •Recharging booking system. •Interface is developed. •Modified A* algorithm for shortest path finding. •Tested over differently sized maps.	•Reduced overall trip time and waiting time. •50% cost time could be reduced.

Continued on next page

Table 2.3 – *Continued from previous page*

References	Problem Name	Charging Constraint(s)	Key Findings	Outcomes and Remarks
[103]	EVRP	TW, FC, NCF	•To determine the minimum cost route. •Formulated the problem as MILP model. •Mat-heuristic based solution approach. •Utilizes ALNS. •M/G/1 queuing model. •Penalty for late arrivals. •CPLEX optimizer was used for small instances. •Implementation in Java. •Instances from M. Schneider et al. [24].	•Total journey cost may be increased by 1% to 26% due to waiting in queue. •Waiting time did not effect when customer has wider time window.
[109]	EVRP	TW, FC	•Objective is to minimize the total traveling and charging cost. •MILP based model. •SA algorithm as solution. •M/M/s queuing system. •Based on FCFS policy. •Multi-graph for alternative path. •GAMS and CPLEX solver. •Test instances from M. Schneider et al. [24].	•The number of CS and charging slots in the CS should be increased. •Minimized waiting time at CS. •Multi-graphs may reduce the number of CS visits. •Found best solution with minimum number of CS visits.
[209]	EVRP-MPQ	-	•Objective is to estimate the remaining SoC and queue waiting time identification at CS. •Considered the parameters such as charging capability, priority, remaining charge, SoC, distance, and traffic flow. •Multi-priority queuing algorithm. •Importance was given to the user's priority.	•Accurately calculated the waiting and service time at CS. •EV and queuing algorithm show promising results.
[211]	SCS	FC, BSS	•Objective is to minimize the total journey time including waiting time and charging cost. •Facilitate multiple charging option, dynamic pricing, and SoC. •Problem formualation as MILP model. •ACO-based solution. •M/M/s/C queuing model. •Extensive simulations over Washington city transportation network.	•Simulation confirms the reduction in average charging delay up to 25% and cost up to 15%. •Queuing algorithm show promising results.

Table 2.4: Key Findings and Outcomes of TDTSP-based Approaches

References	Problem Name	Charging Constraint(s)	Key Findings	Outcomes and Remarks
[133]	EVRP-ACO	TW	•Multiple Objectives considering the aspects of route length, traveling time, energy, cabin temperature. •Proposed a temporal multi-objective ant colony optimization algorithm. •Extensive simulations. •Pareto sets.	•Guaranteed solutions to multiple objectives and driver's constraints. •Produce better routing plan with dynamic traffic environment.
[115]	GVRP-TDTW	TW	•MILP formulation for the proposed problem. •CPLEX optimizer. •Randomly generated instances. •Sensitivity analysis.	•Minimized the total operation cost. •Reduced carbon emission.
[113]	EVRP-CTVTT	TW, FR, FC	•Objective is to minimize the total operating cost, such as charging, penalty, travel cost. •Dynamic Dijkstra algorithm for finding the shortest route. •GA as solution approach. •Different datasets including road network, facilities, travel speed. •Representation of a case study.	•Reduced the operational cost. •Prevented battery power depletion.
[214]	D-EVRP	FC	•Objective is to minimize total duration of delivery. •A finite-horizon Markov decision process formulation. •Analytical battery model for charging and discharging pattern of EV. •A hybrid roll-out algorithm proposed as solution. •A case study of Singapore.	•Minimizes the overall service duration. •Robust solution over the large scale instances.
[117]	TD-GVRP	TW, BSS	•To minimize vehicle cost and energy consumption. •Formulated the problem as MILP. •Constructive heuristic as solution. •RR approach. •Xpress solver. •Randomly generated instances.	•Heuristics perform well as compared to the exact ones. •Produce better routing plan in dynamic traffic environment.

S. Shao et al. [113] were the first to cope with such a time-dependent traffic state challenge. They considered the EVRP along with the constraints of charging time and variable travel time. This problem was inspired by the real-life problem from Beijing, China. The study included the Dijkstra algorithm for non-persistent graph's weight and used the GA approach. Moreover, the authors incorporated fluctuations and speed variations in travel time due to traffic dynamicity in the proposed model. Later, another variant of dynamic traffic inclusion was presented by S. Mirmohammadi et al. [115]; and the problem was formulated as green heterogeneous VRP in the time-dependent urban traffic environment. The supremacy of the proposed framework was tested over ten randomly generated instances by the CPLEX optimizer. Further, a sensitivity analysis was carried out to determine the effect of essential parameters on the total cost. S. Zhang [133] considered a temporal multi-objective ACO algorithm for generating EV route plans in a time-dependent stochastic traffic environment. The author utilized real-time traffic conditions provided by the Baidu Map. The performance evaluation of the proposed framework was compared with the other two models in the same domain. Conclusively, they emphasized on two things: firstly, guaranteed solutions generated by the T-mACO, which demonstrated multi-objectives and driver's constraints; secondly, the proposed algorithm ensured a better routing plan in the dynamic traffic environment. X. Bi and W. K. Tang [214] introduced a dynamic EVRP model for itinerary planning for goods delivery in consideration of the time-dependent traffic network. Most recently, A. Haghani et al. [117] addressed mixed fleet heterogeneous GVRP in a time-dependent vehicle routing environment intending to achieve minimum cost routing and optimal fleet size. The problem was formulated as the MILP model. A heuristic algorithm based on the Ruin and Recreate (RR) approach was introduced to generate the initial solution, which was further improved by the improvement heuristic.

Here, a discussion on EVRP solution strategies based on time-dependent traffic state is presented. In the present scenario, traffic is the major factor that decides our travelling time to our destination. The studies conducted so far by different researchers have considered different traffic phenomena along with their uncertainty of occurrence. Out of these, the prominent ones studied here focus on the variations of weather conditions, traffic jams either by accidents, or some snag in traffic regulatory machinery. A glance at these studies showing that ignoring the multifarious nature of travel time will result in vehicles being stuck in traffic jams, road congestion and excessive drainage of batteries, and frequent charging cycles [216]. Therefore, the EVRP solution must be a multi-objective function with at least one component for real-time traffic and travelling speed scenarios analysis to cope with the dynamicity of traffic and travel time [117, 203, 213–216]. The Table 2.4 summarizes some of the major findings and outcomes of above-mentioned TDTSP-based approaches.

2.2.5 Dynamic and Time-of-Use-based Energy Pricing Problem (D-ToU-EPP)

Many researchers are currently seeking to identify the optimal off-peak period of use, i.e., ToU, that can result in the cheapest electricity price and reduce the power grid load. Although, maximum studies overlooked this aspect and utilized fixed energy prices. But in real-time, ToU price fluctuates based on the load valley, peak demand, and power source at CS [118]. Chinese energy companies are providing step-wise power tariff, and ToU pricing catalogue, which shows that dynamic and ToU energy pricing schemes can't be overlooked in determining the efficient route plan for EVs and require further attention [119]. The relevant studies on the underlined domain have been reviewed as follows:

Only a limited number of studies available that have represented EVRP in the context of dynamic and ToU energy pricing. T. Wang et al. [129] presented the MINLP model for minimizing the total elapsed time to reach the destination by locating routes along with charging cost. In addition, the authors further decomposed the initial problem into a sub-problem of in-homogeneous prices at the recharging node. Moreover, multi-vehicle variants were discussed by exploring the general properties of the proposed problem. The projections revealed that an optimum solution was discovered with reduced computational complexity. H. Yang et al. [125] studied the LPG algorithm for EV route optimization coupled with ToU energy prices where the objective was to minimize the energy prices. Competitive results were obtained on different case studies with respect to network sizes of 36 and 113 nodes. Ultimately, they summarized that i) high charging prices incurred rise in charging cost; ii) the shortest route would not equate to the minimum costs; iii) under the ToU energy pricing, fast and regular charging time would avoid the system peak load; and iv) the night distribution could reduce the total cost. Later, C. Liu et al. [20] developed an en-route charging navigation model based on the dynamic programming considering route optimization and joint charging. They considered the real-time electricity prices environment because it could affect the routing and charging decision while optimizing the journey cost in the time-dependent network. Moreover, a simplified charging control algorithm was also proposed to track the charging control decision in the fluctuations of real-time electricity prices. The results revealed that the proposed system could reduce computational complexity by producing minimal routing and charging costs. Recently, G. Ferro et al. [120] presented an extended version of the problem attained by M. Schneider et al. [122] with the additional parameter of ToU energy prices and partial recharge in the EVRP environment. They introduced an MILP model for verifying the significance of ToU on energy pricing. A set of randomly generated test instances along with fixed energy cost slots, each of four hours, was involved in verifying the significance of the proposed model. Most recently, H. J. Lee et al. [128] addressed an economic routing of electric vehicles charging control strategy while considering the dynamic pricing and system voltage. In fact, the routes of EVs could change indirectly by changing the price in real-time due to voltage fluctuation on the CS. They comprised Dijkstra's algorithm and charging control strategy to verify the proposed model using MATLAB simulation. Four numerical simulations were carried out; and updated route information was shared with EVs to choose the best economical route. G. Ferro [199] also extended the GVRP simultaneously considering ToU energy pricing and EVs' energy consumption. An MILP model was formulated and evaluated over an e-NV200 Nissan 2017 EV model case study. Moreover, H. Liu et al. [207] introduced a routing decision model that took into account the dynamic traffic condition, charging prices, and charging waiting time before heading to the CS.

Here, an attempt has been made to review the different types of work done in the field of ToU energy pricing which has strong influence on the routing decisions of EVs. It becomes even more vital to optimize when it is provided with varying prices associated with the different time slots of the day. There is a sufficient evidence of using the ToU energy pricing in conjunction with the routing of EVs in the literature. However, it is felt that still a large room exists for improvement by way of taking into account the many variables that are associated with ToU energy pricing, such as incentive-based pricing, energy grid load balancing, penalty-based pricing on late arrivals, etc. [120, 128, 199, 206, 207]. The Table 2.5 has summarized some of the major findings and outcomes of the above-mentioned D-ToU-EPP-based approaches. Moreover, it has also been divided into five broad categories which help to understand the state-of-the-art ideology and constraints used by the different authors.

2.2.6 Location Routing Problem (LRP)

The development of an energy network is one of the critical barriers to the effective deployment of EVs. The count of CSs is relatively low due to the lower market share of EVs. Consequently, the penetration of EVs into logistic services is hindered. Thus, the classical LRP has been modified as electric LRP, which helps in finding the location of CSs and identifying the service route between CSs and EVs depot. The simultaneous decision of EV routing and the installation of CSs attracts a significant potential for research and development. As a potential contribution to the literature, the recent contributions to E-LRP, have been reviewed as under:

Table 2.5: Key Findings and Outcomes of D-ToU-EPP-based Approaches

References	Problem Name	Charging Constraint(s)	Key Findings	Outcomes and Remarks
[125]	EVRP-ToU	FC	•Objective is to minimize the routing distance and reduce the number of vehicles. •LPGA optimization. •Based on TSP problem. •MATLAB simulation. •A number of case studies. •Instances from COIN-OR [48]. •Numerical test on 36 and 112-node systems.	•Minimized the total distribution cost. •Shortest route does not corresponds to the minimum costs route. •Under the ToU energy pricing, fast charging would avoid the system peak load. •The total cost could be reduced by the night distribution.
[20]	EVCNS	FC	•Dynamic programming based model. •SCC algorithm for deterministic traffic. •OSR algorithm for navigation control in time-dependent traffic. •Extensive numerical simulations. •Real-time electricity pricing instances from A. H. Mohsenian-Rad et al. [126].	•Minimal routing and charging cost. •Relieved in computational complexity.
[120]	EVRP-ToU	TW, PR	•Aim is to minimize the traveling and charging cost. •MIP model for energy consumption. •Different charging technology. •CPLEX optimizer. •OPL is used. •Randomly generated test instances. •A case study is highlighted.	•Optimal solution can be found with limited number of customers. •Minimized energy purchased.
[128]	EVRP-DP	FC	•Objective is to en-route the EV based on the dynamic changes in the cost of electricity. •Incorporated Dijkstra's algorithm along with charging control strategy. •MATLAB simulations. •Driving data created based on probability model. •Different case studies have been addressed. •Considered the dynamic pricing and ToU.	•Economic routing of EV. •Reduces the power grid load.

Continued on next page

Table 2.5 – *Continued from previous page*

References	Problem Name	Charging Constraint(s)	Key Findings	Outcomes and Remarks
[207]	EVRP	FC	•Objective is minimize charging expense and time consumption. •ToU energy pricing. •Reserving Charging Decision-Making Model. •KSP routing algorithm. •Different case studies have been addressed. •Dynamic pricing and ToU.	•EV user able to choose ideal CS. •Time and money saving.
[199]	EVRP-ToU	FC, PR	•Objective is minimize charging expense and travel distance cost. •ToU energy pricing. •MILP model. •Preprocessing algorithm. •LDM vehicle model. •Different case studies have been addressed. •Dynamic pricing and ToU.	•High computational complexity. •Suggested meta-heuristic based solution. •Found the effectiveness of the proposed approach after performing comparative analysis from literature.

Table 2.6: Key Findings and Outcomes of LRP-based Approaches

References	Problem Name	Charging Constraint(s)	Key Findings	Outcomes and Remarks
[136]	LRP	TW, BSS	•Objective is to minimize the construction cost of CS, electricity cost, and driver wages. •AVNS/TS based hybrid-heuristic solutions. •Penalty for violating the constraints. •Randomly generated instances. •CPLEX optimizer and java implementation.	•Found better solutions as compared to single charging infrastructure. •AVNS/TS got optimal solution for small instances. •Found moderate run time solutions for large scaled instances.
[138]	BSS-LRP	BSS, CC	•To achieve minimum construction cost of BSSs and shipping cost for EVs. •Introduced Four-phase heuristic named SIGALNS. •Two-phase TS, TS-MCWS algorithm. •Instances from publicly available data set of CVRP [139]. •CPLEX optimizer and java implementation.	•3.16% less time taken by SIGALNS as compared by TS-MCWS. •Optimal solution for small scaled instances. •Computationally better solutions for large-scaled instances. •Less number of BSSs and vehicles.

Continued on next page

Table 2.6 – *Continued from previous page*

References	Problem Name	Charging Constraint(s)	Key Findings	Outcomes and Remarks
[137]	BSS-LRP	BSS, CC	•The objective is to get minimum construction cost of BSSs and shipping cost for EVs. •Introduced AVNS algorithm as solution. •CPLEX optimizer. •Utilized modified instances from NEO [139]. •Comparative study of AVNS, CPLEX, TS-MCWS and SIGALNS. •Improvement to the benchmark instances.	•Better solutions provided in the contrast of SIGALNS, and TS-MCWS. •83% candidate constructed BSSs for zero construction costs.
[135]	ELRP	PR, TW, BSS	•ALNS Meta-heuristic solution approach. •Uses local search and dynamic programming. •Created their own real world benchmark instances. •Gurobi optimizer and implementation in c++. •Comparative study of ALNS with EVRP-TWPR and BSS-EV-LRP.	•ALNS improved the solution generated by Gurobi. •ALNS proved to be faster in runtime on the 255-customer instance while compared with BSS-EV-LRP. •Number of vehicles were reduced using 10 instances while compared with EVRP-TWPR.
[100]	ELRP	PR, FR, TW, CC	•Different objectives of minimizing the total cost, number of CS cited, and total journey time. •MIP formulation of the problem. •Strengthened model. •Siting decisions with partial recharging. •Gurobi Optimizer. •Instances from M. Schneider et al. [24].	•Heuristic approach needed to be introduced for large size instances. •Case specific results. •Bring down overall route time. •Charging while servicing. •ELRP perform better in all test instances.
[134]	ELRP	PR	•The goal is to minimize the total sum of routing costs, fixed costs of opening stations, charging costs and cost of using vehicles. •MIP formulation and exact approach. •BDA. •Heterogeneous fleet. •IBM CPLEX Optimizer. •Instances presented by M. Schneider et al. [24].	•Needed meta-heuristic approach. •Optimal solution to all instances of 5 and 10 customers and 80% instances were solved for 15 customers. •Harder solutions were found with smaller vehicle capacities.

Continued on next page

Table 2.6 – *Continued from previous page*

References	Problem Name	Charging Constraint(s)	Key Findings	Outcomes and Remarks
[140]	ELRP-SD	BSS, FC	•Objective is to minimize the construction cost of BSSs and travel cost. •HVNS algorithm as solution. •Random computer simulation. •Implementation in java. •Comparative study of HVNS, ILS, VNS, BPSO-VNS and DE-VNS, GA-VNS.	•Fluctuations in the expected cost, if the maximum capacity of EV's increased. •Best solution provided by HVNS among the algorithms.
[79]	LRP	-	•Objective is to minimize the total cost including construction cost of depot, distance cost of vehicle, vehicle using cost. •Introduced new heuristic solution namely MSBRH. •BR-VNS algorithm. •CPLEX and Gurobi solver. •Implementation in java. •Comparative study on Barreto, Akca, and Prodhon's benchmarks instances.	•BR-VNS outperformed MSBRH for larger instance. •MSBRH computationally faster then BR-VNS. •MSBRH is suitable for real-time applications.

It is believed that, O. Worley et al. [105] were the first to address the problem of E-LRP; and they formulated it as a discrete integer programming optimization problem to minimize the travel cost, charging cost, and the cost for locating CS. M. Schiffer and G. Walther [100] presented the E-LRP clubbed with constraints of time windows and partial recharging for route planning of logistics electric fleets and siting decision for CSs simultaneously. For this purpose, the authors proposed an MIP model for achieving the different objective functions taking into account the count of vehicles, travelled distance, total cost, and siting of CSs. A comparative study for VRP and LRP was also performed over low-scaled test instances. Conclusively, the findings suggested that charging EVs during service could reduce the overall journey time and routing cost. H. Calik et al. [134] focused on LRP with heterogeneous fleet and partial recharging to deliver goods in a distributed network. The authors presented an MIP formulation to be solved by benders decomposition algorithm to accomplish the goals. Moreover, they further decomposed the mathematical model into two phases: firstly, one CS visit was allowed at most; and secondly, multiple CS visits were allowed. The proposed model's supremacy was presented over a variety of comparative studies on different sets of instances. M. Schieffer and G. Walther [135] presented an ALNS-based model for the LRP with additional Intra-route facilities to deal with loading and unloading some of the crucial vehicle operational resources like fuel, charging, and waste materials. Moreover, they presented a novel approach for a corridor-based penalty that could consider dynamic feasibility states. W. Li-ying and S. Ycian-bin [136] illustrated the problem of LRP with multiple charging stations under the constraints of customer time windows, vehicle load capacity, and battery capacity. The problem was addressed by the hybrid heuristic integration of AVNS and TS algorithms. It is pertinent to note that the additional facility of choosing a different type of charging infrastructure was optimized in this script. Computational results showed that AVNS/TS nearly got the optimal solution compared to CPLEX optimizer for small instances, and found moderate run time solutions for large-scale instances. J. Yang and H. Sun [138] presented an integer programming model for the LRP with BSSs problem. The goal was to achieve the minimum construction cost of BSSs and shipping cost for EVs. They proposed a four-phase heuristic and two-phase TS. The proposed approach was tested against the CPLEX solver for the small instances, and a nearly optimal solution was obtained. Moreover, heuristic methods obtained computationally better solutions for more significant instances. The findings also suggested that the requirement of BSSs and EVs was reduced during the routing. Similarly, J. Hod et al. [137] addressed the same problem with additional intermediate stop facility and obtained solution through the AVNS approach. Conclusively, the proposed approach produced a better outcome as compared to the result obtained by J. Yang et al. [138]. Recently, S. Zhang et al. [140] introduced an E-LRP with BSSs in the stochastic demand environment. An HVNS algorithm was proposed that comprised VNS with binary PSO, GA, and DE, to deal with the problem interactively. After simulations, the HVNS algorithm effectively solved the discussed problem and was observed to be much more effective when compared with the other similar domain approaches. Most recently, in his work, A. Almouhanna [79] studied a particular case of LRP with distance constraint. This problem aimed to minimize the total cost and took into account the simultaneous decisions on routing, location of depots, and vehicles routes assignment. The researchers proposed a multi-start heuristic and a meta-heuristic approach for the proposed problem. C. Zhang et al. [227] introduced a TS-based heuristic algorithm for the time-dependent GLRP with time windows and produced a static solution on Solomon's test instances.

A summary of the studies representing the solutions about the location of CSs based on the routing of EVs is presented in this subsection. The researchers, in their studies, signified that while recommending an optimized route to destination for EVs, the location of charging stations, i.e., on-route or off-route, must also be considered with caution. As in the absence of a proper location identification strategy, many times, off-route CSs directly impacted the travel time to destination in terms of additional kilometers and incurred an extra cost to EV user [79, 138, 140, 198, 227]. The probability of failure of the entire charging infrastructure was also high, if CS deployment location was not carefully chosen [197]. Moreover, it also incurred an unregulated load on the electric distribution grid. Hence, the issue requires more attention from the researchers. In Table 2.6, some of the major findings and outcomes of the above-mentioned LRP-based approaches, have been summarized.

2.3 Solution Approaches

A considerable amount of research work has been undertaken since the inception of VRP. Therefore, many problem-solving approaches that produce optimal or near-optimal solutions have been proposed over the years. Many VRP solving techniques are directly applicable for solving EVRP because it inherits the properties of VRP. Existing EVRP solution approaches can be broadly categorized into four main classes, viz. data-driven approach, exact approach, heuristic approach, and meta-heuristic approach. The Fig. 2.1 demonstrates their fundamental properties along with the key attributes.

2.3.1 Exact Approach

These approaches are managed to get the optimal solution for fewer number of instances. For example, in their work [101, 131], the authors managed to solve the problem up to 100 customers and 21 charging stations for VRPTW as well as 110 customers for the problems GVRP. Exact algorithms have been basically classified into three different categories: i) dynamic programming-based; ii) integer linear programming-based, and; iii) direct tree

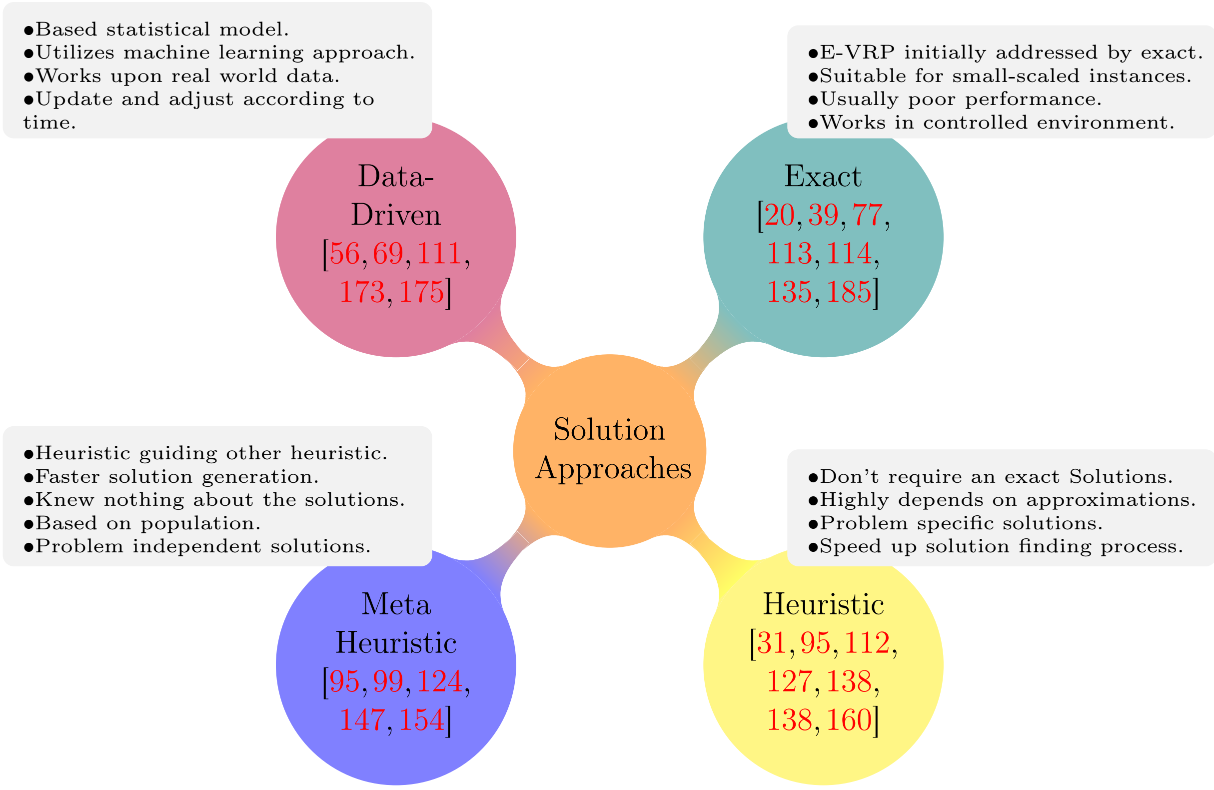


Figure 2.1: Different Solution Approaches and their Prime Highlights

search methods [182, 201]. Many researchers have adopted these approaches; and the density of the usage of differently exact solution approaches has been summarized in the Table 2.7.

Table 2.7: Different Exact Solution Approaches Adopted by the Researchers

References	**Exact Approaches**
[158], [135], [114], [77], [39], [20], [185]	Dynamic Programming
[105], [110], [158], [95], [129], [123], [122], [138], [102], [99], [141], [156], [168], [115], [161], [96], [100], [5], [32], [146], [134], [120], [121], [109], [103], [67], [181], [178], [172], [174] , [185], [191]	Integer Programming
[113], [128]	Dijkstra's Algorithm
[159] [141] [5] [101]	Branch and Bound Algorithm
[172], [60]	K-shortest Path Algorithm

2.3.2 Heuristic Approach

It seeks to employ a practical method that does not produce an optimal solution, nevertheless, generating sufficient or short-term goals based on the specific observations of the unsolved problem. Moreover, the heuristic procedures speed up the solution-finding process where it is nearly impractical or impossible to get solutions. The density of usage of differently heuristic solution approaches in EVRP has been summarized in the Table 2.8.

Table 2.8: Different Heuristic Solution Approaches Adopted by the Researchers

References	Heuristic Approach
[127], [138]	Clarke and Wright Saving
[138]	Sweep Algorithm
[31], [112]	A* Algorithm
[95]	k-pseudo Greedy
[160]	Nearest Neighbor

2.3.3 Meta-heuristic Approaches

It selects a heuristic to provide an adequate solution to an optimization problem, particularly with less computational complexity. Although some assumptions might be taken, yet these do not ensure that solution would lead to the global optimum solution. These solution approaches are mainly classified into two groups: local search-oriented and population-oriented, as shown in the Fig. 2.2. The figure demonstrates their fundamental properties and key attributes. Moreover, the density of usage of different meta-heuristic solution approaches over the years has been summarized in the Table 2.9.

Table 2.9: Different Meta-heuristic Solution Approaches Adopted by Researchers

References	Meta-heuristic Approaches
[124], [154], [138], [136], [125]	Tabu Search
[95], [99], [109]	Simulated Anneal
[155], [156], [5], [140], [76], [178]	Iterated Local Search
[24], [136], [122], [102], [137], [140]	Variable Neighborhood Search
[147], [125], [151] [168], [113], [148], [140], [11], [184], [194]	Genetic Algorithm
[152], [151], [133], [61], [68], [150], [211]	Ant Colony Optimization
[153], [70], [30], [58]	Particle Swarm Optimization
[104], [119], [108], [123], [138], [106], [159], [99], [145], [142] [141], [135], [19], [32], [103]	Others including Adaptive Large Neighborhood Search and Hybrid Combinations

2.3.4 Data-driven Approaches

Since EV routing is a well-known research problem, numerous solution generation approaches have been adopted. However, data-driven procedures, which rely upon artificial intelligence, can be long-lasting because of their forecasting capabilities, predictive analysis, state estimation, and decision-making. Most of the proposed algorithms use a

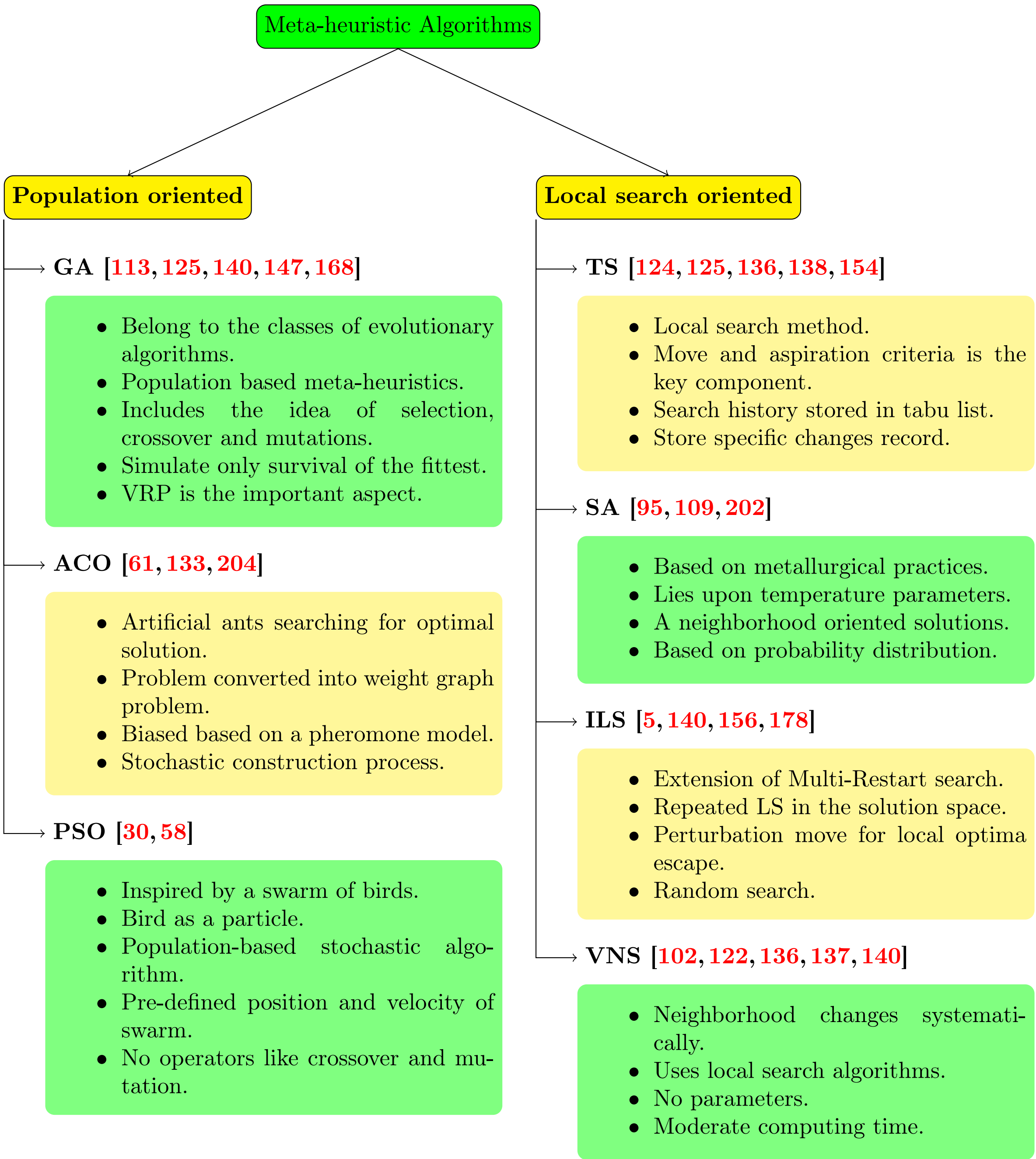


Figure 2.2: Key Aspects Pertaining to Widely used Meta-heuristic Algorithms: Population Oriented (on the left), Local Search Oriented (on the right)

stationary stochastic network, but data-driven approaches utilize statistical models which can be updated according to the necessity of the environment. The Table 2.10 summarizes the density of usage of data-driven approaches under the umbrella of EVRP.

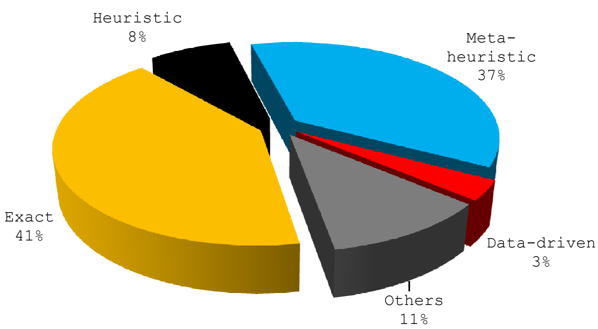
2.4 Literature Analysis

This chapter presents an exhaustive survey of recent and state-of-the-art research work elaborating the latest advancements in the solution of EVRP and its variants. The analysis

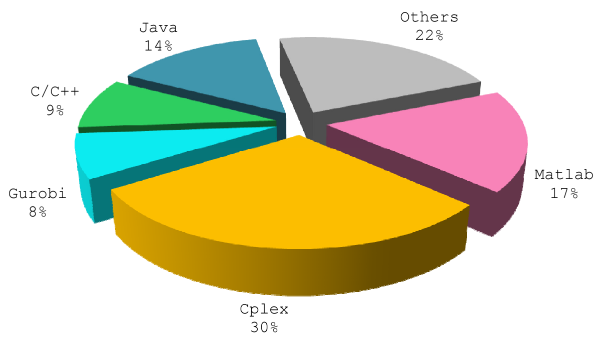
Table 2.10: Different Data-driven Approaches Adopted by the Researchers

References	Data-driven Approaches
[111], [69]	Data Mining
[56], [66]	Neural Network
[173], [175]	Machine Learning

of EVRP is not a straightforward task as it consists of an extensive array of variants, constraints, data-sets, instances, methods, different frameworks, etc. The chapter presents a novel perspective of categorizing the existing literature on EVRP and its variants into subgroups, viz. EEPP, DCTP, CWTP, TDTCP, DToUEEP, and LRP. Every sub-group represents a set of approaches that aims to solve a specific routing challenge faced in EVRP. From the literature survey, it can be concluded that the problems relating to EEPP, DCTP, CWTP, TDTCP, DToUEEP, and LRP are most popular and have been widely explored by the researchers all over the globe. Also, this survey addresses the different constraints of time window (TW), fast charging (FC), full recharge (FR), and partial recharging (PR) associated with EV charging. Among the various EVRP variants, the TW constraint has been the most frequently used. This literature survey is likely to help the bidding researchers to get a complete 360-degree view and understanding of the domain. In this context, a collection of research publications has been shortlisted and presented in Table 2.11 which broadly discusses and covers every aspect and challenge pertaining to EV routing. It can be observed that a higher proportion (approximately 60%) of solution approaches formulate EVRP as a single objective optimization problem in comparison to the multi-objective optimization problem (40%). Among these, greater emphasis has been laid on minimizing cost, distance travelled, number of vehicles or time taken.



(a)



(b)

Figure 2.3: Distribution of Applied Methods/Techniques (a), and Different Tools/Programming Languages (b)

Table 2.11: Comparison of State-of-the-art EVRP Studies

Reference	Objective		Tools/Programming Language Used						Applied Techniques				Shortcomings
	Single	Multiple	Matlab	Cplex	Gurobi	Java	C/C++	Others	Exact	Heuristic	Meta-heuristic	Data-driven	
[227]		×	×								×		High computation burden, No real life demonstration
[197]		×		×					×				The crucial aspect of CS such as Fast charging, dynamic pricing, number of charging heap, etc. are overlooked
[214]	×							×			×		Other constraints such as time windows and partial recharging could provide more flexibility to the User.
[211]		×	×								×		Require a math-heuristic solution exposure. No evaluation on real-time data. TW and PR could provide better results.
[209]	×		×						×				Overlooked user's convenience and economics. Limited to small size test instances.
[207]		×						×	×				Suitable for static environment. limited to small size test instances.
[199]		×	×					×	×				Works on the smaller number of instances. Require meta-heuristic approach.
[194]		×						×			×		Lack of real world demonstration. Higher burden of computational complexity.
[14]		×		×							×		More realistic scenarios could be included. Problem limited to single depot only.
[31]								×		×			Neglected the real-time complexities of the network. Static model.
[104]	×							×	×				Evaluation on charging cost, time etc. is missing.
[153]	×							×			×		No evaluation on real-time data.
[108]	×							×			×		Not suitable for real life applications.
[152]	×		×								×		No evaluation on traffic and regenerating braking factor.
[158]	×							×	×				High computational burden.

Continued on next page

Table 2.11 – *Continued from previous page*

Reference	Objective		Tools/Programming Language Used						Applied Techniques				Shortcoming
	Single	Multiple	Matlab	Cplex	Gurobi	Java	C/C++	Others	Exact	Heuristic	Meta-heuristic	Data-driven	
[24]		×		×				×	×		×		Neglected the crucial constrains like time windows, payload, grades etc.
[129]	×							×	×				Not suitable for real life application. Limited only for single EV.
[154]	×		×								×		No evaluation real-time data-sets.
[127]	×			×			×			×			Evaluation on several important aspects such as soft time window, in-homogeneous fleets, customer satisfaction etc. are ignored.
[70]	×						×				×		Regenerated braking factor and real-time evaluation is not considered.
[147]	×							×			×		Limited to single modality and concurrent charging requests were not entertained.
[95]	×			×				×	×		×		Ignored the well known parameters such as time windows, dynamic traffic, multi-depots, etc.
[123]	×			×			×		×	×			Evaluation on different pricing technique such as congestion, delay, etc. are missing.
[157]	×		×						×		×		No experiment on large scaled instances.
[155]		×					×				×		No evaluation on real-time data or bench-mark instances.
[138]		×		×		×			×	×	×		Not covered the crucial constraints like time windows, capacity of BSSs.
[102]		×		×				×	×		×		Not suitable for real-time problem. Ignored regenerating breaking.
[62]	×		×						×				Lead to more computational complexity in higher dimension network.
[106]	×							×				×	Optimization on other parameters such as pricing, charging technology etc. is missing.
[125]		×	×								×		No investigation on traveling and charging behavior.
[136]		×		×		×					×		Limited to single depot and EVs only.
[39]	×		×						×				

Continued on next page

Table 2.11 – *Continued from previous page*

Reference	Objective		Tools/Programming Language Used						Applied Techniques				Shortcoming
	Single	Multiple	Matlab	Cplex	Gurobi	Java	C/C++	Others	Exact	Heuristic	Meta-heuristic	Data-driven	
[101]	×			×			×		×				Parameter such as waiting time, dynamic traffic, etc., are not considered.
[159]		×		×		×			×		×		Neglected the partial recharging. Computationally overloaded.
[156]		×		×			×		×		×		Ignored the impact of dynamic traffic condition, dynamic pricing and different charging techniques.
[151]		×						×			×		Neglected the possible constraints such as regenerating braking, multi-route facility, depot-charging, etc.
[145]		×	×						×				Smart charging strategy such as charging/discharging of EVs is missing.
[142]	×		×						×				Distributed charging scheduling of EVs is missing. Limited to static traffic conditions.
[141]		×		×		×			×		×		The flexibility of customer demand uncertainty is not provided.
[111]	×							×				×	Effect of dynamic traffic, charging cost, charging technology etc. is not considered.
[133]		×						×			×		No evaluation on real-time data-sets.
[99]	×			×		×			×		×		The authors restricted only to partial recharge option. Other important parameters such as dynamic traffic, queue in CS, battery health, etc. were ignored.
[30]	×		×								×		Ignored dynamic traffic condition and negative edge weight cycle.
[161]	×				×	×			×		×		Not evaluated on the bases of capacity constraints of the CS.
[20]		×						×	×				Limited for only one EV. Higher complexity burden.
[149]	×		×								×		Lack of parameters sensitivity analysis. Dynamic traffic condition is overlooked.

Continued on next page

Table 2.11 – *Continued from previous page*

Reference	Objective		Tools/Programming Language Used						Applied Techniques				Shortcoming
	Single	Multiple	Matlab	Cplex	Gurobi	Java	C/C++	Others	Exact	Heuristic	Meta-heuristic	Data-driven	
[69]	×							×				×	Route selection based upon the historical data does not reflect the real-time traffic information.
[148]		×						×			×		No evaluation over benchmark instances.
[115]	×			×					×				Impractical for larger instances and dynamic nature of demand.
[137]		×		×							×		The influencing factors such as dynamic traffic, time windows, charging costs. etc are ignored.
[5]		×			×	×			×		×		No evaluation on real-time data.
[100]	×			×					×				Not applicable for larger instances and real world conditions.
[61]		×	×								×		Not suitable for real-time traffic condition, regenerating braking factor could generate better results.
[113]		×	×						×		×		No evaluation on real-time traffic data and other important aspects.
[53]	×		×						×				Not suitable for practical applications, higher computational time.
[135]	×				×		×		×		×		Not test on real data. Higher computational burden.
[96]		×		×					×				High computational complexity. Not suitable for real life.
[56]	×							×				×	Im-practical for higher number of vertices and edges.
[19]	×							×	×				Impact of crucial parameters such as time windows, dynamic pricing, etc. are missing.
[112]		×						×	×				Computationally inefficient and no evaluation on the parameters such dynamic pricing, battery temperature, different charging technologies etc.

Continued on next page

Table 2.11 – *Continued from previous page*

Reference	Objective			Tools/Programming Language Used						Applied Techniques				Shortcoming
	Single	Multiple		Matlab	Cplex	Gurobi	Java	C/C++	Others	Exact	Heuristic	Meta-heuristic	Data-driven	
[32]		×			×		×			×				Not evaluation of the some important parameters like dynamic traffic condition, charge waiting time at CS, etc.
[120]		×			×					×				Not feasible for larger size of instances.
[68]	×				×			×				×		Ignored the very crucial constraints like time windows, partial recharging and multi-depot.
[146]	×				×			×		×				Higher complexity burden. Neglecting the routing of EVs.
[144]	×			×			×						×	Dynamic modifications of real-time constraints is missing.
[134]		×			×		×			×				Harder solution for large instances. Several important constraints such as time windows, multi-depot, dynamic traffic, charging cost etc. are missing
[76]	×				×							×		Lack of comparative analysis with similar domain algorithms.
[109]		×			×					×		×		Not suitable for real-time applications.
[128]	×			×						×				Considered the static road network data. Evaluation on real-time data is missing.
[103]	×				×		×			×				No evaluation on other useful parameters and real-time data.
[150]	×								×			×		All the constraints and network are taken is static. Ignored the realistic constraints.
[117]	×					×				×	×			
[140]		×					×					×		The model did not consider the time windows, BSSs capacity, price incentives.
[60]		×	×								×			Proposed model is static in nature, limited to small scaled network.
[67]	×				×		×			×				Neglected evaluation on crucial parameters such as dynamic traffic condition, fast charging, etc., and real data.

Continued on next page

Table 2.11 – *Continued from previous page*

Reference	Objective		Tools/Programming Language Used						Applied Techniques				Shortcoming
	Single	Multiple	Matlab	Cplex	Gurobi	Java	C/C++	Others	Exact	Heuristic	Meta-heuristic	Data-driven	
[58]	×							×			×		No evaluation on real-time data.
[66]		×						×			×		
[181]		×			×			×	×				Not suitable for higher number of instances. Not tested on real data.
[178]	×				×			×	×				Not suitable for higher number of instances. Not tested on real data.
[79]		×		×	×	×				×	×		Not suitable of stochastic network. Evaluation on heterogeneous fleets should be done.
[11]		×	×								×		They ignore the practical aspect of charging. No evaluation over the crucial aspects such as time windows, dynamic traffic, waiting time at BSSs.
[172]		×	×	×					×				No evaluation on real-time parameters.
[173]		×	×	×								×	It would be interesting if author correlate the energy consumption to adjacent links and add the dynamic factor such as link blockage into the model.
[184]	×		×	×							×		Lack of comparative analysis with similar domain algorithms.
[185]	×							×	×				No evaluation in the real life scenario. Require more attention in the identification of CS.

An attempt has been made through the literature survey to investigate the existing solution approaches for the techniques or algorithms used by different researchers to solve EVRP and analyse them on their implementation aspect. In other words, the proposed survey also highlights the different tools and programming languages used by different solution approaches to solve the targeted EVRP challenges. In this regard, Fig. 2.3 has presented two distribution pie charts. The first pie chart (see Fig. 2.3a) classifies the applied methods as exact, heuristic, meta-heuristic and data-driven approaches. It is pertinent to note that exact algorithms (integer linear programming, dynamic programming, Dijkstra's, branch and bound, etc.) have the highest (about 41%) number of applied methods falling in its category. Despite the massive popularity of exact algorithms to provide an optimal solution to the optimization problem of EVRP, these algorithms are limited in their ability to work only on a small set of instances. Therefore, different approaches are proposed to work on large instances. For this purpose, the use of the approximation heuristic has been adopted. Heuristic algorithms such as Clark and Write, Sweep, A*, K-shortest, etc. have contributed to the extent of 8% of the total approaches reviewed in this survey. Also, meta-heuristics-based approaches contributed nearly 37% of the total approaches reviewed in this survey. Genetic algorithms (GA), adaptive large neighborhood search (ALNS), tabu search (TS), iterative local search (ILS), variable neighborhood search (VNS), and ant colony optimization (ACO) have been widely used in the reviewed literature. Another 3% of the total reviewed approaches are the data-driven approaches. The decisions pertaining to these approaches will be made on the basis of data analysis. These approaches mainly rely upon artificial intelligence (AI) or data mining. From the review of literature, it can be concluded that a huge potential lies in the use of meta-heuristics which have already proven their worth by efficiently solving various variants of EVRP. The second pie chart, in Fig. 2.3b, shows the distribution of applied methods among different tools/programming languages such as IBM CPLEX, MatLab, Gurobi, java, c/c++, and others (Xpress/Ampl/Sumo/Weka/Fortran/Opl) used in their implementation. It has been observed that CPLEX (30%), MatLab (17%), java (14%,), c/c++(9%), and gurobi (8%) are the commonly used tools/programming languages in most of the studies.

An attempt has also been made to compile a list of all the test instances and datasets (either real or synthetic) that the solution approaches have used to solve the different EVRP variants. The Table 2.12 presents the list of all such datasets referred in the reviewed literature.

Table 2.12: Instances/Datasets Used in EVRP Variants

EVRP Variants	Instances	Datasets
EEPP	M. Schneider et al. [24], M. M. Solomon et al. [59], A. Artmeier et al. [52], A. Burtchen et al. [54], J. Ward et al. [21], R, Basso et al. [173]	Google Maps, MapQuest, OpenStreetMap (OSM), T. Coosemans et al. [57], EVTecLab [45], NV [46], NVDB [50]
DCTP	A. Felipe et al. [95], M. Schneider et al. [24], E. Labs [98], M. M. Solomon [59]	
CWTP	M. Schneider et al. [24], M. M. Solomon et al. [59], A. Artmeier et al. [52], J. Ward et al. [21], A. Burtchen et al. [54]	Google Maps, MapQuest, OpenStreetMap (OSM), M. M. de Weerdt [47], T. Coosemans et al. [57], EVTecLab [45], NV [46]
TDTCP	M. Schneider et al. [24]	Baidu Map
D-ToU-EEPP	COIN-OR [48], A.-H. Mohsenian-Rad and A. Leon-Garcia [126]	
LRP	[24], Schneider et al. M. M. Solomon et al. [59], S. Barreto et al. [80], A. Akca et al. [81], J.-M. Belenguer et al. [82]	NEO [139]

2.5 Summary and Research Directions

According to the UK Climate Change Act, the country has decided to have net-zero greenhouse gas emissions by 2050. This decision has led to the EVs' widespread use and adoption in the transportation sector. Therefore, it is safe to conclude that the work done in EV routing is at the initial stage only. There is enormous potential for future research to explore various logistical and infrastructural related challenges to EVRP and propose feasible and economically viable solutions. Therefore, some of the prominent challenges can be summarized as below:

- *Energy Consumption*: This challenge involves the computation of energy consumed by the EV following a particular route from source to destination (can be a charging station). After analyzing a number of EVRP models, it has been observed that only a few energy consumption models are available in the literature that may predict energy consumption with uncertainties in a real transportation network. In fact, traffic uncertainties may be induced by several factors, such as adverse weather conditions, traffic accidents, vehicle malfunctions, demand variations, etc. Only a handful of papers have addressed the issues of charging schedules, recharging station location, recharging technology, etc. into the EVRP. Several real-time parameters, including dynamic pricing and ToU, time-dependent traffic, demand uncertainty, queue at CS, etc. have not been analyzed up to their desired strength. Therefore, the existing energy consumption models can be extended to render a more realistic model dealing with the aforementioned constraints/parameters.

- *Charging Station Recommendation*: EV has a fixed amount of energy available depending upon the capacity of battery packs, which may not be enough for driving from source to destination. Therefore, after hitting a threshold SoC level, it is necessary to locate a charging station that can meet the demands of the user and EV. However, the underdeveloped charging infrastructure, coupled with the network's dynamic constraints, has rendered a novel research challenge for locating a suitable charging station. Only a few scripts addressed the problem of locating an appropriate charging station during the routing of EVs. There is potential concerning this challenge especially for solutions that would optimize several critical parameters such as waiting time, time windows, service time, demand uncertainties, EVs compatibility with charging infrastructure, and energy pricing along with location routing problem of EVs.

- *Dynamic Pricing*: Charging price is one of the critical aspects related to the use of EVs because it directly affects the average cost of travel during the EV's routing. Different ways of charging an EV during peak and off-peak hours need to be explored because of the high charging price difference in both scenarios. The need of the hour is to explore more ways of charging EVs while taking into account parameters like ToU pricing into EVRP that could ultimately satisfy the customer's need. Moreover, several other factors influencing real-time pricing, such as charging scheduling, waiting time, and stochastic network are worth investigating and open up a whole new dimension for further research.

- *Hybrid Methods*: The research conducted earlier on EVRP was mainly based on exact solutions not limited to mathematical models and dynamic programming. Due to technological advancements and the growing popularity of meta-heuristic, the research focus has shifted towards tabu search, simulated annealing, particle swarm, ant colony optimization, genetic algorithm, or even adaptive large neighborhood search procedure to address the problem optimally. However, during the course of this survey, several hybrid methods were observed that were able to optimize more real-time parameters; and hence, outperformed other existing meta-heuristic or exact solution-based approaches when tested over benchmark instances. It is pertinent to point that several other sim-heuristic, mat-heuristic, or any other hybrid combination of methods need further exploration for improving the results. Also, some additional constraints not limited to the constraint of CS, vehicle, and delivery time windows, should be a part of the original variant of the problem.

Chapter 3

A Meta-heuristic-based Energy Efficient Route Modeling for EVS on Non-identical Road Surfaces

The preceding chapter's primary goal was to review the current literature on the subject under study, i.e., electric vehicle routing. It was a modest endeavor to study the existing EVRP modelling methodologies in depth. It allowed gaining a thorough understanding of the numerous issues and aspects of current research. It also served the purpose of identifying the research gaps.

This chapter proposes a meta-heuristic routing model based on the principles of Artificial Bee Colony (ABC). The proposed model has been designed to consider prominent energy consumption influencing parameters like speed, battery health, road elevation, etc. Moreover, tractive effort modeling on different road surfaces like dry, wet, snow, and icy is also embedded in the design of EV route modeling. The simulation of the proposed model has been done to quantify its performance by utilizing route maps as well as real-time information of vehicles' location by the Warrigal project as input [1].

Section 3.1 covers the problem formulation and modelling for energy consumption and road surface condition, while Section 3.2 provides a high-level description of the ABC-based meta-heuristic and how it maps the formulated EV routing problem. Section 3.3 undertakes the case study by analyzing the available datasets and produces the findings. Finally, Section 3.4 concludes the chapter under study.

[1] The contents of this chapter are partly published in:

- Ashwani Kumar, Ravinder Kumar, and Ashutosh Aggarwal, "A meta-heuristic-based energy efficient route modeling for EV on nonidentical road surfaces", Neural Computing and Applications (NCAA), pp. 1-14, 2022.

3.1 Energy Efficient Routing Problem of EVs

When we select to drive from source to destination, a route needs to be picked up among the number of different routes in the routing problem of the vehicle. Though the route that consumes the least energy and time will be preferred, eventually, it leads to the route with a shorter distance and less conjunction but, finding the global minimum solution is challenging due to the numerous variable parameters such as environmental condition, traffic conjunction, driving pattern, battery state of charge, battery health, etc. So, the closer solution to the global minimum solution will be preferred because the route that consumes less energy or least time may not be viable, and a compromised solution must be accepted.

3.1.1 Modeling for Energy Consumption

The desired energy consumption model has been inspired by the vehicle longitudinal dynamics model [232]. This model calculates the mechanical energy (traction force) required to propel the EV. Eq. (3.1), as given below, expresses the mechanical system relationship between the various longitudinal resistances and acceleration force that work upon the tractive force to enable the acceleration:

$$F_{tt} = F_{acc} + R_{grad} + R_{roll} + R_{aero} \tag{3.1}$$

Where, F_{tt}, F_{acc}, R_{grad}, R_{roll} and R_{aero} are total tractive force, acceleration force, grading resistance, rolling resistance and aerodynamic resistance respectively.

- *Acceleration Force*: The acceleration force (F_{acc}) is presented here in Eq. (3.2):

  $$F_{acc} = \left(\frac{mr^2 + I_m (ra)_g^2 + 4I_w}{r^2} \right) a \tag{3.2}$$

  Where, vehicle mass (m) having the value of $1250kg$; motor inertia (I_m) is equal to 0.0384 kgm^2; wheel inertia (I_w) is equal to 0.75 kgm^2; tyre radius (r) is equal to 0.278m; gearbox ratio (ra_g) is equal to 8.654; and a is vehicle acceleration.

- *Grading Resistance*: This force works against the forward motion because when a vehicle travels an inclined road (up or down), it always directs downward. This grading resistance performance model is shown in Eq. (3.3) with a road inclination of θ, only for the uphill because it hinders the tractive force.

  $$R_{grad} = mgsin(\theta) \tag{3.3}$$

Where, g is a gravitational force which is equal to 9.8 m/s^2, moreover, if θ is very small angle, then, tan θ = sin θ. Therefore, this approximation can be written as:

$$R_{grad} = mgtan(\theta) \tag{3.4}$$

- *Aerodynamic Resistance*: This type of resistance is generated when air travels across the vehicle's body. It does not only create pressure on the body of vehicle, but also works against the movement of vehicle. The mathematical equation presenting aerodynamic drag resistance is given in Eq. (3.5).

$$R_{aero} = .5\rho C_{ad} A_{fr} (v + v_{wind})^2 \tag{3.5}$$

Where, air density (ρ) has given the value 1.1839kg/m^3; aerodynamic drag coefficient (C_{ad}) is taken as 0.24, vehicle's frontal area (A_{fr}) is equal 2.341m^2; and wind speed (v_{wind}), against the vehicle movement, is considered as zero. All the parameters of EV (for this study, Nissan e-NV200, Nissan (2017)) are taken from the manufacturer website [72, 236].

- *Rolling Resistance*: It is the force that opposes the motion of a vehicle on a surface. The given Eq. (3.6), mathematically presents the rolling resistance (R_{roll}).

$$R_{roll} = f_z C_{roll} cos(\theta) = mg C_{roll} cos(\theta) \tag{3.6}$$

Where, f_z represents the normal load, while C_{roll} represents rolling resistance coefficient. In addition, E. Schaltz and S. Soylu [64] follows the definition of C_{roll} that can be found in Eq. (3.7).

$$C_{roll} = (1 + .036v) * 1\% \tag{3.7}$$

Putting all the resistances and acceleration force values into **??**, we can find the total tractive force (F_{tt}) required to propel a vehicle, given by the Eq. (3.8).

$$F_{tt} = \left(\frac{mr^2 + I_m (ra)_g^2 + 4I_w}{r^2} \right) a + mgsin(\theta) + mgcos(\theta)((1 + .036v)/.01) + .5\rho C_{ad} A(v + v_{wind})^2 \tag{3.8}$$

With the help of the total traction force (F_{tt}), the tractive power (P_t) (battery output power) can be calculated as per Eq. (3.9).

$$P_t = F_{tt}.v \tag{3.9}$$

Substituting the value of parameter F_{tt} (Eq. (3.8)) into Eq. (3.9), we can derive the following Eq. (3.10):

$$\begin{aligned} P_t = \left(\left(\frac{mr^2 + I_m(ra)_g^2 + 4I_w}{r^2}\right) a + mgsin(\theta) + mgcos(\theta)((1 + .036v)/.01)\right. \\ \left. + .5\rho C_{ad} A (v + v_{wind})^2 . v \right. \end{aligned} \tag{3.10}$$

Before we continue with the modeling of attained problem, we need to describe that minimizing equation alone, will not yield optimum output. Some other crucial factors can also affect the energy efficiency of EVs. These factors include battery constraints, and road surface conditions. The definition of battery constraints is termed as preventing the battery's depth of discharge (DoD), depleting upto 100% before reaching the destination. While DoD can be defined as the discharged capacity percentage relative to overall capacity (C_{all}) of the battery.

$$DoD = \frac{C_{dis}}{C_{all}} 100\% \tag{3.11}$$

Where, C_{dis} is represented as the discharge capacity of battery current. Once the EV reaches its destination, the state of DoD is called as $endDoD$. Therefore, the modified problem will be single objective optimization problem as shown in Eq. (3.12).

$$Minimize\ endDoD \tag{3.12}$$

Mathematically, $endDoD$ can be accumulated as per Eq. (3.13).

$$endDoD = DoD_{initial} + \triangle DoD \tag{3.13}$$

Here, $DoD_{initial}$ is represented as initial DoD; and $\triangle DoD$ (difference of the DoD in operating period) can be calculated as shown in Eq. (3.14).

$$\triangle DoD = \left(\frac{-\int_0^t I_{batt}(t)dt}{C_{all}}\right) 100\% \tag{3.14}$$

Where, t and I_{batt} tells about travel time and battery current. Moreover, I_{batt} is negative while discharging.

3.1.2 Tractive Effort Modeling for Different Road Surfaces

The vehicle maximum tractive effort is directly proportional to the tyre slip ratio on the surface. While, the difference between tyre angular speed and vehicle speed is termed as tyre slip ratio. Mathematically, it is expressed in Eq. (3.15) for both front (η_f) and rear (η_r) tyres.

$$\eta_f = \frac{R_{wf}\xi_f - v}{R_{wf}\xi_f}, \eta_r = \frac{R_{wr}\xi_r - v}{R_{wr}\xi_r} \tag{3.15}$$

Where, R_{wf}, R_{wr}, ξ_f and ξ_r are the front tyre radii, rear tyre radii, front tyre angular speed and rear tyre angular speed respectively. Slip-friction coefficient characteristics of a tyre have a non-linear relationship and depend on the road surface conditions. Several friction/slip characteristics between road and tyres have been experimentally studied over different driving conditions and surfaces [239]. For simplicity, we have included four types of road conditions in our model: dry, wet, snow, and icy surface. Fig. 3.1 represents the elementary mapping interpretation of different road surfaces with traction force and highlights the level of traction for each type of road surface; for instance, the traction force increases as EV toggle between the surfaces (read from left to right in Fig. 3.1) and it falls within the range as depicted [63]. Fig. 3.2, graphically represents the variation of the tyre friction coefficient (ψ) with slip ratio (η) of mentioned surfaces. The Pacejka Tyre Model is widely used to define these characteristics [65]:

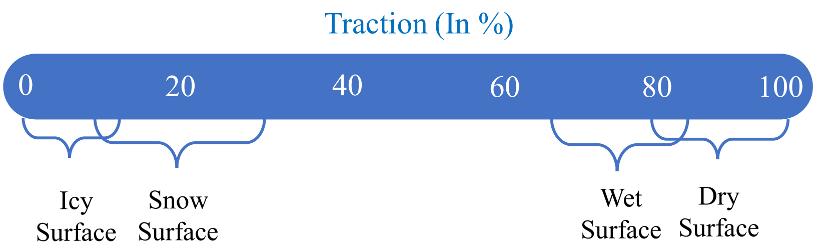


Figure 3.1: Level of Traction over Different Road Surfaces

$$\psi_i = \gamma sin(\beta arctan(\alpha\eta_i - \delta(\eta_i\alpha - arctan(\eta_i\alpha)))), \quad i \in f, r \tag{3.16}$$

Where, ψ_i is the friction coefficient of the front and rear tyre. $\alpha, \beta, \gamma, \delta$ are the tyre coefficients and their values depend on the road surface conditions. These values (see Table 3.1) are well determined in the Pacejka tyre model and are required to produce the slip/friction relationships (see Fig. 3.2). The tractive force between a car wheel and the surface can be expressed as:

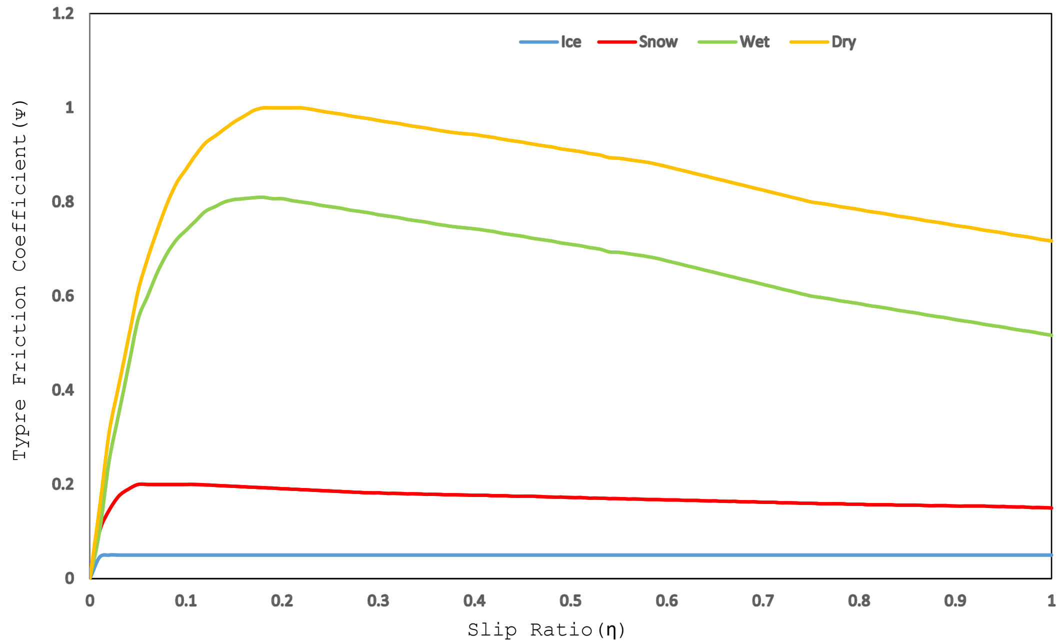


Figure 3.2: Typical Tyre Slip Ratio Friction Coefficient Characteristics

$$F = \psi_i W = \psi_i m a_g, \quad i \in f, r \tag{3.17}$$

Where, F is the tractive effort caused due to different surfaces; m is the vehicle mass; a_g is gravity acceleration. While Eq. (3.18) represents the tractive effort (F) in terms of power required for the different surfaces.

$$Surface_{tp} = F.v = (\psi_i W)v = \psi_i m a_g v, \quad i \in f, r \tag{3.18}$$

Where, $Surface_{tp}$ is termed as tyre's tractive power on the different surfaces and considered to be one of the dry, wet, snow and icy surface, at a time.

Table 3.1: Tyre Coefficients [65]

Surface	α	β	γ	δ
Dry	10	1.9	1	0.97
Wet	12	2.3	.82	1
Snow	5	2	0.3	1
Ice	4	2	0.1	1

$$Energy_{total} = \int P_t \, dt + \int Surface_{tp} \, dt \tag{3.19}$$

Eq. (3.20) calculates the initial battery energy, where $Capacity_{Batt}$ is pre-known battery capacity in joules and $DoD_{initial}$ assumed to be 0% at the beginning of the journey. Whereas, the output of Eq. (3.20) is used to calculate the endDoD as shown in

Eq. (3.21).

$$BattEnergy_{start} = Capacity_{Batt} * DoD_{initial} * 0.01 \tag{3.20}$$

$$endDoD = BattEnergy_{start} - \sum_{source}^{destination} Energy_{total} \tag{3.21}$$

3.2 Artificial Bee Colony-based Solution Method

The ABC is a population-based meta-heuristic algorithm that inherited honey bees' intellectual behavioral properties applied in search of food source. Recently, this type of meta-heuristic algorithm has attracted much attention. Because when the honey bee's biological tendency of social communication is extended to the route planning process, it excels in terms of quicker convergence to solutions and producing high-quality solutions. Though, such combinatorial problems have been solved with a different flavour of bee algorithms. But most of them used the traditional search pattern of having a food source as a partial or complete solution. In the meantime, the bunch of bees attempt to explore the food sources to obtain the qualitative nectar (i.e., food source with higher quality (fitness value) will have higher probability to be selected) for the development of the hive. Thus, the task of foraging can be accomplished by the collective cooperation of honey bees i.e., by exchanging information about the search space and the food sources by performing a waggle dance.

Table 3.2: Notations and their Respective Definitions

Notations	Definition
$S_k,\ k = 1, 2, 3...., \epsilon$	The number of food sources or solutions
ψ	Random number, $0 \leq \psi \leq 1$
ϕ	Random number, $-1 \leq \phi \leq 1$
D	Domain of individual solution
N_r	Random number
$X_{old}, X_{partner}, X_{update}$	Current, randomly chosen and updated solution respectively
$Prob(S_k)$	Probability of solution selection
$Fit(S_k)$	The fitness of solution S_k
$trail$	Iterations to improve the solution for a particular bee
$limit$	The maximum number of trails to improve the solution

There are three kinds of bees through which the composition of the ABC algorithm has been made, named as employed bees, onlooker bees, and scout bees. Employed bees search the food in the vicinity of the food source available in the memory and communicate with the onlooker bees to provide information about the food sources. In particular, onlooker bees try to look for the best food source among those founded by the employed bees

Table 3.3: Relied Equations and their Respective Numbers of ABC Algorithm

Equation Representation	Equation Number
$X_{initial} = Bound_L + \psi(Bound_U - Bound_L)$	22
$X_{update} = X_{old} + \phi(X_{old} - X_{partner})$	23
$Fit(S_k) = \begin{cases} \frac{1}{1+f_k} & \text{if } f_k \geq 0 \\ 1 + abs(f_k), & \text{if } f_k < 0 \end{cases}, \forall k$	24
$Prob(S_k) = \frac{Fit(S_k)}{\sum_{k=1}^{\epsilon} Fit(S_k)}, \ where, \ k = 1, 2, 3...., \epsilon$	25

based on the probability. Moreover, they choose the qualitative (higher fitness value) food source over the one which has the minor qualitative food source. Later, the scout bees abandon the solution (food sources) based on the limit values and generate a new random solution [237]. Notations and explanations are provided in Table 3.2, which have been used for subsequent elaboration.

Initially, the ABC algorithm starts producing arbitrary solutions (within a given intrinsic domain) in the form of food sources (refer to Table 3.3, Eq. 22). Meanwhile, each food source has been assigned to the individual employed bee. In the continuation, a new food source has been computed by the employed bees near its previously assigned two food sources iteratively (see Table 3.3, Eq. 23). Moreover, the evaluation of new food sources is performed based on the fitness value, calculated as per Table 3.3, Eq. 24. If the fitness value of the current food source is higher than the old one, then it is substituted by the new one. All the employed bees carry out this exploitation process; and food source nectar information has been communicated with the onlooker bees. Depending upon the probability of each food source (see Table 3.3, Eq. 25), onlooker bees select a food source. Later, by utilizing the neighborhood operator, they try to locate the new source near the food source they selected earlier and identify the nectar amount. Then, identifying the best food source among all the food sources in the vicinity of the old food source is considered. Moreover, the old food source is abandoned only if the new one is found superior as compared to the old one and consequently assigned to the employed bees. Apart from it, employed bees also abandon the food source based on predetermined limit value. Such employed bees are called scout bees and look forward to randomly hunting for new food sources. Later, scouts become employed again if they get the new food source. This iteration of the ABC algorithm is repeated until the termination condition is met. The Fig. 3.3 highlights the process flow structure of the ABC algorithm that describes the four phases' mentioned theory.

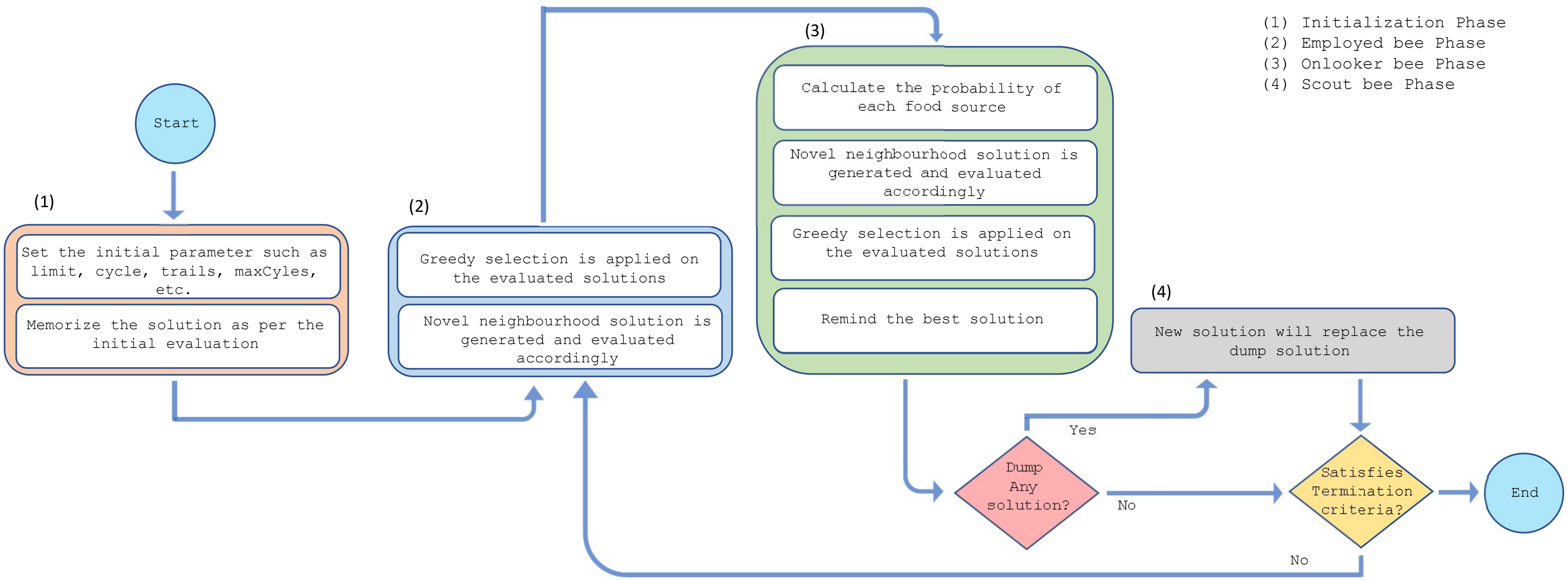


Figure 3.3: Process Flow of ABC Algorithm

3.2.1 An Application to ABC Algorithm

The ABC algorithm studied through Fig. 3.3 is required to be modified to achieve the desired objective as specified in Eq. (3.21). All the parameters studied in Section 3 are required to be included in the developed Algorithm 1. Initially, the algorithm is required to set the starting and destination node (see line 3). Further, a pre-defined set of the random food source is initialized at the starting node; and an employee bee is assigned to each food source (see line 4). The map size or the search space is directly proportional to the number of employee bees. Lines 2 to 7 not only calculate the fitness of each food source, but also route each employed bee using the $\boldsymbol{PickRandomRoute}$ function. An employed bee is placed at $\boldsymbol{'StartNode'}$, and through the random route selection, the bee is routed to the next connected node and so on. Apart from that, line 5 can be defined as three termination conditions: (i) bee reached the destination node; (ii) route had already been explored; and (iii) reached the maximum threshold of searching the routes. Line 8 calculates the Z*, where, $f(B_i)$ represents the $\boldsymbol{endDoD}$ which is calculated as per the Eq. (3.21).

$$Z^* = min\{f(B_i)\}, \quad \forall B_i \; reached\; their\; destination\; point. \tag{3.22}$$

Further, the artificial bee (the replica of EV) generates anything other than the Z^* is required to get into the search space, but not through the random selection of routes. This time, it is a three-step process: (i) Employed bee phase: Each employee bee assigned a food source and tries to find its neighborhood for a better solution (see lines 13-19); (ii) Onlooker bee phase: They follow certainly employed bees; and food sources are exploited randomly, while roulette wheel mechanism is used to compute the probability of selection (see lines 21-27); and (iii) Scout bee phase: The exhausted food source can't be improved after a certain point of time, so is abandoned by the scout bee (see lines 29-33). Z^* is updated as per the most reliable solution. Each artificial bee continues routing till the destination node is reached; and after reaching the destination, the energy cost calculation ($\boldsymbol{endDoD}$) of the newly generated route takes place as per Eq. (3.22). The new solution reflects the Z* (see line 35), only if the new solution performs better than the previous Z* value.

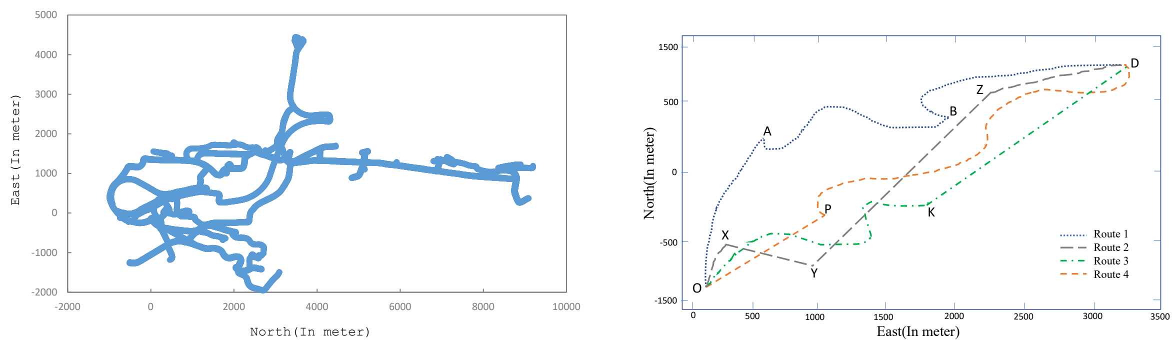
3.3 Computation Experiments

This section undertakes a case study to identify the necessity of the proposed algorithm by utilizing the dataset of the Warrigal project [21]. This dataset provides the actual driving state information of the vehicle along with the vehicle's coordinates (East and North), V2V communications, speed, and altitude for a period of three consecutive years. This

Algorithm 1: Proposed ABC Algorithm

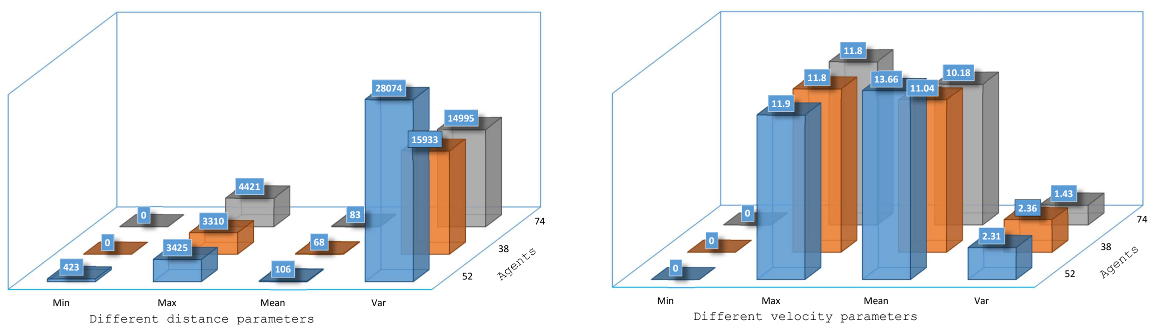
```
   Require: Source and destination node
   Ensure : EnergyEffRoute
1  Initialize : N random artificial bee at the start point 'StartNode'
2  for K<N do
3      EmployedBee=S_k
4      Route=EmployedBee
5      while ¬ TerminationCondition do
6          Route_k = pickRandomRoute(Route_k)
7      K+=1;
8  Calculate Z* as per Eq. (3.22)
9  while Cycle! = MaxCycles do
10     for K < N do
11         while Route_k != Z*route do
12             while Next node!= destination node do
13                 EmployedBeePhase()
14                 Calculate new food location as per Table 3.3, Eq. 23
15                 if Fit(X_update) > Fit(S_k) then
16                     S_k = X_update
17                     trial_k = 0
18                 else
19                     trial_k = trial_k + 1
20                 OnlookerBeePhase()
21                 Calculate the probability (S_k) using Table 3.3, Eq. 25
22                 if N_r < Prob(S_k) then
23                     Create and update solution as per Table 3.3, Eq. 24
24                     trial_k = 0
25                 else
26                     trial_k = trial_k + 1
27                     Update the solution
28                 ScoutBeePhase()
29                 if trial_k > limit_k then
30                     Dump that particular solution
31                     Generate random solution using Table 3.3, Eq. 22
32                 else
33                     Ignore the scout phase
34             Z*← Update, as per requirement
35             if Z* Updated then
36                 Goto line 9
37             else
38                 Continue
39         K+=1;
```

rich dataset is split on a daily basis. The road map according to the Warrigal dataset has been depicted in Fig. 3.4. Statistical analysis of speed and velocity for different agents (as per the datasets 52, 38, and 74) on the various parameters such as variance, mean, minimum, and maximum, has been conducted (see Fig. 3.5). Moreover, the dataset is also enriched by altitude (Min.-Max.) to encounter the realistic scenarios of different inclined roads. Therefore, the findings of this study are not just restricted to level roads surfaces



(a) (b)

Figure 3.4: Representation of Road Map based on Dataset (a), and Identified Routes from the Case Study (b)



(a) (b)

Figure 3.5: Statistical Analysis of Dataset based on Distance (a), and based on Velocity (b)

but also address the inclined roads conditions. Unfortunately, this dataset does not yield information about energy consumption of the vehicle. So, on the basis of proposed EV model in Section 3, the energy consumption of the vehicles has been computed. Matlab R2019a was used to implement the developed ABC algorithm; and the simulations were executed on AMD Ryzen 5 3500U processing at 2.10 GHz.

Firstly, the routing service is activated to determine the origin and destination points as O and D, respectively. Then, the developed algorithm is evaluated with the defined vehicle model in Section 3. Later, plugging in the respective coordinates of O and D to Google Maps will lead to generate three different routing possibilities (route 1, 2, and 3), while route 4, simulated based on the ABC algorithm, is generated, as shown in the Fig. 3.4b. The information, including route number, route length, segment code, average speed, maximum speed, min-max altitude, travel time, energy consumption, average energy consumption, start DoD, and end DoD has been summarized in Table 3.4 for different route agents. It is quite significant to note that the route generated by the ABC method was not only the most energy-efficient, but it was also found to be 7.1% more energy-efficient than routes generated by Google Maps. Another observation that can be drawn from Eq. (3.8) is that speed of the moving object is directly proportional to its energy consumption. As a result, route 3 is regarded as the most energy-consuming route among all the routes.

Table 3.4: Route Properties and their Respective Energy Consumption

Route Number	Route Length (m)	Segment Code	Avg. Speed (km/h)	Max. Speed (km/h)	Min.-Max. Altitude (m)	Travel Time (s)	Energy Consumption (KJ)	Avg. Energy Consumption (KJ)	Start DoD (%)	End DoD (%)
1	3314	OA	10.5	16.1	649-836	83	1071.71	703.23	0	0.1
		AB	12.5	18.05	670-816	18	136.8		0.1	1.35
		BD	13.3	16.2	642-642	97	897.2		1.35	2.12
2	3294	OX	13.2	14.1	642-836	116	954	754.23	0.1	0.67
		XY	10.1	12.1	662-756	105	986.4		0.66	1.14
		YZ	13	14.3	642-777	87	916.92		1.13	2.45
		ZD	11.5	13.9	742-836	8	155.6		2.44	2.88
3	3415	OK	18	19.8	752-816	201	2229.2	1115.24	0	2.75
		KD	17.2	19.2	817-836	95	1029		2.76	4.2
4	3345	OP	11.5	13.6	842-936	91	652.2	624.36	0	0.79
		PD	12.6	13.8	742-936	132	596.52		0.82	1.85

Moreover, route 2 is the shortest route out of four candidate routes; and route 1 leads to the shortest travel time among all the routes. Conclusively, neither the shortest route length nor the least travel time route is inherently the route with minimum energy consumption. After reviewing the findings, the driver of route 2 will save 1.5% longer drive length at the cost of 17.2% more energy usage than the driver of route 4.

Fig. 3.6 depicts DoD, energy consumption, and speed profile for the concerned route taken by the agents of routes 1 to 4. Each route is viewed as a collection of two or more route segments, and the different colors highlight that segment. At the start of the journey, DoD is believed to be 0%, or in other words, a fully charged battery is taken into account. Moreover, DoD variations remain minimal because of the shorter route length. While examining the findings, it has been observed that the route with maximum acceleration and deceleration demands more energy consumption and vice versa. Likewise, route 3 candidates have the highest energy consumption requirement due to multiple acceleration and deceleration. Each speed profile of each route is the combination of route segments formed by the combinations of speed profiles. The effective speed profile obtained for each segment is combined to form the route's speed profile. Besides this, each respective graph of DoD and energy consumption are also highlighted according to each route segment.

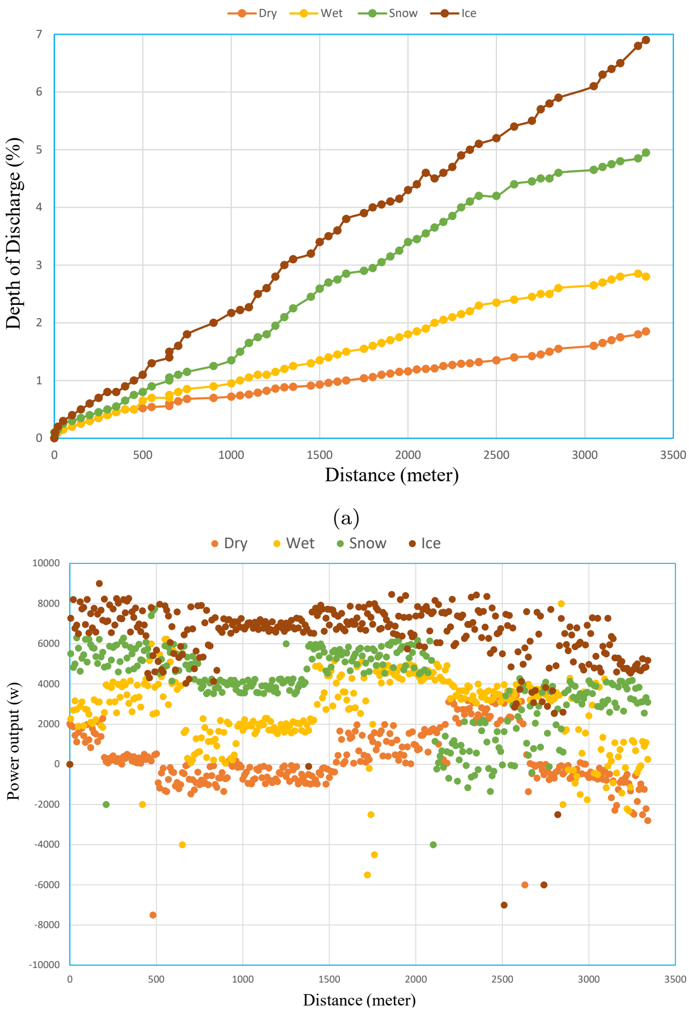
Table 3.5: Essential Findings after Analysis over Different Road Surface Conditions

Route 4 Surface	Avg. Speed (km/h)	Travel Time (s)	Energy Consumption (KJ)	Start DoD (%)	End DoD (%)
Dry	13.8	223	624.36	0	1.85
Wet	12.3	267	712.6	0	2.8
Snow	11.6	270	1078	0	4.95
Icy	8.6	460	1423	0	6.9

The road surface has a substantial impact on the energy consumption of the vehicle because the road slip friction ratio is directly proportional to the energy demand of the vehicle, and that ratio varies from one surface to another such as dry, wet, snowy, and icy (see Fig. 3.2). The road surface-based energy usage was tested over route 4, which was recommended as the least energy-demanding route by the presented ABC algorithm. Fig. 3.7 depicts DoD and energy consumption for different road surfaces. If we equate the icy surface to the dry surface, the DoD difference is enormous; that is why the energy demand is the largest of all road surfaces. It can also be verified from the results shown in Table 3.5 that icy surface consumes 128% additional energy as compared to the dry surface.

As per the expectation, the developed ABC meta-heuristic algorithm outperforms Google Maps, owing to the fact that this routing system employs Dijkstra or Dijkstra-like algorithm (Bellman-ford, Johnson etc.), which focus on optimizing the distance or time,

Figure 3.6: Depth of Discharge (DoD) (a), Energy Consumption (b), and Speed Profile (c) for Respective Routes (route 1 to 4) taken by the Different EV Agents under the Objective to Minimize the Energy Consumption



(a)

(b)

Figure 3.7: Effect of Different Road Surface Conditions on the DoD (a), and Energy Consumption (b) of EV

rather than energy consumption [30, 39, 238]. Moreover, such a system also lacks computational performance as they use deterministic algorithmic approaches. The Bellman–ford method is widely recognized for solving the shortest path problem even when there are negative edges [37]. The proposed ABC algorithm progressed to optimality after 265 iterations with a simulation time of 0.321 seconds (see Fig. 3.8a). The execution time can be reduced even further if code optimization is done. In contrast to the ABC algorithm, Bellman-Ford can take more time to evaluate if we account for the larger map size, which replicates a real-life scenario (see Fig. 3.8b). For instance, for a map size of 567 vertices and 2752 edges, Bellman-Ford would take 621 seconds for the evaluation, but the proposed meta-heuristic can deliver the result in just 102 seconds. Furthermore, the computation variance may be considerably more extensive if the study takes into consideration a transportation network with thousands of nodes and edges [30].

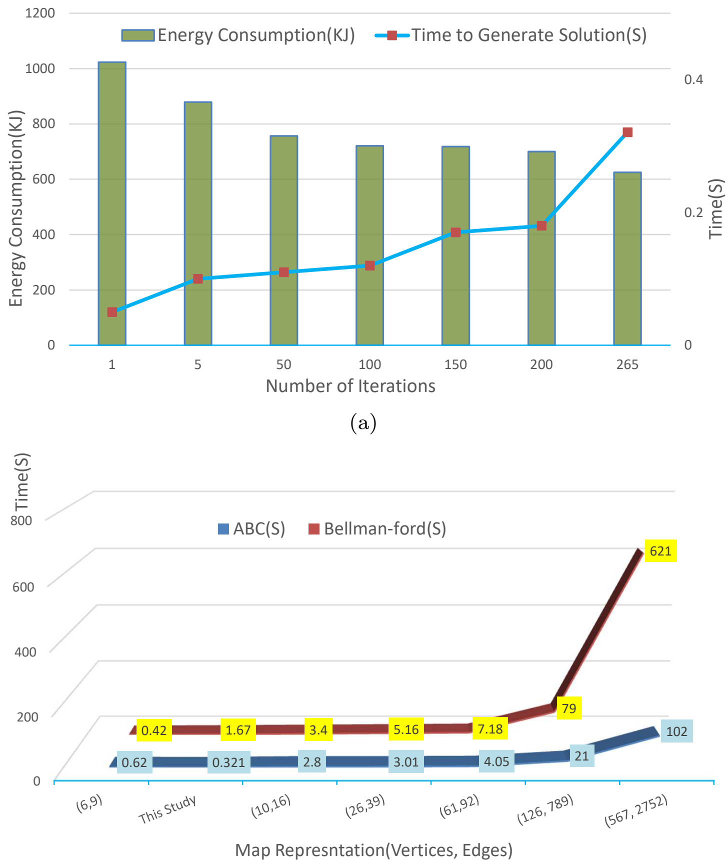


Figure 3.8: Representation of the Solution Convergence towards Optimality (a), and Comparison of Computation Time (b) between ABC Approach and Bellman-ford

3.4 Summary

A meta-heuristic optimization algorithm has been proposed to minimize the energy consumption of the novel generated EV model. Further, the EV model has been extended to examine the effect of different road surfaces on the EV's energy consumption. The ABC meta-heuristic is a relatively recent approach that has been modified to map into the known issue of energy-efficient EV routing. The model was evaluated using historical dataset to generate the most energy-efficient route between the specified source and destination. It can be concluded that neither the shortest distance, nor the shortest time route ensure that the route would demand the least energy. Several other constraints, including driving speed and slope, also have a substantial influence on energy consumption. These factors are considered in the proposed approach since they are either neglected or assumed to be constant by the current routing algorithms. The findings reveal that the ABC heuristic generated a 7.1% more energy-efficient route than the ones generated by Google Maps. The proposed model also estimates the tyre-road friction directly connected to the energy consumption in real-time conditions. The simulations also verify the significance. The results obtained during the study have significantly contributed to address the problem and benefits associated with EVs' energy-efficient routing problem.

Chapter 4

S^2RC: A Multi-objective Route Planning and Charging Slot Reservation Approach for EVS considering State of Traffic and Charging Station

The previous chapter presents the mathematical model to ensure the energy optimality during the EV routing inculcating the tractive effort modeling for different road surfaces. To accomplish this task, a meta-heuristic routing model based on the principles of Artificial Bee Colony (ABC) is also presented. The presented system added extensibility, generalizability, and adaptability to the existing literature.

The current chapter attempts to present the challenging problem of locating a charging station that offers the utmost user convenience. The proposed approach is an improvised distributed system, namely, $\boldsymbol{S^2RC}$ *(Smart Search of Route and Charging) which plans an energy efficient EV route considering EV's state-of-charge (SoC) level, traffic conditions, the frequency of charging stations and the state of charging station (the charging resources of the charging station along with their occupancy levels, etc.). This distributed architecture employs the proposed agile charging slot reservation approach for the EVs that wish to get recharged at a particular charging station. Besides, to delineate the interactive mechanism of EVs recharging, three non-identical objective functions are formulated to minimize the overall energy consumption of EVs, waiting time at charging station, and total charging expenditure. After performing the extensive simulations on the weighted directed real transportation graph of Chandigarh, India, the proposed* $\boldsymbol{S^2RC}$ *system recommends a charging station in accordance to the preferences given by the EV user* [1].

The Section 4.1 presents the system topology which describes $\boldsymbol{S^2RC}$ *system and communication flow among the various aspects of the distributed system. The mathematical*

[1]The contents of this chapter are partly published in:

- Ashwani Kumar, Ravinder Kumar, and Ashutosh Aggarwal, "S^2RC: A multi-objective route planning and charging slot reservation approach for electric vehicles considering state of traffic and charging station", Journal of King Saud University - Computer and Information Sciences, 34(5), pp. 1319-1578, 2022.

modeling for the proposed work has been covered in Section 4.2. Whereas, the Section 4.3 and 4.4 represents the solution approach and discussed case study respectively. Section 4.5 brings the chapter to a conclude.

4.1 System Topology

Assume that an EV user intends to drive from one location to another. In such a situation, a distributed system is vital to take a request from the EV user and efficiently plan their route, which also consists of recharging stops, to attain its destination. However, EV users can also alter their destination during the voyage but need to make a new request. As a result of this study, a distributed system named S^2RC has been established, and it is anticipated that communication between the EV and S^2RC will take place wirelessly through advanced technologies like wi-fi and V2X. The standard communication protocol such as TCP/IP has been used. Crucial information like source and destination locations and the SoC level can be transmitted wirelessly along with user preferences. Also, S^2RC has real-time access to the state of road networks and CS occupancy, as well as communication with traffic regulators. Therefore, the S^2RC distributed model defines a mechanism to effectively communicate across the numerous EV routing resources that are dispersed globally. Whenever EV requires any service, it needs to initiate the corresponding request to S^2RC, and as an acknowledgment, S^2RC responds with the solution based on the nature of the request made by the EV.

The S^2RC, which makes use of the client/server approach to deal with various computing environments, balances the different limitations and constraints enforced by the users, EV, and CSs as well as all incoming requests. In this direction, the parametric trade-off (balancing) is performed between the various computing environments such as EVs, CSs, TR, and transportation networks, by the proposed mathematical model recommends an optimal path along with appropriate CS. The general constraints of EVs include optimizing the use of battery SoC with regard to recharging during routing and travel along a forced trajectory that maps the recharging constraints. Although the recommended CS should be the nearest, their geographic locations, charging technologies, and user requirements impose limitations when dealing with public CSs. S^2RC seeks to determine the most energy-efficient route to raise the euphoria of EV users (minimize charging waiting time and reduce charging cost) subject to the constraints such as SoC dynamics, traffic conditions, and CS slot availability. Fig. 4.1 highlights the proposed architecture and its association with geographically scattered components as well as their interaction.

A better way to understand the communication flow between EV, S^2RC, and CSs has been illustrated in Fig. 4.2. Further, it also describes the various constraints and technicalities explored in this paper. The information exchange has been portrayed as follows under the umbrella of two different scenarios:

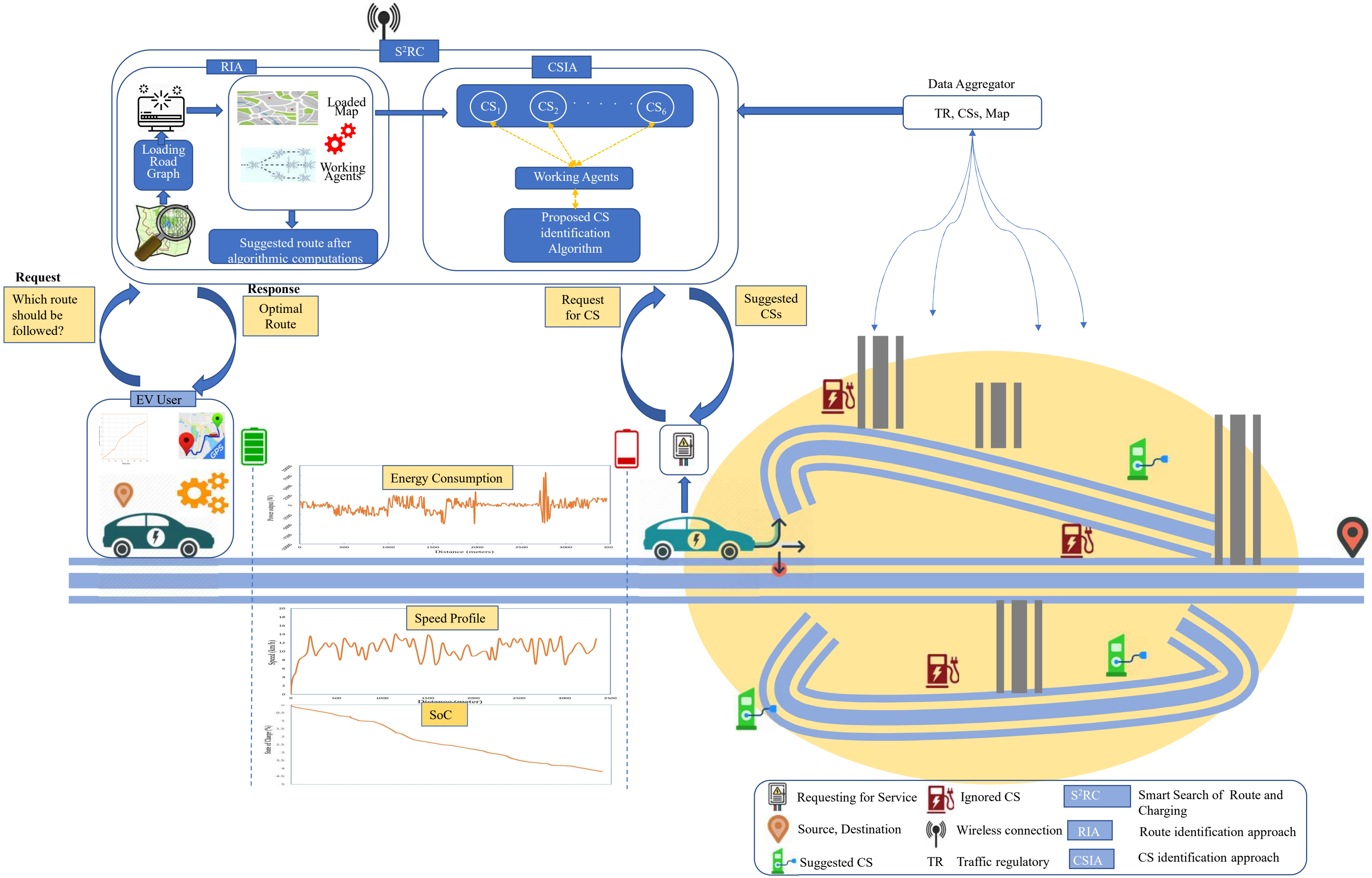


Figure 4.1: Distributed S^2RC Architecture and its Active Components

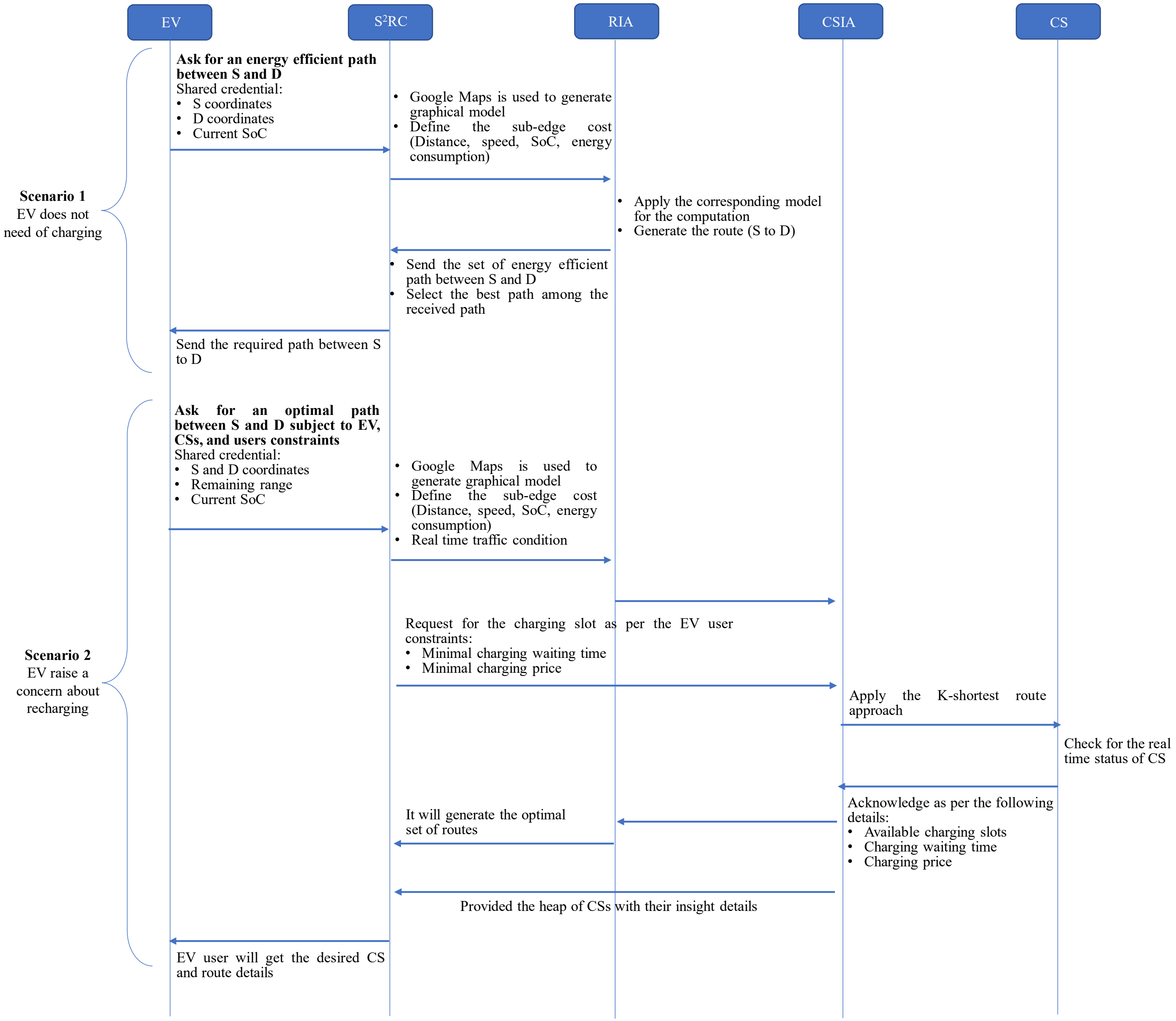


Figure 4.2: Information Flow between EV, S^2RC, and CS under the Different Scenarios

- **Scenario 1:** It denotes that the EV does not need charging because it has sufficient SoC level to reach its destination. As shown in Fig. 4.2, it is a three-tier information flow in which the required information is communicated by EV to S^2RC to obtain a route plan (as per the objective of minimal energy consumption) and then transfers to the associated sub-module (RIA). As an acknowledgment, the EV user gets the optimal route plans.

- **Scenario 2:** It demonstrates the five-tier information flow hierarchy (EV $\rightarrow$ S^2RC $\rightarrow$ (RIA, CSIA), CSIA $\rightarrow$ CS) when an EV expresses a concern about charging during the course of action. As an acknowledgment, S^2RC gets back to the EV with the required list of CSs and their route plans in accordance with multiple non-identical objectives as stated in Section 1.

4.1.1 Transportation Network Layout

Fig. 4.3 describes the transportation network with complete directed graph $G = (\mathbb{N}, \mathbb{A})$. Where, $\mathbb{N} = \{1......n\}$ is a collection of nodes; and $\mathbb{A}$ is a set of arcs (formed between two nodes treated as edge e). $\mathbb{N}$ and $\mathbb{A}$ indicate the number of nodes and arcs respectively. Node 1 and n represent the O (origin) and D (destination) of any journey. The distance of an arc or distance between any two nodes can be expressed as the vector $l^{a,b}$, if and only if $arc(a, b) \in \mathbb{A}$. Some of the available nodes at a certain location are designated as CSs (e.g., CS1, CS2, CS3, CS4, and CS5), where batteries can be recharged with varying electricity cost, while each CS can have different waiting time. A set of CSs is symbolized by $\aleph$, where ($\aleph \subseteq \mathbb{N}$). S^2RC quantifies the graph G comprising all roads in the territory of service and traffic density on each arc.

4.2 Mathematical Modelling and Allied Notations

A mathematical model is developed to trace the applicability of the proposed optimization problem that quantifies the characteristics of transportation networks and EV charging. Since the focus was on building a robust system, we overlooked adopting the heuristic approaches related to the solution of the developed model. This model is also different from the traditional VRP models as it accentuates EV charging characteristics, allowing it to be more adaptable to energy-efficient routing and potential power distribution systems. To understand the mentioned mathematical model more clearly, the respective notations have been presented in Table 4.1 and Table 4.2.

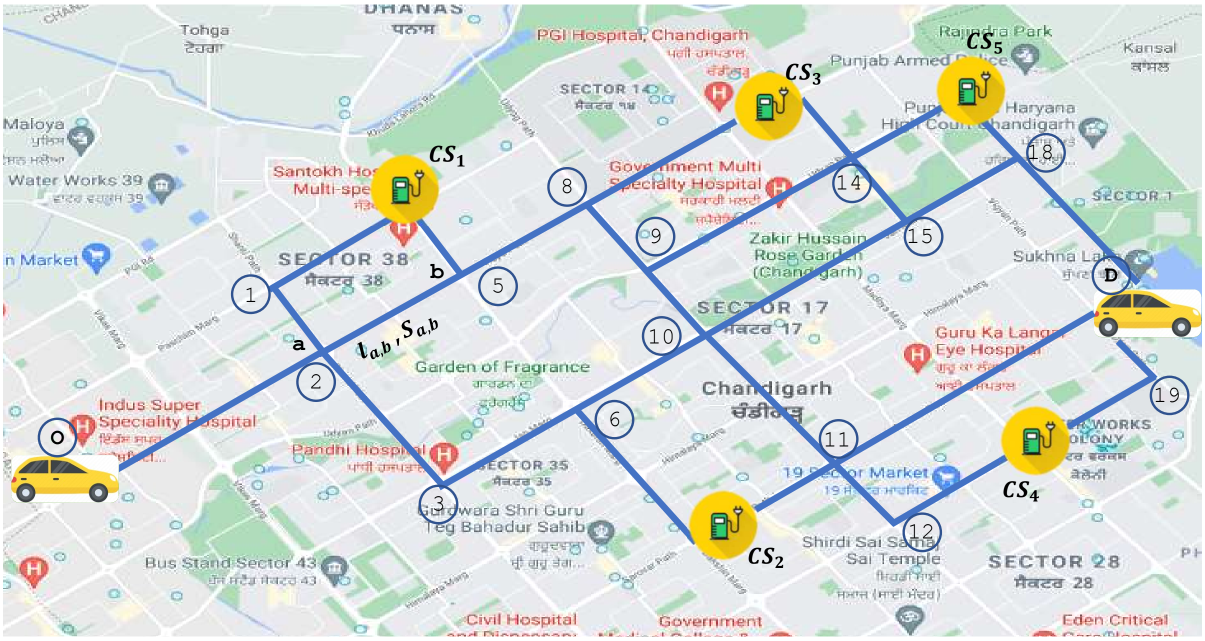


Figure 4.3: Illustration of the Road Network Consisting of Multiple Nodes, Charging Stations, and Sub-arcs

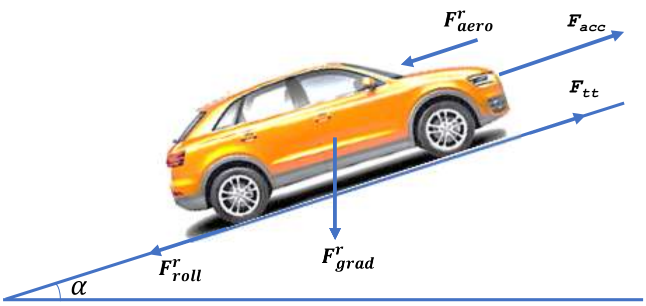


Figure 4.4: Diagram Representing the Different Operating Forces on Vehicle's Body

4.2.1 Force Modeling to Evaluate Energy Consumption

While identifying the consumed energy during routing, it is necessary to quantify the total traction force required throughout the route because a lot of energy is spent for traction. This work employed the vehicle longitudinal dynamics model's principles, which operates on the acting forces on the vehicle's body (see Fig. 4.4) [232]. This model calculates the mechanical energy (traction force) required to propel the EV. Eq. (4.1) expresses the mechanical relationship to find the total tractive force (F_{tt}):

$$F_{tt} = F_{acc} + F^r_{grad} + F^r_{roll} + F^r_{aero} \tag{4.1}$$

Whereas, the Eq. (4.2) represents F_{acc} as follows:

Table 4.1: Key Abbreviation and their Respective Description

Symbol	Description	Symbol	Description
$\mathbb{N}$	Set of all nodes	$\aleph$	Set of all CSs
$l^{a,b}$	Distance between node a and b respectively	$E_c^{a,b}$	Energy consumption between node a and b
$S^{a,b}$	Speed between node a and b	F_{tt}	Total tractive force
F_{acc}	Acceleration force	F^r_{grad}	Grading force resistance
F^r_{roll}	Rolling force resistance	F^r_{aero}	Aerodynamic force resistance
P_t	Tractive power	Z_{init}	Initial SoC
E_c^{route}	Total energy consumption on a route	E_{max}	Maximum possible battery capacity
d	Duty cycle	ϵ_{dc}	Efficiency of the DC-DC converter
v_{DC}	DC link voltage	v_b	Battery voltage
i_c	Cell current	b_{nc}	Count of battery cell
it	Extracted capacity	v_{exp}	Exponential voltage
E_0	Cell constant voltage	K	Polarization constant
Q	Cell maximum capacity	R_{int}	Cell internal resistance
M	Exponential capacity variables	I_b	Discharge current
$Q^{\mathbb{K}}$	Charging power at $\mathbb{K}$th CS	τ^i	Service time at $\mathbb{K}$th CS
$Z_A^{\mathbb{K}}/Z_D^{\mathbb{K}}$	Arrival/Departure SoC at $\mathbb{K}$th CS	$C_{cap}^{\mathbb{K}}$	Charging capacity of $\mathbb{K}$th CS
$E_d^{\mathbb{K}}$	Energy demand at $\mathbb{K}$th CS	Z_{min}	Minimum SoC needed
$\delta_Z^{\mathbb{K}}$	SoC difference between departure and arrival at $\mathbb{K}$th CS	$Z_D^{a,b}$	SoC after charging in node b and arriving from a
$j_{a,b}$	Sub-arc indicator, $j_{a,b} \in 0,1$	ξ	Traffic information
τ_z	Driving time with no traffic	$\tau_{a,b}$	Driving time on the sub-arc (a,b)
$T^e_{a,b}$	Estimated arrival time	$\tau^{arc}_{a,b}$	Travel time on arc (a,b)
T^p_a	Present time on ath CS	$t^l_{\mathbb{C},b}$	Charging time of lth EV at node b
C_p	Charging power at node b	ψ_b	Charging price at node b
$\$_{\mathbb{C}}$	Energy cost at the $\mathbb{K}$th CS	η^0_a	Base value of service cost
β_a	A coefficient	η^{msc}_a	Maximum service cost
η^{misc}_a	Minimum service cost	t_s	Service start time
t_f	Service finish time	Z_D	SoC at destination

$$F_{acc} = \left(\frac{mr^2 + I_m(ra)^2_g + 4I_w}{r^2} \right) a \tag{4.2}$$

F^r_{grad} works against the forward motion because when a vehicle travels on an inclined road (up or down), it always directs downward.

$$F^r_{grad} = mgsin(\alpha) \tag{4.3}$$

F^r_{roll} opposes the motion of a vehicle on a surface. Mathematically, it is presented in Eq. (4.4) as follows:

$$F^r_{roll} = mgC_{roll}cos(\alpha) \tag{4.4}$$

F^r_{aero} is generated when air travels across the vehicle's body. It exerts pressure on the body of the vehicle and acts against its movement, that is why it is directly proportional to the vehicle's speed. However, the speed along the arc O to D (see Fig. 4.3) can't be uniform because every sub-arc lying between O to D is composed of several sub-arcs. Every sub-arc possesses a different speed that is given by the TR to the S^2RC distributed model. Thus,

$$F^r_{aero}(a,b) = (.5\rho C_{ad}A_{fr}(S^{a,b} + S^{a,b}_{wind})^2) * l^{a,b} \tag{4.5}$$

On the basis of above discussion, Eq. (4.2) can be rewritten as:

$$F_{acc}(a,b) = \left(\frac{mr^2 + I_m(ra)^2_g + 4I_w}{r^2}\right) * a * l^{a,b} \tag{4.6}$$

With the help of F_{tt}, as shown in Eq. (4.1), the tractive power can be estimated as:

$$P_t = S * \sum F_{tt} \tag{4.7}$$

Hence, energy consumption of any particular sub-arc can be estimated as Eq. (4.8); and by integrating each arc power consumption along the route, we can now determine the overall energy consumption of an EV when travelling from source to destination as denoted in Eq. (4.9).

$$E^{a,b}_c = l^{a,b} * P^{a,b}_t \tag{4.8}$$

According to the computation of EVs energy consumption, without taking into account recharging activity throughout the trip,

$$E^{route}_c = \sum_{arc=1}^{k} \sum_{a,b} E^{a,b}_c \tag{4.9}$$

4.2.2 Battery Modelling to Evaluate SoC

We need to define a battery based-model in order to trace down the SoC profile. Here, the most advanced power technology of lithium-ion (Li-ion) battery stack has been considered as it capable of having a large life span capability and shorter charging time. The battery current (i_b) is identified as per following equation:

$$i_b = \frac{i_{DC}}{(1-d)\epsilon_{dc}} = \frac{i_{DC}}{(1-(1-\frac{v_b}{v_{DC}}))\epsilon_{dc}} = \frac{i_{DC} * v_{DC}}{v_b * \epsilon_{dc}} \tag{4.10}$$

Where, i_{DC} is represented as DC link (normally, DC link is used to interface between the DC-DC converter and EV battery) current. From Eq. (4.10), cell current can be identified as:

$$i_c = \frac{i_b}{b_{nc}} \tag{4.11}$$

The Shepherd battery model [231] has been modified for the proposed EV model. The internal resistance of cell is assumed to be constant throughout the cycle of charging and discharging. Moreover, apart from ignoring the battery temperature effect, the identical parameters have also been considered for discharging as well as charging model.

For charging cycle (if $i^* < 0$)

$$V_c = L - K.(X.i^*_{cell} - Y.it) \tag{4.12}$$

For discharging cycle (if $i^* > 0$)

$$V_c = L - Y.K(i^*_{cell} - .it) \tag{4.13}$$

Where, the following equations represent L, X and Y mathematically:

$$L = E_0 - R_{int}i_{cell} + v_{exp}\exp(-M.it) \tag{4.14}$$

$$X = \left(\frac{Q}{it - 0.1Q}\right), Y = \left(\frac{Q}{Q - it}\right) \tag{4.15}$$

and $it, v_{exp}, E_0, K, Q, R_{int}$ and M can be obtained from the battery data-sheet. With the help of cell voltage, battery voltage can be identified as shown in the following equation:

$$V_b = N_s V_c \tag{4.16}$$

Now, battery power (P_b) can be identified as follows:

$$P_b = V_b * i_b = (N_{bc}V_c) * i_b \tag{4.17}$$

In order to ensure safe operation of the battery, SoC, as defined below, has been considered as a constraint in the routing algorithm:

$$Z = \left(1 - \frac{1}{E_{max}} \int_{t_0}^{t_0+\gamma} I_b(t)dt\right) * 100\% \tag{4.18}$$

The maximum and minimum values of Z are 100% and 0% which refer to fully charged and discharged states of the battery respectively.

4.2.3 Calculation of Waiting Time of EV at CSs

The waiting time at $\mathbb{K}$th CS is the time elapsed between the arrival of EV at the $\mathbb{K}$th CS and the assignment of a charging slot to the EV. One can't neglect the charging waiting time at CS as it is directly proportional to the overall energy consumption and time. If the CS has sufficient charging resources, the EV will be allotted a charging slot immediately upon arrival. However, in the case of insufficient resources, EV has to wait, as depicted in the Fig. 4.5.

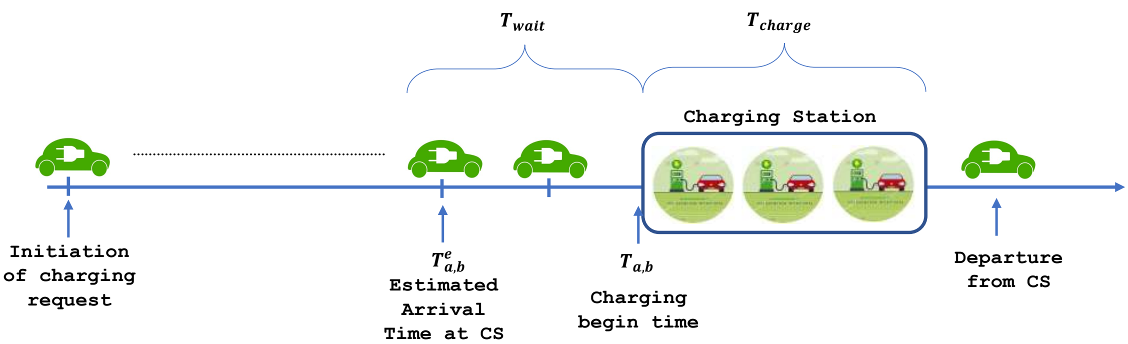


Figure 4.5: Parametric Timeline Representation for Minimizing Waiting Time at CS Model

4.2.3.1 Calculation of Delay Occurred due to Traffic

The traffic condition has an indirect relationship with the speed of the vehicle. It not only degrades the vehicle's performance, but also cause annoyance. The traffic information beyond the specific sub-arc can adversely affect the travelling speed for that sub-arc and hence, the driving time. To obtain the estimated arrival time of an EV at $\mathbb{K}$th CS, it is necessary to compute the driving time of that sub-arc. The time required to travel through any sub-arc is denoted by Eq. (4.19); and Fig. 4.6 shows how the different levels of traffic information (normal, moderate, and severe) are mapped with the ξ. τ_z represents the driving time; where, ξ is having the value zero. It can also be inferred from the Eq. (4.19) that the travel time on arc (a, b) tends to infinity under severe traffic conditions.

$$\tau_{a,b} = \frac{1}{2}\tau_z \left(1 + \frac{1}{1-\xi}\right) \tag{4.19}$$

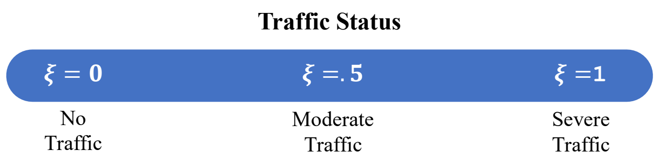


Figure 4.6: Illustration of Different Road Traffic Density Mapping with Respective Variable

We can determine the overall driving time of each arc bounded by a and b, by summing up the driving time of sub-arcs of the route.

$$\tau^{arc}_{a,b} = \sum_{a,b} \tau_{a,b} \tag{4.20}$$

We can now calculate the arrival time of an EV at $\mathbb{K}$th CS by adding the current position of EV and arc travel time $\tau^{arc}_{a,b}$.

$$T^e_{a,b} = T^p_a + \tau^{arc}_{a,b} \tag{4.21}$$

4.2.4 Estimation of Charging Costs at Different CSs

The cost of recharging an EV at a CS can be divided into two different parts; energy cost and service cost. The energy cost varies depending on the power providers' policies since at-home charging rates are similar to household energy cost, whereas utilizing centralized or public CS, charges are identical with industrial usage. Further, it also encourages to adopt the time-of-use (ToU) energy pricing to recharge amid off-peak time. Considering the service cost at the CS, the base value of service cost $\eta^0_a(t)$ is concatenated with a coefficient factor $\beta_a(t)$, which emphasizes on the ample availability of charging resources. $\beta_a(t)$ operates as a demand-supply factor. For instance, if there are enough charging resources and fewer charging events are occurring, then $\beta_a(t)$ attains a low value to attract more users. However, if the value of $\beta_a(t)$ is comparatively higher, it reflects that there are long recharging waiting queues at the CS due to insufficient charging resources. So, apart from the energy cost, the service cost at the station a directs the users to recharge their EVs in a coordinated manner:

$$\eta_a(t) = \begin{cases} \$_a(t) + \eta_a^{msc}, & \eta_a^{msc} < \kappa \\ \$_a(t) + \eta_a^{misc}, & \eta_a^{misc} > \kappa \\ \$_a(t) + \kappa, & \eta_a^{misc} \leq \kappa \leq \eta_a^{msc} \end{cases} \tag{4.22}$$

Where, $\kappa = \beta_a(t)\eta_a^0(t)$. $\$_a(t)$ tends to represent the energy cost at the ath CS. $\eta_a^0(t)$, usually a fixed service cost owing to operational activity for sustaining the CS, while η_a^{msc} and η_a^{misc} are calibrated to prevent competition CSs.

The following optimization model of an EV itinerary (T_{ope}) mainly aims objective function consists of three parts; the first objective is to frame the minimizing the energy consumption of a route without taking into account the recharging activity. The second objective is to minimize the waiting time at CS, and the sole purpose of the third objective is to minimize the recharging cost, where it is necessary to optimize the charging expenditures that occur through the course of activity to deliver the most cost-effective EV route to those who care more about charging costs. Moreover, we have assigned weights (φ_1, φ_2, φ_3) to each objective. If there is partial or complete conflict in multi-objective functions, the user can adjust the weights according to their preferences and interests.

$$min\, T_{ope} = E_{ope} + T_{wait} + R_{cost} \tag{4.23}$$

$$\begin{aligned} min\, T_{ope} = \varphi_1 \left(\sum_{arc=1}^{k} \sum_{a,b} E_c^{a,b} * J_{a,b} \right) + \\ \varphi_2 \left(\sum_{b=1}^{k} \sum_{a=1}^{k} (T_{a,b} - T_{a,b}^e) * X_{a,b} \right) + \\ \varphi_3 \left(\sum_{t=t_s}^{t_f} \eta(t) C_p \tau \right) \end{aligned} \tag{4.24}$$

subject to:

$$Z_{init} \leq E_{max} \tag{4.25}$$

$$Z_{min} \leq \left(Z_{init} - \frac{E_c^{route}}{E_{max}} \right) \tag{4.26}$$

$$\delta_Z^{\mathbb{K}} = \begin{cases} Z_A^{\mathbb{K}} - Z_D^{\mathbb{K}} \\ \frac{\tau^{\mathbb{K}} * Q^{\mathbb{K}}}{E_{max}} \end{cases} \tag{4.27}$$

$$\delta_Z^{\mathbb{K}} \geq \frac{E_c^{a,b}}{E_{max}} \tag{4.28}$$

$$C_{cap}^{\mathbb{K}} \geq E_d^{\mathbb{K}} \tag{4.29}$$

$$Z_{min} \leq Z_D \leq \rho + Z_{min} \tag{4.30}$$

$$Z_D = \left(\sum_{b=1}^{k} \sum_{a=1}^{k} (Z_D^{a,b} - \frac{E_c^{a,b}}{E_{max}}) * X_{a,b} \right) \tag{4.31}$$

$$\forall\ \lambda_a(t) = 1, t \in \{t_s, t_f\} \tag{4.32}$$

$$J_{a,b} = 0, 1,\ \forall a, b \in N \tag{4.33}$$

$$X_{a,b} = 0, 1,\ \forall a, b \in N \tag{4.34}$$

Constraint (4.25) check for the initial (at source) status of battery SoC. Constraint (4.26) satisfies the minimum battery SoC required to attain the destination. It is also required that if an EV passes through a CS and uses the appropriate charging services, it should have a sufficient level of SoC, either to reach the destination or the next CS. The constraint (4.27) provides the SoC level comparison between the SoC level after charging at any particular CS and estimated SoC consumption to reach the target destination. The constraint (4.28) determines that the EV is reachable to the next CS or destination. It is also necessary to ensure that the charging capacity of the $\mathbb{K}$th CS should be greater than the energy demand of $\mathbb{K}$th CS, as shown by the constraint (4.29). The constraints (4.30) and (4.31) highlight the conditions for minimum waiting time at CS. The constraint (4.32) indicates that when an EV arrives at the CS, it is sure to be offered a charging slot throughout the process of recharging. The decision variable in (4.33) is 1 when the vehicle visits the arc (a, b); otherwise, it is treated as 0. Whereas decision variable in (4.34) is 1 if EV leaves charging station a to b; otherwise, it is 0.

Table 4.2: Description of Parameters Used in the Vehicle Model and their Tuning Values

Symbols	Description	Value	Unit
m	Vehicle mass	1250	kg
I_m	Motor inertia	0.0384	kgm^2
I_w	Wheel inertia	0.75	kgm^2
r	Tyre radius	0.278	m
ra_g	Gearbox ratio	8.654	-
g	Gravitational force	9.8	m/s^2
ρ	Air density	1.1839	kg/m^3
C_{ad}	Aerodynamic drag coefficient	.24	-
A_{fr}	Vehicle's frontal area	2.341	m^2
$S_{wind}^{a,b}$	Wind speed	0	-
c_{roll}	Rolling resistance coefficient	.02	-
Z_{init}	Initial SoC	[.7, .35]	-
$Z_A^{\mathbb{K}}$	On arrival SoC at $\mathbb{K}$th CS	5	%
E_{max}	Maximum battery capacity	16	kw

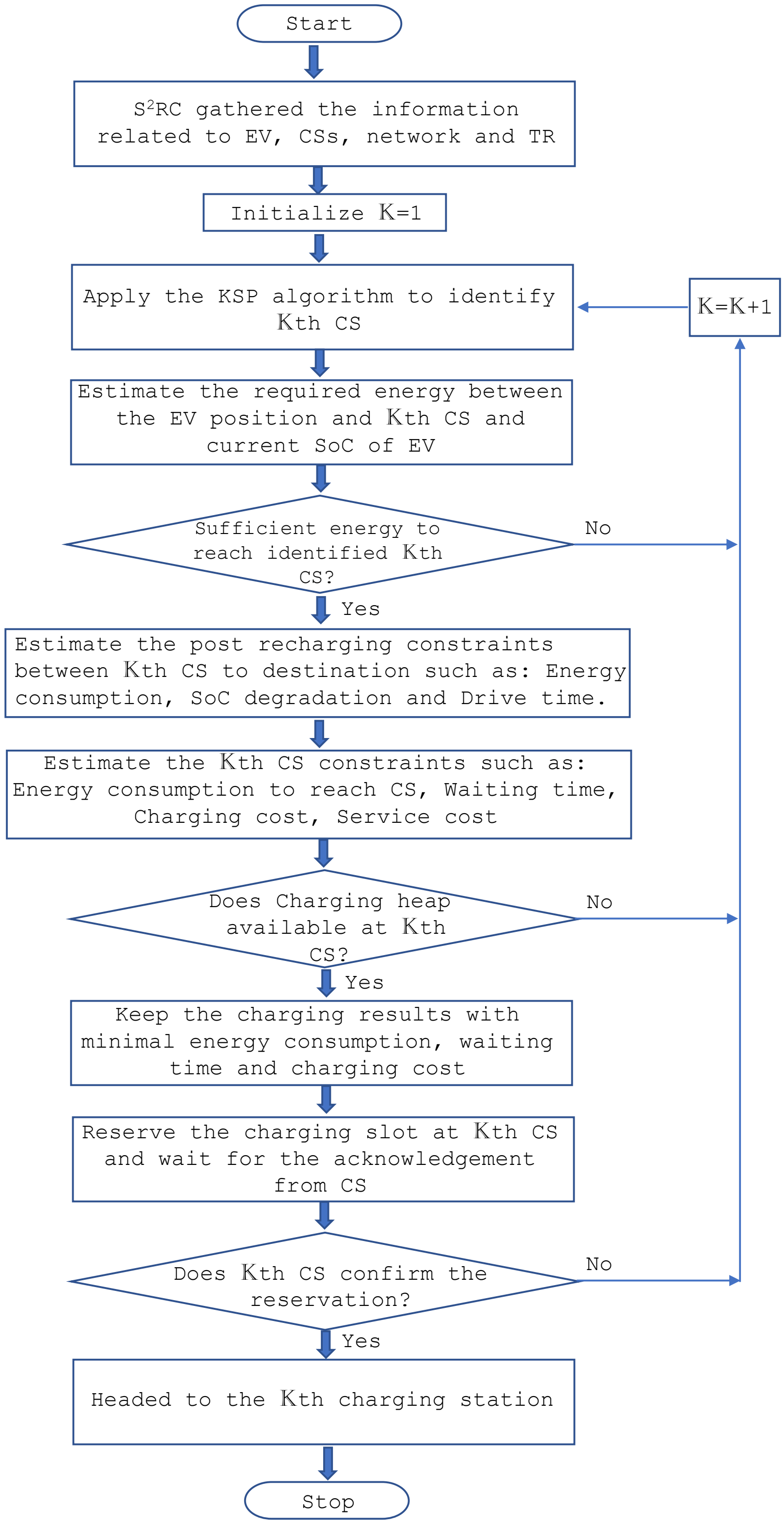
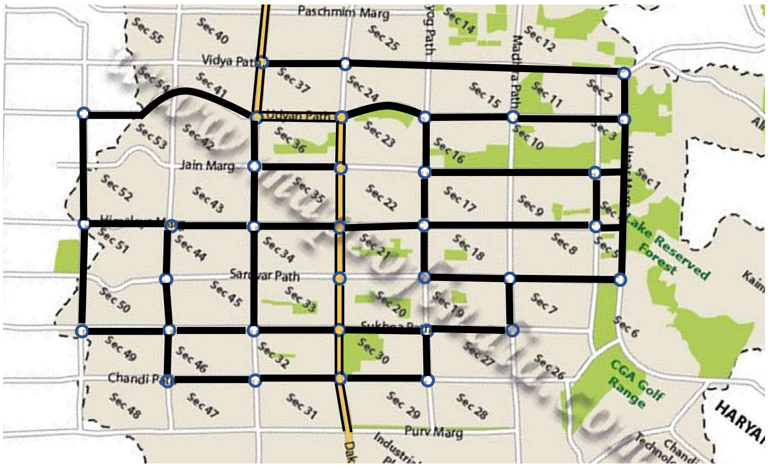
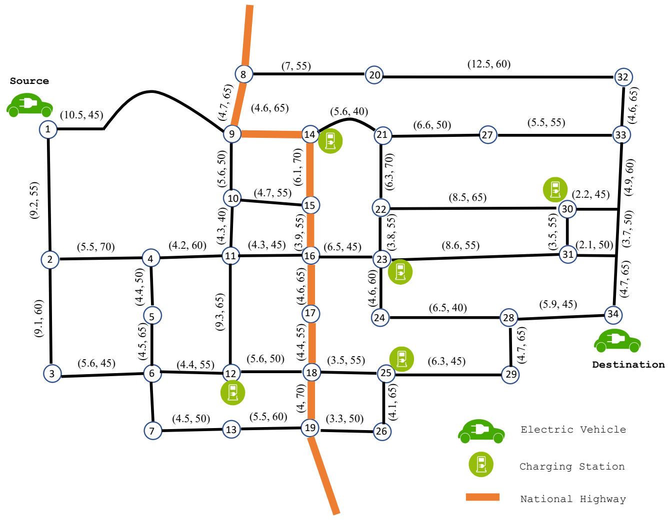


Figure 4.7: Agile Charging Slot Reservation Process



(a) Simplified transportation network of Chandigarh(India) [38]



(b) A topological structure of transportation network

Figure 4.8: Different Levels of Transportation Networks

4.3 Solution Approach

This section discusses how to address the problem of an EV that requires recharging and must stop to recharge at a suitable charging node. To overcome this problem, the KSP algorithm was employed that had its applications to the directed or undirected networks with non-negative edge weights. This algorithm approaches in such a way that it can have multiple paths between any two nodes, and the preferred one is chosen from among all the routes once the optimization is completed depending on the stated objective in Eq. (4.24). The transportation network was modelled as a weighted directed graph, with nodes serving as initial and destination nodes as well as charging nodes and road junctions. The nodes, not satisfying the inequalities, were discarded; and the graph was recreated. To solve the agile charging slot reservation approach with the objective of minimizing energy consumption, the weight of each graph arc (a, b) is given as per the first objective function of Eq. (4.24) as well as for objective of minimizing charging waiting time and charging cost at CS, the charging node is labelled as the values obtained through the second objective of Eq. (4.24) and third objective of Eq. (4.24) respectively. Fig. 4.7 depicts the process of finding a suitable route plan and the charging strategy.

The steps taken to solve the agile charging slot reservation process are described as follows:

Step 1. When the charging demand triggers, the S^2RC system obtains the required statistics from the EV (current coordinates, destination, SoC status), CS (locations, charging heap availability, charging waiting time, and charging cost), and traffic authorities.

Step 2. Using the KSP algorithm, the S^2RC system identifies the k-shortest routes (in terms of energy consumption) from EV current position to the $\mathbb{K}$th CS, if the condition (remaining $SoC \geq SoC$ to travel through $\mathbb{K}$th CS) is found satisfied.

Step 3. Estimate the post-recharging ($\mathbb{K}$th CS to the destination or another CS) constraints such as SoC level and energy consumption.

Step 4. S^2RC estimates the waiting time, charging cost as well as the charging heap availability at the $\mathbb{K}$th CS. If the charging heap is not available, then move to Step 2.

Step 5. S^2RC system delivers the most optimum route among all the routes obtained through the KSP algorithm.

Step 6. The EV user must select the CS and route based on the preferred choice among the objectives; and then, submit the charging slot reservation request and wait for an acknowledgment.

Step 7. The CS looks into the request generated by EV. If CS refuses the request, EV is forced to accept the sub-optimal solution.

Table 4.3: Energy Prices Corresponding to the CSs

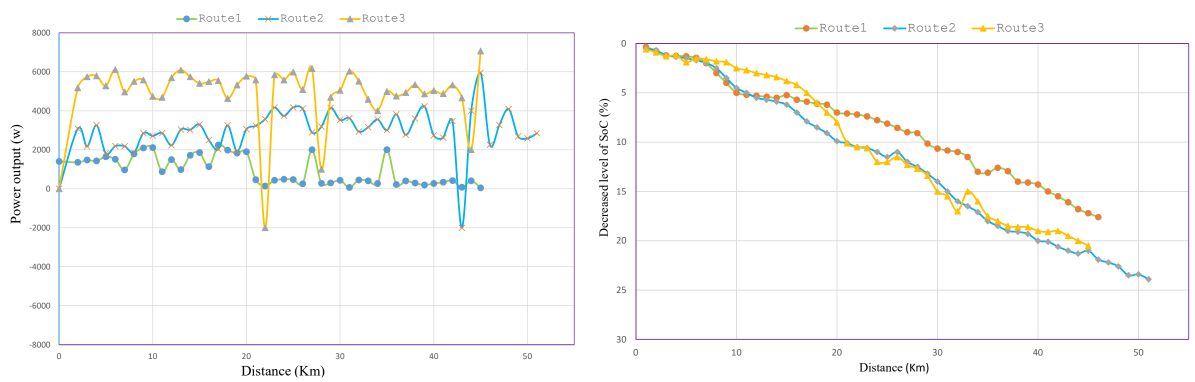
CS Number	Node Number (as per Fig. 4.8b)	ToU Energy Price ($/kWh)					
		00≤t≤04	04<t<08	08≤t≤12	12<t<16	16≤t≤20	20<t<24
1	12	0.5	0.52	0.70	0.73	0.81	0.77
2	14	0.45	0.52	0.60	0.69	0.77	0.90
3	23	0.55	0.60	0.80	0.83	1.02	0.96
4	25	0.41	0.59	0.85	0.85	0.91	0.87
5	30	0.35	0.65	0.91	0.81	0.99	0.91

4.4 Case Study for Chandigarh Transportation Network

4.4.1 Experimental Set-up

A real transportation network, Chandigarh (India) has been opted for the analysis of proposed model (see Fig. 4.8a) [34, 35]. This scenario is a publicly accessible open-source network that tries to deliver a dynamic transit demand considering heterogeneous EV users with a high degree of geographic precision. The original scenario was turned into a corresponding topological network with 34 nodes and 50 edges for the ease of statistical analysis, as shown in Fig. 4.8b. The specific information of edges has been labelled with the corresponding edge in the format of (a, b), where a denotes the distance between two nodes; and b represents the constant speed limit. The source and destination location of EV are configured to be node numbers 1 and 34 respectively. The vehicle parameters, for this study Tesla S P85, has been taken to calculate the different active forces on the vehicle's body [33]; and the Li-Ion battery parameters are collected from the battery cell data-sheet, as mentioned in Table 4.2 [69]. All KSP algorithm scripts were written in MATLAB R2021b, whereas the problem identified in Eq. (4.24) has been solved in CPLEX Optimization Studio 20.1 on AMD Rygen 7 processor with 8GB RAM [36].

In this case study, ToU (Time-of-Use) energy cost has been used at five different CSs. The data related to CS specifications (for eg. CS number, respective position, and count of charging heaps) and various charging cost profiles under the six distinct time-of-day (ToD) profiles at different CSs is provided in Table 4.3. The charging cost encompasses the cost of energy and service that are highly dependent on the source of the energy, geographic location, and commercial considerations. The adoption of charging cost coefficient is considered quite significant when looking for the real-time difference in ToD service cost at CS. As a result, the different charges are incurred while visiting different CSs.



(a) Energy consumption mapping

(b) SoC level mapping

Figure 4.9: Key Findings of Different Routes

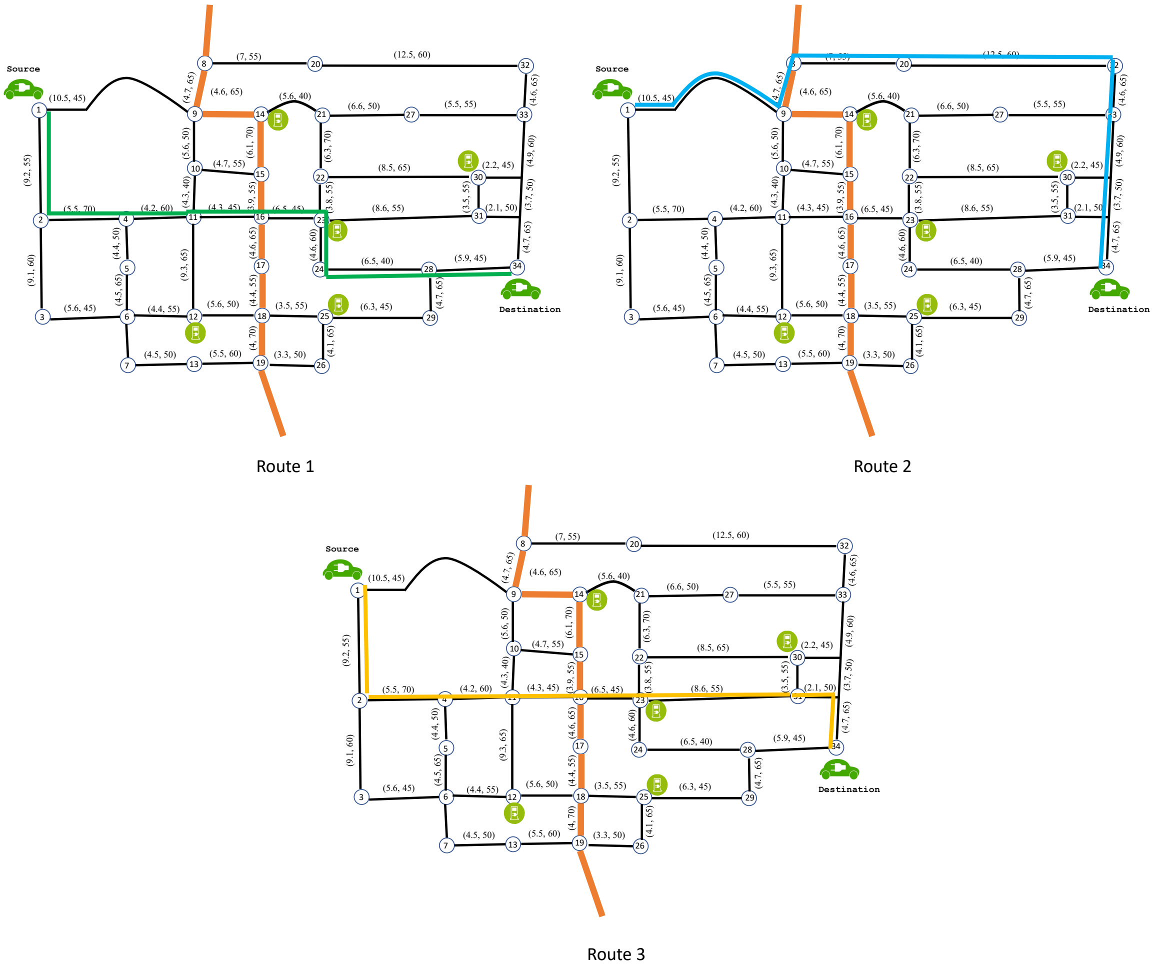


Figure 4.10: Different Energy Optimum Routes

4.4.2 Analysis based on Scenario 1

4.4.2.1 Route Planning Accounting Energy Consumption

After tuning all the parameters, the energy consumption was estimated through Eq. (4.9). Eqs. (4.28) and (4.29) are assumed to meet the requirements of reachability and energy demand in the simulated scenario. Then, the implemented KSP algorithm was used to generate the route. After the simulation, the proposed approach generated three best routes, taking energy consumption as an objective function. Table 4.4 explains the respective routes, their energy consumption and the route distance. Furthermore, Fig. 4.9 graphically depicts energy consumption and SoC profile for all the three generated routes as shown in Fig. 4.10. All the three routes have shown substantial variation in energy consumption and SoC levels. It was observed that the factors such as traffic condition, battery health, and road slope influenced energy consumption. For example, the route 3 is the shortest route among all the three generated routes; and it should be the most energy optimal route. However, route 1 found to be the most energy-efficient route as it avoided the factors affecting the energy efficiency of the EV.

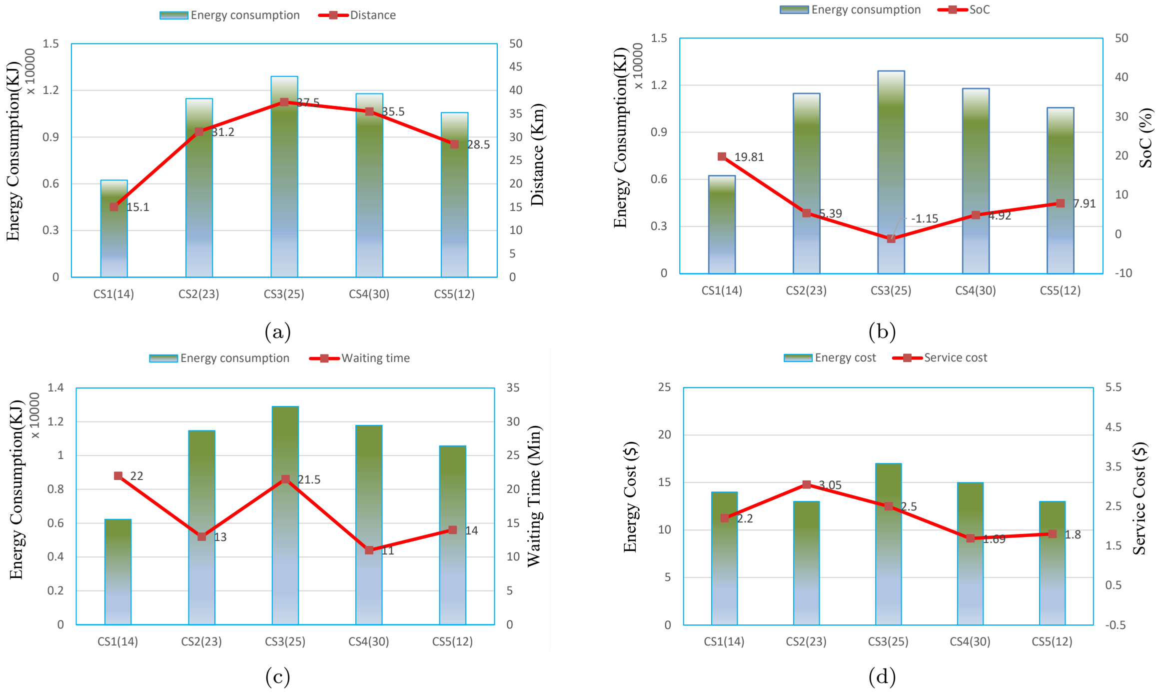


Figure 4.11: Computation of Different Parameters and Constraints Considering Minimal Charging Waiting Time as Objective

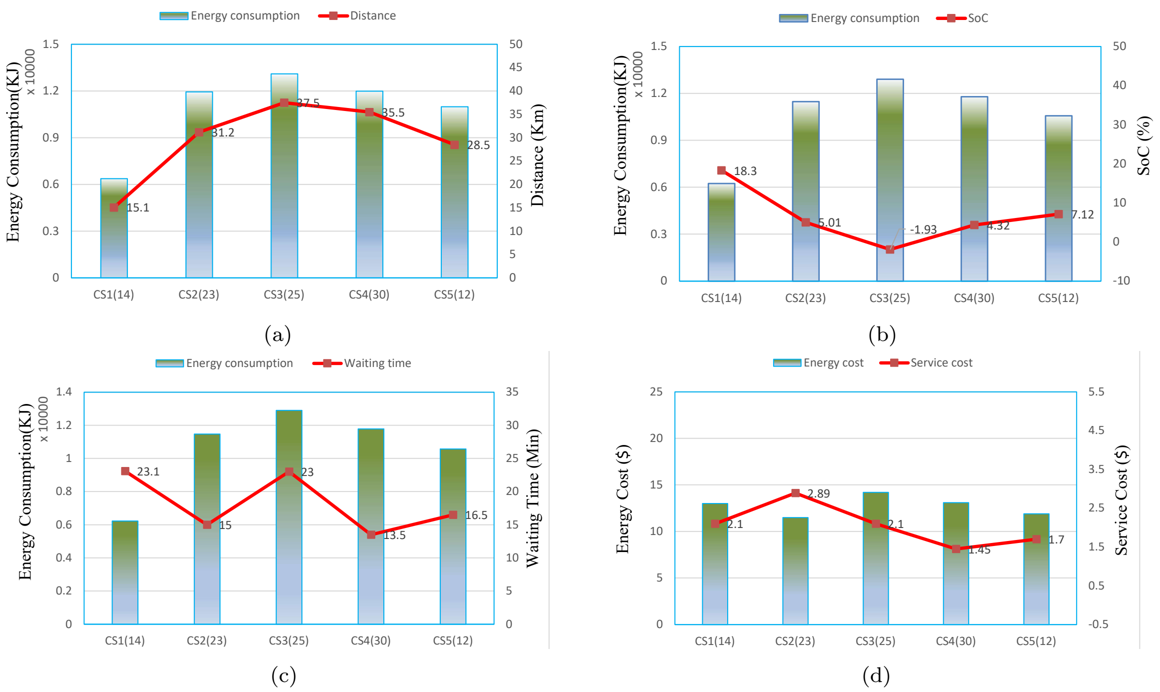


Figure 4.12: Computation of Different Parameters and Constraints Considering Minimal Charging Cost as Objective

Table 4.4: Terrain Properties of Different Routes and their Energy Consumption

Route No.	Route Consisting Sub-arcs	Energy Consumption(KJ)	Total Distance(Km)
1	S(1)→2→4→11→16→23→24→28→D(34)	17207	46.7
2	S(1)→9→8→20→32→33→D(34)	17793	52.6
3	S(1)→2→4→11→16→23→31→D(34)	17419	45.1

Table 4.5: Weighing Analysis

Key Findings	Different Cases of Weighing Factors		
	φ_1=1,φ_2=0,φ_3=1	φ_1=1,φ_2=1,φ_3=0	φ_1=1,φ_2=1,φ_3=0
Route	S(1)→2→4→11 →16→23→24→28 →D(34)	S(1)→2→4→11→16 →23→24→28 →D(34)	S(1)→9→10→11→16 →23 →31→ D(34)
Energy Consumption(KJ)	17919	18132	18125
Suggested CS	CS2	CS2	CS2
Waiting Time(min)	13.45	13.25	13.05
Charging Cost($)	13.9	14.01	13.32

4.4.3 Analysis based on Scenario 2

4.4.3.1 Route Planning Accounting Minimal Waiting Time at CS

It is quiet disturbing to drive near the threshold level of SoC due to the limited cruising range of EVs. Consequently, it requires frequent recharging throughout the voyage. Based on the SoC level, EV user requests S^2RC distributed model, which activates the agile charging reservation system. First of all, it fetches valuable information such as SoC level and traffic condition, then calculates reachability by estimating the amount of energy required to reach the available CSs. It also calculates the depreciation level of EV's SoC, if each CS is anticipated to be visited. After performing a thorough computation, the energy demand (from an initial position to CS) depending on the travelled distance to each CS (CS1, CS2, CS3, CS4, and CS5) and SoC status have been computed (see Figures Fig. 4.11a and Fig. 4.11b respectively). Using the KSP algorithm, routes are searched from the EV initial location different CSs or destination. It is necessary to estimate the charging waiting time at every CS to achieve the objective of minimal waiting time at the station. Therefore, the agile charging reservation system uses Eq. (4.21) to minimize the charging waiting time. Following the simulation, the Figs. 4.11c and 4.11d highlight the result of statistical analysis of both waiting time and ToU energy expenditure at each CS. The findings emerging from the discussion made above are as follows:

- The energy consumption from the initial position to CS3 (12905 KJ) surpasses the EV's required energy consumption (11802 KJ), putting CS3 out of option.

(a) Minimal waiting time at CS

(b) Minimal recharging cost

Figure 4.13: Optimum Routes based on Different Objectives

- Though the EV meets the energy requirements to travel CS4, it would fail to maintain the on arrival SoC level ($Z_A^{\mathbb{K}} = 5\%$) at that particular CS, therefore, ruling out the opportunity to recharge at CS4.
- S^2RC distributed model optimizes the waiting time at the remaining charging stations CS1, CS2, and CS5 as 22 min, 13 min, and 14 min respectively, based on the agile charging slot reservation procedure.
- The energy costs at CS1, CS2, and CS5 are \$14, \$13, and \$13, respectively, while the service charges are \$2.2, \$3.05, and \$1.8, resulting in a total recharging cost of \$16.2, \$17.05, and \$14.8 at CS1, CS2, and CS5 respectively.
- Of all the charging stations, CS1 has the longest waiting time; and CS2 has the minimal waiting time. The charging stations CS2 and CS5 have almost identical waiting time, but the charging costs, especially the service charges are significantly different. The reason behind this phenomenon is the peak ToD, where the charging price usually is high. But, as per the agile charging slot reservation policy, this works aims to minimize the charging waiting time. Thus, the EV user prefers to choose CS2 as an optimum choice (see Fig. 4.13a).

4.4.3.2 Route Planning Accounting Minimal Charging Cost at Charging Station

This section examines the influence of varying charging costs at diversely located CSs on the routing and charging decisions. Keeping in mind the objective of minimizing the charging price (see Fig. 4.12a), it displays the driving distance from the source to the various CSs and the energy required to reach the cost-effective CS. Moreover, Fig. 4.12b depicts the corresponding remaining SoC level after attaining the specific CS concerning the energy consumption. Fig. 4.12c exhibits the charging waiting time of each CS after a request is received for the purpose. Whereas, Fig. 4.12d describes the total charging expenditure for the energy and service charges, at the CS under enquiry. More details on the subject cited above are provided as hereunder:

- The energy consumption from the initial position to CS3 (13102 KJ) surpasses the EV's required energy consumption (11802 KJ), putting CS3 out of option.
- Though the EV meets the energy requirement of travelling to CS4, yet it fails to maintain the on arrival SoC level ($Z_A^{\mathbb{K}}= 5\%$) at that particular CS, therefore it rules out the opportunity to recharge at CS4.
- The energy costs at CS1, CS2, and CS5 are \$13, \$11.5, and \$11.91 respectively, while the service charges appear as \$2.1, \$2.89, and \$1.7, resulting in a total recharging cost of \$15.1, \$14.39, and \$13.61 at the respective charging stations.
- Though the charging cost of CS5 is the lowest, but it is quite close to that of CS2 and displays the lowest waiting time. However, price is not the only factor which affects decision-making for routing and charging. Thus, a priority is given to agile charging slot reservation by the EV user which makes the difference. In such a situation, this work aims to minimize the total charging cost. So, CS5 will be the optimum choice for recharging the EV as shown in Fig. 4.13b.

4.4.4 Simultaneous analysis of all the Objectives accounting Weighing Factor

Route planning and CS selection, based on the agile charging slot reservation process, react differently when it comes to prioritizing the three non-identical objectives according to the EV user's choice and convenience. The multi-objective function can be reduced to a single-objective function by normalizing them and assigning weights to individual objectives. The findings pertaining to the different weighing cases are exhibited in Table 4.5. For example, cases 1 and 3 are significantly different with respect to the route followed, energy consumption, waiting time, and charging cost. It is due to the reason that different objectives have been assigned different weights.

4.5 Summary

Today, EVs are in great demand due to the depletion of limited crude energy resources and global warming caused by their use in different kinds of vehicles. This study is a modest attempt to strengthen the EV technology by overcoming the challenges experienced by the users during the routing and recharging of their vehicles. First of all, it proposes a distributed system with bidirectional communication with EVs and all other system components, including CSs and traffic authorities. Then, after considering the combined information about EV battery, traffic condition, energy cost, and agile charging slot reservation process, an analysis has been conducted over energy consumption, SoC level, waiting time at CS, and charging fees. Besides, considering the recharging process behaviors of EVs, three single-objective models have been developed to accomplish the task of minimal energy consumption and waiting time and the charging expenditure while availing the services of a CS. The computational study has revealed that the proposed agile charging slot reservation strategy employed by the distributed $\boldsymbol{S^2RC}$ system not only suggests EV users the route that helps them in reducing the energy usage and waiting time, but also the recharging cost.

The major findings of the case study mainly contribute two-fold to the literature.

- According to the scenario stated in section 6.2, route 1 is determined to be the most energy-efficient route by 3.4% and 1.23% when compared to routes 2 and 3, indicating that the shortest route is not necessarily the most energy-efficient route.
- According to the scenario stated in section 6.3, as far as minimal waiting time and charging cost are concerned, CS2 discovered reduced waiting time by 7.6% and 69.3% when compared to CS1 and CS5, respectively, whereas CS5 has the lowest charging prices by 5.7% and 10.94% when compared to CS2 and CS1.

Furthermore, EV users have the liberty to modify the balancing factor to select the most appropriate preference among the objectives based on their convenience.

Chapter 5

A Meta-heuristic-based Energy Efficient Route Modeling for EVS Integrating Start/Stop and Recapturing Energy Effect

The previous chapter proposed an improvised distributed system, namely, $\boldsymbol{S^2RC}$ which plans an energy efficient EV route considering EV's state-of-charge (SoC) level, traffic conditions, the frequency of charging stations and the state of charging station. This distributed architecture employs the proposed agile charging slot reservation approach for the EVs that wish to get recharged at a particular charging station.

The current chapter expands the mathematical model introduced in chapter 3 by taking into consideration the impact of vehicle start/stop and recuperation energy on the EV's energy expenditure while routing. Moreover, it also introduces an Amplified-ACO ($\boldsymbol{A^2CO}$), a routing algorithm based on Ant Colony Optimization (ACO) principles that makes use of the probabilistic selection model ($\boldsymbol{DS^2}$ relies on Distance, Speed, and State-of-Charge). This study simulates the proposed model over the real-time map of Chandigarh (India) and provides a comparative study against some of the nature-inspired meta-heuristic approaches such as classical ACO and PSO.

Section 5.1 discusses the problem formulation and mathematical modeling of EV's energy consumption accounting vehicle's start/stop condition and recuperation energy. Section 5.2 provides details about the proposed $\boldsymbol{A^2CO}$ meta-heuristic approach and how it translates the specified EV routing problem. Computational experiments have been carried out in Section 5.3. Finally, Section 5.4 discusses about the summary of the chapter.

5.1 System Methodology

We begin by defining a transportation network that is expressed as a complete weighted directed $\mathbb{G} = (\mathbb{V}, \mathbb{R})$, where $\mathbb{V}$ is a set of nodes; and $\mathbb{R} = \{(x, y)|x \neq y \in \mathbb{V}\}$ is the set of arcs. Further, $d_{x,y}$, and $V_{x,y}$ respectively represent the distance and speed of each arc (x, y) as illustrated in Fig. 5.1b.

5.1.1 Energy Consumption Mathematical Formulation

The energy consumption model employed in this study is based on Newton's law of vehicle motion, that represents the acting forces on vehicle's body during the motion, known to be vehicle's longitudinal dynamics model (LDM) [246, 247]. So, the following standard Eq. (5.1) represents the vehicle's LDM:

$$\mathbb{F}^{\mathbb{T}} = ma + \mathbb{F}^{\mathfrak{R}}_{grad} + \mathbb{F}^{\mathfrak{R}}_{roll} + \mathbb{F}^{\mathfrak{R}}_{aero} \tag{5.1}$$

Where, $\mathbb{F}^{\mathbb{T}}$ is the total traction force required to propel the vehicle; m is the vehicle mass; and a is the vehicle acceleration. $\mathbb{F}^{\mathfrak{R}}_{grad}$, $\mathbb{F}^{\mathfrak{R}}_{roll}$, and $\mathbb{F}^{\mathfrak{R}}_{aero}$ are the force resistance due to gravity, rolling friction, and aerodynamics friction. The mathematical representations for each of the forces are shown in Eqs. (5.2) to (5.4).

$$\mathbb{F}^{\mathfrak{R}}_{grad} = mgsin(\alpha) \tag{5.2}$$

$$\mathbb{F}^{\mathfrak{R}}_{roll} = mgC_{roll}cos(\alpha) \tag{5.3}$$

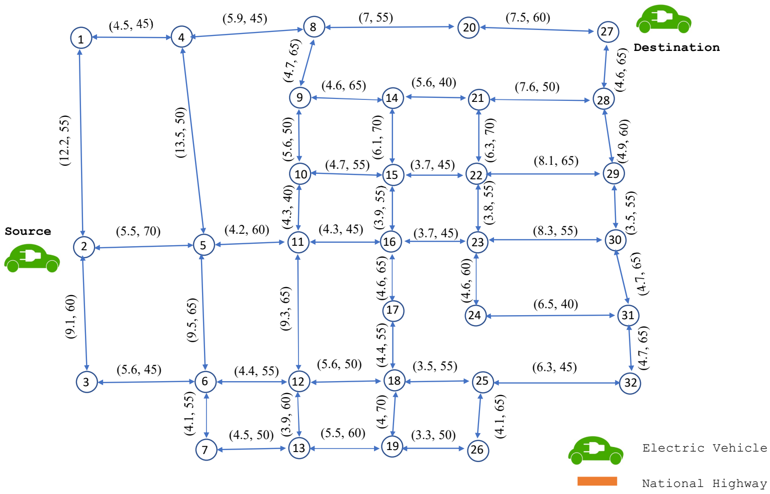
$$\mathbb{F}^{\mathfrak{R}}_{aero} = .5\rho C_{ad}A_{fr}(\mathcal{V} + \mathcal{V}_{wind})^2 \tag{5.4}$$

Where, g is the gravitational constant; α is road inclination angle; C_{roll} is the rolling resistance coefficient; ρ is the air density; C_{ad} is drag the coefficient; A_{fr} is the vehicle's frontal surface; and $\mathcal{V}$ and $\mathcal{V}_{wind}$ represents the vehicle's instantaneous speed and wind speed respectively. Eq. 5.5 illustrates the mathematical representation of electrical power $(\mathbb{P}_{\mathfrak{M}})$ required/generated to propel/braking the vehicle.

$$\mathbb{P}_{\mathfrak{M}} = \frac{(ma + mgsin(\alpha) + mgC_{roll}cos(\alpha) + .5\rho C_{ad}A_{fr}(\mathcal{V} + \mathcal{V}_{wind})^2)\mathcal{V}}{\Psi_{em}\Psi_{te}} + \mathbb{P}_{in} \tag{5.5}$$

Where, $\mathbb{P}_{in}$ is the vehicle's internal power consumption for using entertainment system, air condition, and lighting, while Ψ_{em} and Ψ_{te} are known to be the efficiency of electric motor and transmission.

(a) Simplified transportation network of Chandigarh(India) [205, 276]



(b) A topological structure of transportation network

Figure 5.1: Transportation Networks at Various Levels

5.1.2 Regenerative Braking Mathematical Formulation

The EV's energy consumption has the basic properties of discharging energy (as mentioned in Section 5.1.1) and recuperation energy, which is generated through the vehicle's brakes (referred as regenerative braking). It is also possible to recharge the vehicle during motion using regenerative braking power since the kinetic energy generated using brakes can be converted into electrical energy and used to replenish the batteries of EV [275]. The partial energy ($\odot \in 0, 1$) can be recovered and restored into the battery whenever brakes are applied, as modeled in the following mathematical formulation [247].

$$\mathbb{P}_{\Re} = \odot \Psi_{em} \Psi_{te} (ma + mgsin(\alpha) + mgC_{roll}cos(\alpha) + .5\rho C_{ad} A_{fr} (\mathcal{V} + \mathcal{V}_{wind})^2) \mathcal{V} + \mathbb{P}_{in} \quad (5.6)$$

5.1.3 Incorporation of Vehicle's Start/Stop Effect

The calibration of energy consumption is necessary to define the power used when driving and power absorption while braking. So, we have distinguished total energy consumption into two non-identical categories to facilitate the necessity of energy consumption; one in which the vehicle speed is constant, and the other in which the vehicle speed varies substantially, implying multiple starts and stops over the course of action.

The first term ($\odot^{ec}_{\rightarrow}$) of energy consumption where the vehicle average speed ($\overline{\mathcal{V}}$) considered as constant, can be computed as per Eq. (5.8). As we know, the transportation network is the combination of multiple directed arcs connecting two locations. So, it has been assumed that each arc's topological gradient can be partitioned into two components; the one in which battery is charged during the travelling on arc, denoted as $0 \leq \oplus^{\upharpoonleft} \leq 1$, and the other in which battery is discharged, denoted as $\oplus^{\downharpoonleft} = 1 - \oplus^{\upharpoonleft}$. Eq. 5.7 summarizes a more candid energy consumption formulation.

$$EC = (\odot^{ec}_{\rightarrow} + m * \odot^{ec}_{\rightsquigarrow}) * t \tag{5.7}$$

$$\odot^{ec}_{\rightarrow} = \left(\left(\frac{\overline{\mathcal{V}}}{\Psi_{em}\Psi_{te}} + \odot\overline{\mathcal{V}}\Psi_{em}\Psi_{te}\right).5\rho C_{ad}A_{fr}(\overline{\mathcal{V}} + \mathcal{V}_{wind})^2 + \mathbb{P}_{in} - \mathbb{P}_{in}\right) \tag{5.8}$$

$$\odot^{ec}_{\rightsquigarrow} = \oplus^{\upharpoonleft}\left(\frac{\overline{\mathcal{V}}}{\Psi_{em}\Psi_{te}}(gsin(\alpha) + gC_{roll}cos(\alpha))\right) + \oplus^{\downharpoonleft}(\odot\overline{\mathcal{V}}\Psi_{em}\Psi_{te}(gsin(\alpha) + gC_{roll}cos(\alpha))) \tag{5.9}$$

To approximate the effect of acceleration and braking accounting traffic lights stops, we have modeled start/stop energy consumption (keeping acceleration constant to $\overline{a}$) as follows:

$$e^{\upharpoonleft\downharpoonleft} = (\odot^{\pm}\alpha + m * \odot^{\pm}\beta) * t^{\pm} \tag{5.10}$$

$$\begin{aligned} e^{\upharpoonleft} = &\left(\odot^{\pm}\left(\frac{\overline{\mathcal{V}}}{\Psi_{em}\Psi_{te}}(.5\rho C_{ad}A_{fr}(\overline{\mathcal{V}} + \mathcal{V}_{wind})^2) + \mathbb{P}_{in}\right)\right. \\ &\left. + m\ \odot^{\pm}\left(\frac{\overline{\mathcal{V}}}{\Psi_{em}\Psi_{te}}(\xi\overline{a} + gsin(\alpha) + gC_{roll}cos(\alpha))\right)\right) * t^{+} \end{aligned} \tag{5.11}$$

$$\begin{aligned} e^{\downharpoonleft} = &\left(\odot^{\pm}\left(\odot\overline{\mathcal{V}}\Psi_{em}\Psi_{te}(.5\rho C_{ad}A_{fr}(\overline{\mathcal{V}} + \mathcal{V}_{wind})^2) + \mathbb{P}_{in}\right)\right. \\ & + m\ \odot^{\pm}\ \odot\overline{\mathcal{V}}\Psi_{em}\Psi_{te}\ ((\xi\overline{a} + gsin(\alpha) + gC_{roll}cos(\alpha))) * t^{-} \end{aligned} \tag{5.12}$$

Where, the frequency of starts and stops is represented by $\odot^{\pm}$. It is pertinent to mention here that the energy consumption coefficients on the specific arcs can be computed a priory for a particular road network since they offer a wide range of additional information to the problem. The total energy consumption required to drive through any arc (a, b) has been calculated as follows:

$$E_{ab} = e^{\uparrow} + EC + e^{\downarrow} \tag{5.13}$$

5.2 Amplified Ant Colony Optimization (A^2CO) Solution Approach

This study presents a widely used meta-heuristic ACO approach to solve the underlined problem. Ants can determine the optimum route between food and their nest due to the specific biological patterns of ants when foraging for food. In particular, ants leave the pheromone which accumulates and evaporates along the path to guide other ants. The concentration of the pheromones is directly proportional to the number of ants that travel on the same trail; and it makes the trail more appealing for other ants. Ants gather pheromones by iterating from source to destination and use this method to locate the shortest path between a food source and its nest. The shortest one is always the optimal one for the ants and hence an energy-efficient route. Fig. 5.1 represents the topological structure of the map (Chandigarh, India) that consists of multiple arcs and nodes.

The proposed Amplified-ACO algorithm (see Algorithm 2) consists of three sequential phases, viz. initialization of pheromone, probability identification, and update the pheromone. Before initiating the iteration, all path pheromones are initialized to the same value T_0 for pheromone initialization. Moreover, each ant starts at the source (see Fig. 5.1b), and all the routes to the destination are assumed to be empty. The decision-making process for moving to the next node y in classical ACO primarily lies on a probabilistic method that only accounts for pheromone information and distance visibility parameters. As this study considers vehicle's speed and battery SoC level, and critical constraints, thus, we have designed a new model, called DS^2 (Distance, Speed, and SoC) model which integrates the impact of vehicle's speed and battery SoC level to calculate the probability for moving to the next node. For ant $\mathcal{K}$ at the current position x, the DS^2 probabilistic model is presented in the Eq. (5.14) of Algorithm 2. Where, $Prob_{xy}^{\mathcal{K}}$ gives the probability of $\mathcal{K}$th ant, placed at node x, moves to the next node location y. $Y_{\mathcal{K}}(x)$ denotes the set of neighboring nodes of ant $\mathcal{K}$ on node x. T_{xy}, U_{xy}, V_{xy}, and W_{xy} denote the pheromone density, vehicle's speed, SoC level, and visibility of distance on the arch (x, y) respectively. Whereas, the pheromone trail and remaining three stretching factors are denoted as α, β, γ, and δ respectively. These parameters control the relative degree between the pheromone quantity and the heuristic information. Due to the fact of laying down a certain amount of pheromone, known to be $\Delta\chi^{\mathcal{K}}$ during the course of action, it is necessary to update the pheromone and probability in each iteration. All the arcs in the ant $\mathcal{K}$'s journey have the same $\Delta\chi^{\mathcal{K}}$ value. Eqs. 5.15 and 5.16 in Algorithm 2 represent the expression for updating the pheromone value. The implanted pheromones are dissipated after each iteration. The time it takes for routes to be forgotten is determined by the decay parameter ξ. As a result, pheromones accumulate on crowded pathways, but they dissipate on less active paths, hastening convergence. The ACO algorithm is quick to converge and can traverse several routes. As a result, it is appropriate for the EV, requiring rapid and broad judgments as this study aims to enhance energy efficiency. Thus, the study proposes an objective function that considers the energy consumption and other heuristic parameters (vehicle's speed, SoC level, and distance) as represented in Eq. (5.16) of Algorithm 2. The proposed model aims to reduce the path's objective function to the smallest possible value. The proposed model aims to minimize the objective function for a path. Here, E_{ab} is the amount of energy consumed from the source to the destination node; and the weight parameter (ν) balances the energy consumption and other heuristics information.

Algorithm 2: Procedure for Amplified-ACO

Initialization of parameters : Problem data, Algorithmic parameters
Initialization of pheromone trails on all arcs
Iterate for $max\_criteria$
  For all ants do
    Let Z_0 be the start node for ant $\mathcal{K}$
    Current node= Z_0
    While(Next node!=Destination node)
      Determine the next node based on the following calculated probabilities:

$$Prob_{xy}^{\mathcal{K}} = \begin{cases} \frac{T_{xy}^{\alpha} * U_{xy}^{\beta} * V_{xy}^{\gamma} * W_{xy}^{\delta}}{\sum_{z \in Y_{\mathcal{K}}(x)} T_{xz}^{\alpha} * U_{xz}^{\beta} * V_{xz}^{\gamma} * W_{xz}^{\delta}}, & \text{if } y \in Y_{\mathcal{K}}(x), \\ 0, & \text{otherwise}, \end{cases} \tag{5.14}$$

      Current node = Next node
    End_While
  End_For
  Pheromone is updated according to following equations:

$$\chi_{xy} = (1 - \xi)\chi_{xy} + \Delta\chi^{\mathcal{K}} \tag{5.15}$$

$$Minfun(x) = (\nu * E_{ab}) + (1 - \nu) * \frac{1}{(Speed, SoC, Distance)} \tag{5.16}$$

End_iterate

5.3 Experimental Designing and Case Study Analysis

A simple road network of Chandigarh city in north India has been taken for simulation to identify an optimal energy route. Fig. 5.1 depicts the two levels of transportation

Table 5.1: Symbolic Representation of Mathematical Model Parameters and their Respective Values with Units

Symbol Representation	Description	Value	Unit
m	Vehicle mass	1250	kg
g	Gravitational force	9.8	m/s^2
ρ	Air density	1.1839	kg/m^3
C_{ad}	Aerodynamic drag coefficient	.24	-
A_{fr}	Vehicle's frontal area	2.341	m^2
$S_{wind}^{a,b}$	Wind speed	0	-
c_{roll}	Rolling resistance coefficient	.02	-
ν	Strategic parameter	0.1, 0.3, 0.5	-
ξ	Decay parameter	0.7	-
α	Pheromone trail	1	-
β, γ, δ	Stretching factors	1	-

network; the one shown in Fig. 5.1a describes the simplified map of the transportation network of Chandigarh (India); the second one, Fig. 5.1b shows the topological structure of Fig. 5.1a, consisting all nodes and arcs. The network is comprised of 32 labeled nodes and 104 arcs, where each arc contains information about the distance between two adjacent nodes and the vehicle's speed on that arc. For this simulation, node 2 has been considered as the source node and node 27 as the destination node. The remaining tuning values of the parameters used in the vehicle model have been depicted in Table 5.1 and partially adopted from [245]. This study accounted for two mean distribution methods for the vehicle's speed, noted as Gaussian and Uniform. All trials were carried- out across 400 iterations; and the experimental outcome was the mean of performed experiments. Moreover, the strategic parameter (ν) was employed to balance the energy consumption and other stretching factors. However, it is essential to prioritize the speed over other stretching factors because speed is one of the prominent factors that has the greatest impact on energy consumption [205]. Further, A^2CO's performance is determined by the volume of ants engaged in each experiment. As a result, a baseline experiment was performed to identify the magnitude of ν and the number of artificial ants under the umbrella of Gaussian and uniform distribution.

Fig.5.2 shows the performance according to the strategic parameter, where Figs. 5.2a and 5.2c represents the simulation outcomes of different routes shaded in different colours shown in the Figs. 5.2b and 5.2d respectively. It has been deduced from Fig. 5.2a and also noted in Fig. 5.2b that the energy consumption of route 1 is the highest among all the suggested routes owing to its lowest value of (ν), i.e., 0.1, since it focuses more on the vehicle's speed rather than the energy consumption. As a result, it can be concluded that energy consumption is inversely proportional to the value of (ν) in the Gaussian distribu-

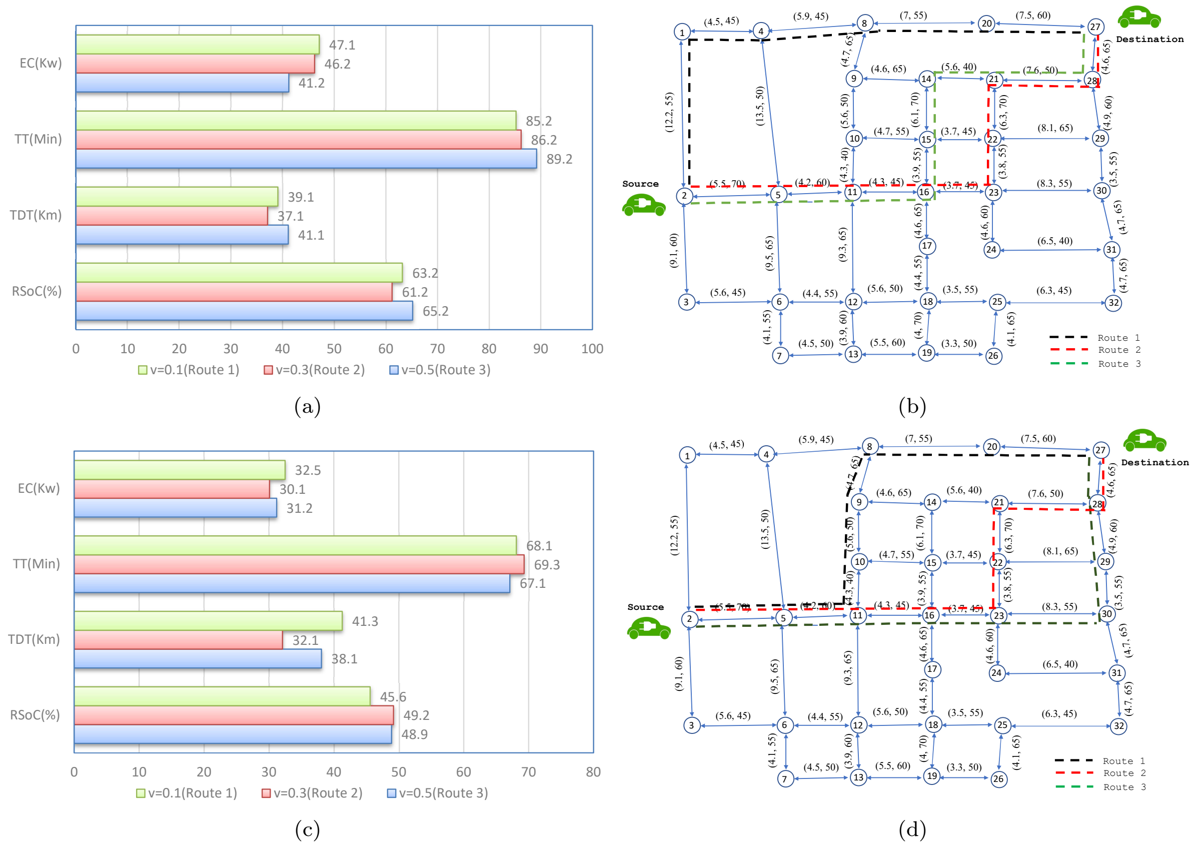


Figure 5.2: Mapping of Performance Comparison (Y-axis, fig.(a) and (b) (labeled as EC (Energy Consumption), TT (Travel Time), TDT (Total Travelled Distance, and RSoC (Remaining State-of-Charge)) and Varying Strategic Parameters (ν) to their Respective Identified Routes, for instance, fig.(a) shows the parameters for the identified routes 1, 2, and 3, in fig. (b) and similarly, fig. (c) for fig. (d), Under the Respective Scenarios of Gaussian and Uniform Distribution

tion. In contrast, when $\nu = 0.3$ (see Figs. 5.2c and 5.2d), the energy usage is minimum under the uniform distribution. Under the respective Gaussian and Uniform distribution scenarios, route 1 has the lowest travel time, whereas route 2 has the highest. Moreover, taking travel distance into account, route 2 takes the minimum travelled distance under both the distributions.

Fig.5.3 depicts the influence of artificial ants on the underlined parameters with both Gaussian and Uniform distributions. If we closely analyze the Figs. 5.3a and 5.3c, we find that if we employ fewer ants, such as 5 or 10, the outcome of energy consumption may be skewed. However, the optimal energy route is generated for a large number of ants (20 in the present case) under both types of data distribution. Moreover, the travel time and distance have also remained the least with the ant size of 20.

The developed Amplified-ACO has been compared with some of the well-known nature-inspired algorithms such as classical Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO). Since a direct comparison is difficult due to the lack of a comparable mathematical model, A^2CO has been supplemented with the conventional ACO and PSO

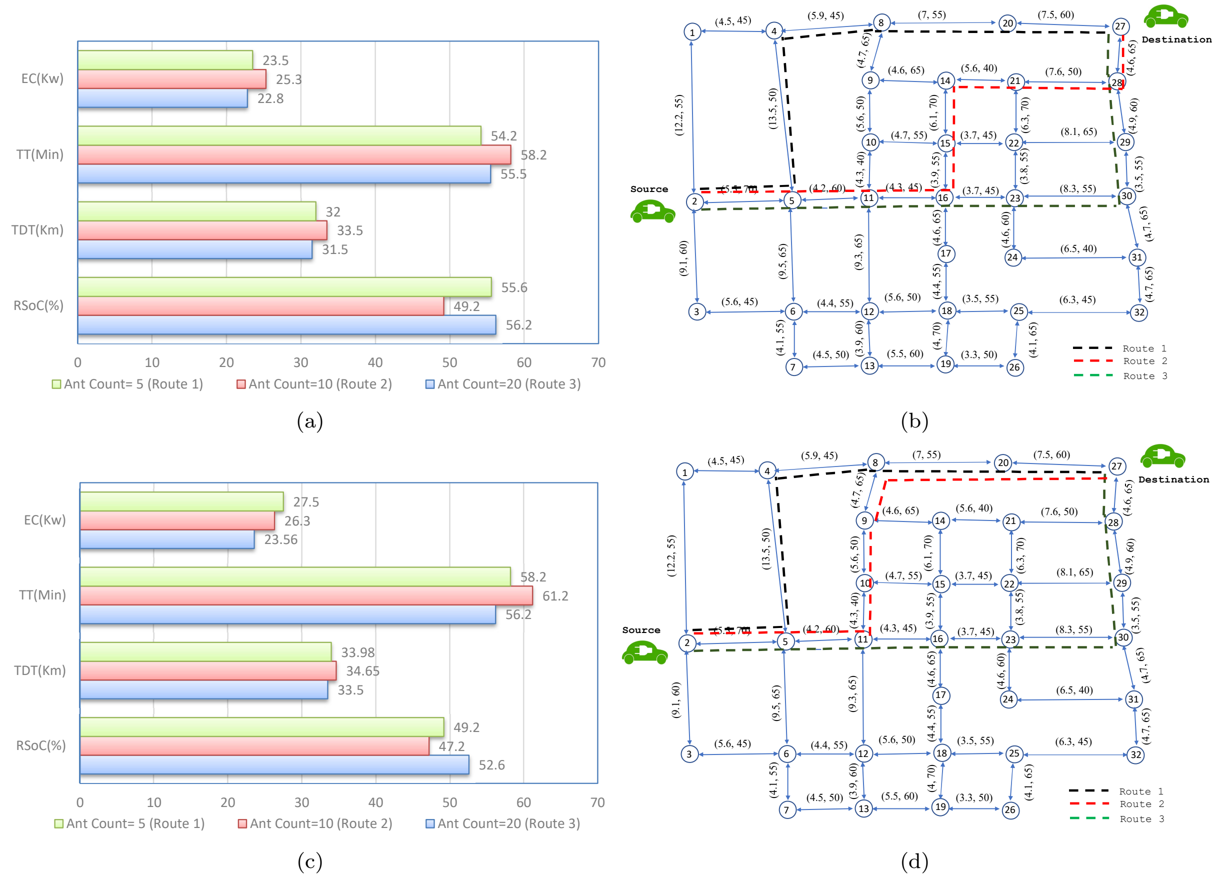
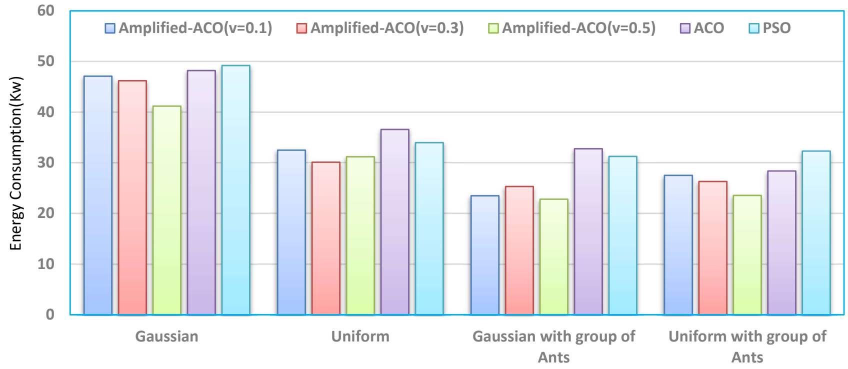


Figure 5.3: Mapping of Performance Comparison (Y-axis, fig.(a) and (b) (labeled as EC (Energy Consumption, TT (Travel Time), TDT (Total Travelled Distance, and RSoC (Remaining State-of-Charge)) and Varying Strategic Parameters (ν) to their Respective Identified Routes, for instance, fig.(a) shows the parameters for the identified routes 1, 2, and 3, in fig. (b) and similarly, fig. (c) for fig. (d), Accounting Varying Number of Artificial Ants

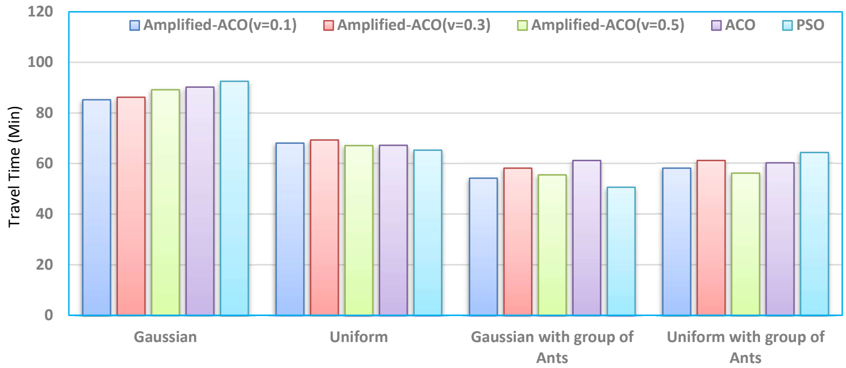
one after the other. It is assumed that the vehicle is fully charged and doesn't require any recharging during the course of action. The Fig. 5.4 reveals the comparison made between the proposed A^2CO with varying strategic parameters, ACO, and PSO. The results have been described as hereunder:

- The average energy consumption of the proposed approach from the initial position to the destination under considered varying strategic parameter readings (ν=0.1, 0.2, and 0.3) with Gaussian data distribution conditions is 44.83Kw which is less than 7.58% and 9.74% as compared to classical ACO and PSO respectively. Similarly, significant improvements have also been observed through the proposed approach in energy consumption with respect to the other addressed data distribution scenarios (Uniform, Gaussian with Ant's count, and Uniform with Ant's count)(see Fig. 5.4a).

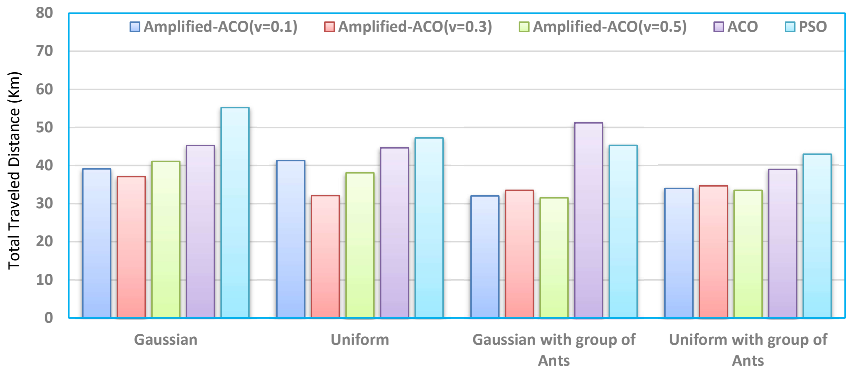
- The Fig. 5.4b highlights the total travel time of the journey from source to destination. As far as the average travel time is considered the Amplified-ACO approach has outperformed under the Gaussian data distribution conditions and Uniform data distribution with ants' count by 3.7%, 6.09%, and 2.85%, 9.05% respectively as com-



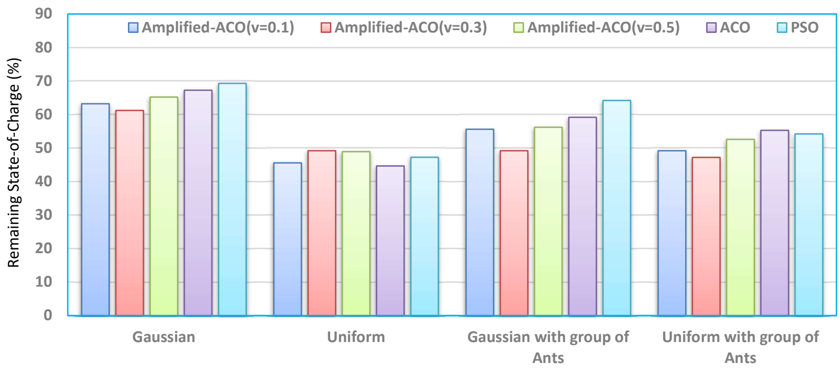
(a)



(b)



(c)



(d)

Figure 5.4: Performance Comparison among Amplified-ACO (ν=0.1, 0.3, and 0.5), Classical ACO, and PSO Under Gaussian Distribution, Uniform Distribution, Gaussian Distribution with Ant's Count, and Uniform Distribution with Ant's Count: (a) Energy Consumption, (b) Travel Time, (c) Total Traveled Distance, and (d) Remaining State-of-Charge

pared to classical ACO and PSO. However, the performance of proposed approach was marginally low in the case of other data distribution methods.

- The figs.5.4c and 5.4d respectively reflect the total travelled distance between source and destination, and the remaining SOC after reaching the destination under the aforementioned data representations and parametric tuning values. It is pertinent to note that the proposed Amplified-ACO approach has performed better as compared to the classical ACO and PSO. However, it was slightly biased, whenever the value of strategic parameter fluctuated.

5.4 Summary

The emergence of EV revolution has been due to the lack of non-renewable energy resources and a world-wide environmental crisis. Thus, this study contributes significantly in addressing the issues related to the energy-efficient routing of EVs. In this regard, a meta-heuristic optimization approach has been presented to reduce the energy consumption of the newly designed EV model. The EV's energy consumption mathematical model has been extended to examine the effect of vehicle start/stop and recapturing energy. The model was evaluated using the actual transportation map of Chandigarh (India) by generating the most energy-efficient route between the specified source and destination. It has been observed that strategic parameters, frequency of ants, and vehicle speed have a significant role in the vehicle's energy consumption under the various data distribution methods. The study also compares the results of proposed algorithm with those of some other well-known nature-inspired algorithms, viz. classical-ACO and PSO which significantly support the proposed approach while contributing to the energy-efficient EV routing problem.

Chapter 6

Conclusion and Scope for Future Research

This chapter serves as the conclusion of this dissertation and makes some recommendations for how the current work can be expanded further. Section 6.1 summarises the overall findings of the research work reported in this dissertation, and Section 6.2 makes recommendations for future study areas and potential expansions of the described work in the dissertation.

This dissertation is an attempt to present the most detailed and comprehensive survey of recent as well as the state-of-the-art techniques related to routing of EVs. Moreover, a novel idea of bifurcation the existing literature on EVRP into eight categories, where each category represents a solution to a unique challenge involved in the routing of EVs. In this direction, a modest attempt has been made to find the much-needed solution to the problem of energy-efficient EV routing by incorporating the effect of various road surface conditions. The subject under study is further extended by identifying the suitable charging station with the help of novel proposed distributed model, named $\boldsymbol{S^2RC}$*, keeping in mind the objectives of minimal waiting time and charging cost at the CS. The K-shortest path (KSP) algorithm has been used to make the route and charging planning more effective. Lastly, this study also accounts for the effect of the vehicle's start/stop energy expenditure and regenerative braking on the energy consumption of the vehicle during the routing.*

6.1 Conclusions

The emergence of EV revolution has been due to the lack of non-renewable energy resources and a world-wide environmental crisis. Thus, this study contributes significantly in addressing the issues related to the energy-efficient routing of EVs. This dissertation concludes with the following remarks done in several phases.

- The main objective of this dissertation is to identify an energy-efficient routing approach for EVs embedded with approach of locating a charging station subject to various active and passive constraints of EV, EV user, transportation network, and charging station.
- This objective has been successfully achieved by the proposed model in this dissertation.
- A meta-heuristic optimization algorithm has been proposed to minimize the energy consumption of the novel generated EV model. Further, the EV model has been extended to examine the effect of different road surfaces on the EV's energy consumption and given a very special attention vehicle's speed, energy-efficiency, and DoD.
- This study is a modest attempt to strengthen the EV technology by overcoming the challenges experienced by the users during the routing and recharging of their vehicles.
- An attempt has been made to present a solution to this very problem. The proposed approach is an improvised distributed system, namely, S^2RC (Smart Search of Route and Charging) which plans an energy efficient EV route considering EV's state-of-charge (SoC) level, traffic conditions, the frequency of charging stations and the state of charging station.
- The proposed distributed architecture employs the agile charging slot reservation approach, inspired from the principles of KSP(K-shortest path) algorithm, for the EVs that wish to get recharged at a particular charging station and an analysis has been conducted over energy consumption, SoC level, waiting time at CS, and charging fees.
- Apart from incorporating the vehicle's territorial parameters including slope of roads, vehicle's mass, variable vehicle speeds, and related resistances and coefficients, this dissertation has also given the special attention to vehicle's start/stop effect on the energy consumption.
- EV recharging is usually a tedious and time-consuming process. Therefore, this

study includes the effect of regenerating braking that produces the recuperation energy when traveling downhill or during the braking operation. This waste energy can be used to replenish the vehicle's battery.

- This study also proposes an amplified ant colony algorithm ($\boldsymbol{A^2CO}$), a routing algorithm based on Ant Colony Optimization (ACO) principles that makes use of the probabilistic selection model ($\boldsymbol{DS^2}$ relies on Distance, Speed, and State-of-Charge).

6.2 Scope for Future Research

As the current research work examines only the specific objectives formulated for the study, there is sufficient scope for further improvements in the field of energy-efficient electric vehicle routing. This section makes some proposals for potential extensions of the underlined subject:

- The model introduced in the chapter 3 can be further improved by taking into account a variety of demanding constraints such time window, multi-depot, partial recharge, and environmental issues. Moreover, in the proposed solution approach, the parameter such as limit is required to be tuned accurately, as the existence of such parameters can not be overlooked because it has a direct impact on the outcome.
- The mathematical model introduced in chapter 4 can be further extended to adapt various vehicle architectures, including combustion engines. Moreover, energy consumption correlation for adjacent road links can be integrated into the route modeling.
- The proposed model ($\boldsymbol{S^2RC}$) can be expanded to ensure privacy during communication and service/request balancing between EVs and $\boldsymbol{S^2RC}$. Various charging services and energy load balancing technologies can provide a high level of flexibility to the power grid and EV user. The driving behavior needs to be quantified, and the methodologies outlined in this study, especially battery modeling research, can be helpful in predicting vehicle driving range.
- Different charging strategies, such as partial chagrining, battery switching, and different charging modes, can be studied in the proposed problem.
- Novel solution strategies such as meta-heuristics or even mat-heuristics can be employed to accelerate convergence to a solution and enrich the solution space.

References

[1] UN, "Emissions gap report," https://www.unep.org/, 2019, accessed May, 2021.

[2] N. Aayog, "India's energy and emissions outlook," https://niti.gov.in/, 2019, accessed may, 2021.

[3] U.N, "World polulation projections," Available:https://bit.ly/2ljJ7Fg, 2019, accessed September, 2019.

[4] C. Lagarde, "Global co2 emission," Available:https://www.co2.earth/, 2020, accessed January, 2020.

[5] A. Montoya, C. Guéret, J. E. Mendoza, and J. G. Villegas, "The electric vehicle routing problem with nonlinear charging function," *Transportation Research Part B: Methodological*, vol. 103, pp. 87–110, 2017.

[6] S. K.J., "Policy issues to consider for electric vehicles in india," Available:https://www.orfonline.org/, 2021, accessed May, 2021.

[7] C. Baron, "Electric vehicles worldwide," shorturl.at/birDR, 2020, accessed January, 2020.

[8] A. Afroditi, M. Boile, S. Theofanis, E. Sdoukopoulos, and D. Margaritis, "Electric vehicle routing problem with industry constraints: trends and insights for future research," *Transportation Research Procedia*, vol. 3, pp. 452–459, 2014.

[9] C. Sulzberger, "An early road warrior: electric vehicles in the early years of the automobile," *IEEE Power and Energy Magazine*, vol. 2, no. 3, pp. 66–71, 2004.

[10] M. Ehsani, Y. Gao, S. Longo, and K. M. Ebrahimi, *Modern electric, hybrid electric, and fuel cell vehicles.* CRC press, 2018.

[11] J. Li, F. Wang, and Y. He, "Electric vehicle routing problem with battery swapping considering energy consumption and carbon emissions," *Sustainability*, vol. 12, no. 24, p. 10537, 2020.

[12] DoE, "Vehicle charging," https://www.energy.gov/eere/electricvehicles/vehicle-charging, 2019, accessed December, 2019.

[13] Y. Zhou, J. Huang, J. Shi, R. Wang, and K. Huang, "The electric vehicle routing problem with partial recharge and vehicle recycling," *Complex & Intelligent Systems*, vol. 7, no. 3, pp. 1445–1458, 2021.

[14] H. Mao, J. Shi, Y. Zhou, and G. Zhang, "The electric vehicle routing problem with time windows and multiple recharging options," *IEEE Access*, vol. 8, pp. 114 864–114 875, 2020.

[15] M. Bruglieri, S. Mancini, F. Pezzella, O. Pisacane, and S. Suraci, "A three-phase matheuristic for the time-effective electric vehicle routing problem with partial recharges," *Electronic Notes in Discrete Mathematics*, vol. 58, pp. 95–102, 2017.

[16] R. Abousleiman and O. Rawashdeh, "Energy consumption model of an electric vehicle," in *2015 IEEE Transportation Electrification Conference and Expo (ITEC)*. IEEE, 2015, pp. 1–5.

[17] M. Neaimeh, G. A. Hill, Y. Hübner, and P. T. Blythe, "Routing systems to extend the driving range of electric vehicles," *IET Intelligent Transport Systems*, vol. 7, no. 3, pp. 327–336, 2013.

[18] H. Yang, Y. Deng, J. Qiu, M. Li, M. Lai, and Z. Y. Dong, "Electric vehicle route selection and charging navigation strategy based on crowd sensing," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 5, pp. 2214–2226, 2017.

[19] Y. Zheng, Y. Song, D. J. Hill, and K. Meng, "Online distributed mpc-based optimal scheduling for ev charging stations in distribution systems," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 2, pp. 638–649, 2018.

[20] C. Liu, M. Zhou, J. Wu, C. Long, and Y. Wang, "Electric vehicles en-route charging navigation systems: Joint charging and routing optimization," *IEEE Transactions on Control Systems Technology*, vol. 27, no. 2, pp. 906–914, 2017.

[21] J. Ward, S. Worrall, G. Agamennoni, and E. Nebot, "The warrigal dataset: Multi-vehicle trajectories and v2v communications," *Intelligent Transportation Systems Magazine, IEEE*, vol. 6, no. 3, pp. 109–117, Fall 2014.

[22] W. Xu, S. He, R. Song, and S. S. Chaudhry, "Finding the k shortest paths in a schedule-based transit network," *Computers Operations Research*, vol. 39, no. 8, pp. 1812–1826, 2012, special Issue: Advances of Operations Research in Service Industry.

[23] A. W. Brander and M. C. Sinclair, "A comparative study of k-shortest path algorithms," in *Performance Engineering of Computer and Telecommunications Systems*. Springer, 1996, pp. 370–379.

[24] M. Schneider, A. Stenger, and D. Goeke, "The electric vehicle-routing problem with time windows and recharging stations," *Transportation Science*, vol. 48, no. 4, pp. 500–520, 2014.

[25] L. Kang, A. Sarker, and H. Shen, "Velocity optimization of pure electric vehicles with traffic dynamics and driving safety considerations," vol. 2, no. 1, 2021. [Online]. Available: https://doi.org/10.1145/3433678

[26] A. Sarker, H. Shen, and J. A. Stankovic, "Morp: Data-driven multi-objective route planning and optimization for electric vehicles," vol. 1, no. 4, 2018. [Online]. Available: https://doi.org/10.1145/3161408

[27] K. Vatanparvar and M. A. A. Faruque, "Electric vehicle optimized charge and drive management," vol. 23, no. 1, 2017. [Online]. Available: https://doi.org/10.1145/3084686

[28] ICCT, "Air pollution in india," https://theicct.org/india, 2021, accessed may, 2021.

[29] IEA, "Clean energy transitions," https://www.iea.org/topics/clean-energy-transitions, 2021, accessed may, 2021.

[30] R. Abousleiman and O. Rawashdeh, "Electric vehicle modelling and energy-efficient routing using particle swarm optimisation," *IET Intelligent Transport Systems*, vol. 10, no. 2, pp. 65–72, 2016.

[31] M. Sachenbacher, M. Leucker, A. Artmeier, and J. Haselmayr, "Efficient energy-optimal routing for electric vehicles," in *Twenty-fifth AAAI conference on artificial intelligence*, 2011.

[32] M. Keskin and B. Çatay, "A matheuristic method for the electric vehicle routing problem with time windows and fast chargers," *Computers & operations research*, vol. 100, pp. 172–188, 2018.

[33] F. Charged, "Electric vehicle database," https://ev-database.org/, 2021, accessed May, 2021.

[34] Mapsofindia, "Chandigarh road map," https://www.mapsofindia.com/, 2021, accessed May, 2021.

[35] C. Heivly, "Mapquest," https://www.mapquest.com/, 2021, accessed May, 2021.

[36] IBM, "Ibm data science community," https://community.ibm.com/community/user/datascience/blogs/xavier-nodet1/2020/12/11/cos-201-is-available, 2021, accessed May, 2021.

[37] R. Bellman, "On a routing problem (no. rand-p-1000)," *Rand Corp Santa Monica Ca*, 1956.

[38] MoI, "Chandigarh road map," https://www.mapsofindia.com/maps/chandigarh/road.html, 2021, accessed june, 2021.

[39] R. Abousleiman and O. Rawashdeh, "A bellman-ford approach to energy efficient routing of electric vehicles," in *2015 IEEE Transportation Electrification Conference and Expo (ITEC)*. IEEE, 2015, pp. 1–4.

[40] R. Cowan and S. Hultén, "Escaping lock-in: the case of the electric vehicle," *Technological Forecasting and Social Change*, vol. 53, no. 1, pp. 61–79, 1996.

[41] Q. Wang, X. Liu, J. Du, and F. Kong, "Smart charging for electric vehicles: A survey from the algorithmic perspective," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 2, pp. 1500–1517, 2016.

[42] N. Chen, M. Wang, N. Zhang, and X. Shen, "Energy and information management of electric vehicular network: A survey," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 2, pp. 967–997, 2020.

[43] K. Dorling, J. Heinrichs, G. G. Messier, and S. Magierowski, "Vehicle routing problems for drone delivery," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 1, pp. 70–85, 2016.

[44] E. Anzilotti, "World changing ideas," shorturl.at/ehiJT, 2019, accessed January, 2020.

[45] EVTechLab, "Vlaamse proeftuin elektrische voertuigen," http://proeftuin-ev.be/?_ga=1.210822173.940857972.1470907495, 2012, accessed March, 2020.

[46] NV, "Punch powertrain," http://www.punchpowertrain.com/, 2012, accessed March, 2020.

[47] M. M. de Weerdt, "Data for "intention-aware routing of electric vehicles"," https://eprints.soton.ac.uk/383415/, 2015, accessed March, 2020.

[48] COIN-OR, "Data for "intention-aware routing of electric vehicles"," https://projects.coin-or.org/SYMPHONY/, 2011, accessed March, 2020.

[49] CHINA, "Real-time traffic monitoring platform of hangzhou, china," http://www.hzjtydzs.com/, 2020, accessed March, 2020.

[50] NVDB, "Nvdb (national road database)," https://www.nvdb.se/sv, 2020, accessed July, 2021.

[51] G. Hiermann, R. F. Hartl, J. Puchinger, and T. Vidal, "Routing a mix of conventional, plug-in hybrid, and electric vehicles," *European Journal of Operational Research*, vol. 272, no. 1, pp. 235–248, 2019.

[52] A. Artmeier, J. Haselmayr, M. Leucker, and M. Sachenbacher, "The shortest path problem revisited: Optimal routing for electric vehicles," in *Annual conference on artificial intelligence*. Springer, 2010, pp. 309–316.

[53] M. Strehler, S. Merting, and C. Schwan, "Energy-efficient shortest routes for electric and hybrid vehicles," *Transportation Research Part B: Methodological*, vol. 103, pp. 111–135, 2017.

[54] A. Burtchen, H. Maurer, and S. Pickenhain, "Numerical treatment of the optimal energy control problem of hybrid vehicles," in *2016 IEEE 55th Conference on Decision and Control (CDC)*. IEEE, 2016, pp. 7377–7383.

[55] A. Schambers, M. Eavis-O'Quinn, V. Roberge, and M. Tarbouchi, "Route planning for vehicle efficiency using the bellman-ford algorithm on an embedded gpu," in *2018 4th International Conference on Optimization and Applications (ICOA)*. IEEE, 2018, pp. 1–6.

[56] C. De Cauwer, W. Verbeke, T. Coosemans, S. Faid, and J. Van Mierlo, "A data-driven method for energy consumption prediction and energy-efficient routing of electric vehicles in real-world conditions," *Energies*, vol. 10, no. 5, p. 608, 2017.

[57] T. Coosemans, K. Lebeau, C. Macharis, B. Lievens, and J. Van Mierlo, "Living labs for electric vehicles in flandres," *World Electric Vehicle Journal*, vol. 5, no. 4, pp. 1005–1010, 2012.

[58] A. G. Garcia, L. A. R. Tria, and M. C. R. Talampas, "Development of an energy-efficient routing algorithm for electric vehicles," in *2019 IEEE Transportation Electrification Conference and Expo (ITEC)*. IEEE, 2019, pp. 1–5.

[59] M. M. Solomon, "Algorithms for the vehicle routing and scheduling problems with time window constraints," *Operations research*, vol. 35, no. 2, pp. 254–265, 1987.

[60] L. Shen, H. Shao, T. Wu, W. H. Lam, and E. C. Zhu, "An energy-efficient reliable path finding algorithm for stochastic road networks with electric vehicles," *Transportation Research Part C: Emerging Technologies*, vol. 102, pp. 450–473, 2019.

[61] R. Abousleiman, O. Rawashdeh, and R. Boimer, "Electric vehicles energy efficient routing using ant colony optimization," *SAE International Journal of Alternative Powertrains*, vol. 6, no. 1, pp. 1–14, 2017.

[62] A. Liebscher, M. Krumnow, J. Krimmling, F. Hanisch, and B. Bäker, "Energy-efficient routing strategies based on real-time data of a local traffic management center," in *2015 International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*. IEEE, 2015, pp. 74–80.

[63] M. Acosta, S. Kanarachos, and M. Blundell, "Road friction virtual sensing: A review of estimation techniques with emphasis on low excitation approaches," *Applied Sciences*, vol. 7, no. 12, 2017. [Online]. Available: https://www.mdpi.com/2076-3417/7/12/1230

[64] E. Schaltz and S. Soylu, "Electrical vehicle design and modeling," *Electric vehicles-modelling and simulations*, vol. 1, pp. 1–24, 2011.

[65] E. Bakker, H. B. Pacejka, and L. Lidner, "A new tire model with an application in vehicle dynamics studies," *SAE transactions*, pp. 101–113, 1989.

[66] C. De Cauwer, W. Verbeke, J. Van Mierlo, and T. Coosemans, "A model for range estimation and energy-efficient routing of electric vehicles in real-world conditions," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 7, pp. 2787–2800, 2020.

[67] G. Macrina, G. Laporte, F. Guerriero, and L. D. P. Pugliese, "An energy-efficient green-vehicle routing problem with mixed vehicle fleet, partial battery recharging and time windows," *European Journal of Operational Research*, vol. 276, no. 3, pp. 971–982, 2019.

[68] S. Zhang, Y. Gajpal, S. Appadoo, and M. Abdulkader, "Electric vehicle routing problem with recharging stations for minimizing energy consumption," *International Journal of Production Economics*, vol. 203, pp. 404–413, 2018.

[69] A. M. Bozorgi, M. Farasat, and A. Mahmoud, "A time and energy efficient routing algorithm for electric vehicles based on historical driving data," *IEEE Transactions on Intelligent Vehicles*, vol. 2, no. 4, pp. 308–320, 2017.

[70] R. Abousleiman and O. Rawashdeh, "Energy efficient routing for electric vehicles using particle swarm optimization," SAE Technical Paper, Tech. Rep., 2014.

[71] S. Pelletier, O. Jabali, and G. Laporte, "The electric vehicle routing problem with energy consumption uncertainty," *Transportation Research Part B: Methodological*, vol. 126, pp. 225–255, 2019.

[72] G. Ferro, M. Paolucci, and M. Robba, "Optimal charging and routing of electric vehicles with power constraints and time-of-use energy prices," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 12, pp. 14 436–14 447, 2020.

[73] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: optimization by a colony of cooperating agents," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 26, no. 1, pp. 29–41, 1996.

[74] E. Osaba, R. Carballedo, X.-S. Yang, and F. Diaz, "An evolutionary discrete firefly algorithm with novel operators for solving the vehicle routing problem with time windows," in *Nature-inspired computation in engineering.* Springer, 2016, pp. 21–41.

[75] M. Schneider, A. Stenger, and D. Goeke, "The electric vehicle-routing problem with time windows and recharging stations," *Transportation Science*, vol. 48, no. 4, pp. 500–520, 2014.

[76] G. Macrina, L. D. P. Pugliese, F. Guerriero, and G. Laporte, "The green mixed fleet vehicle routing problem with partial battery recharging and time windows," *Computers & Operations Research*, vol. 101, pp. 183–199, 2019.

[77] T. M. Sweda and D. Klabjan, "Finding minimum-cost paths for electric vehicles," in *2012 IEEE International Electric Vehicle Conference*. IEEE, 2012, pp. 1–4.

[78] M. F. Jung, D. Sirkin, T. M. Gür, and M. Steinert, "Displayed uncertainty improves driving experience and behavior: The case of range anxiety in an electric car," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, 2015, pp. 2201–2210.

[79] A. Almouhanna, C. L. Quintero-Araujo, J. Panadero, A. A. Juan, B. Khosravi, and D. Ouelhadj, "The location routing problem using electric vehicles with constrained distance," *Computers & Operations Research*, vol. 115, p. 104864, 2020.

[80] S. Barreto, C. Ferreira, J. Paixao, and B. S. Santos, "Using clustering analysis in a capacitated location-routing problem," *European Journal of Operational Research*, vol. 179, no. 3, pp. 968–977, 2007.

[81] Z. Akca, R. Berger, and T. Ralphs, "A branch-and-price algorithm for combined location and routing problems under capacity restrictions," in *Operations research and cyber-infrastructure*. Springer, 2009, pp. 309–330.

[82] J.-M. Belenguer, E. Benavent, C. Prins, C. Prodhon, and R. W. Calvo, "A branch-and-cut method for the capacitated location-routing problem," *Computers & Operations Research*, vol. 38, no. 6, pp. 931–941, 2011.

[83] S. Sun, J. Zhang, J. Bi, and Y. Wang, "A machine learning method for predicting driving range of battery electric vehicles," *Journal of Advanced Transportation*, vol. 2019, 2019.

[84] B. O. Varga, A. Sagoian, and F. Mariasiu, "Prediction of electric vehicle range: A comprehensive review of current issues and challenges," *Energies*, vol. 12, no. 5, p. 946, 2019.

[85] J. Bi, Y. Wang, Q. Sai, and C. Ding, "Estimating remaining driving range of battery electric vehicles based on real-world data: A case study of beijing, china," *Energy*, vol. 169, pp. 833–843, 2019.

[86] Y. Hübner, P. Blythe, G. Hill, M. Neaimeh, and C. Higgins, “Its for electric vehicles—an electromobility roadmap,” in *IET and ITS Conference on Road Transport Information and Control (RTIC 2012).* IET, 2012, pp. 1–5.

[87] M. Ceraolo and G. Pede, “Techniques for estimating the residual range of an electric vehicle,” *IEEE Transactions on Vehicular Technology*, vol. 50, no. 1, pp. 109–115, 2001.

[88] F. Sun, X. Hu, Y. Zou, and S. Li, “Adaptive unscented kalman filtering for state of charge estimation of a lithium-ion battery for electric vehicles,” *Energy*, vol. 36, no. 5, pp. 3531–3540, 2011.

[89] X. Yuan, L. Li, H. Gou, and T. Dong, “Energy and environmental impact of battery electric vehicle range in china,” *Applied Energy*, vol. 157, pp. 75–84, 2015.

[90] C. Bingham, C. Walsh, and S. Carroll, “Impact of driving characteristics on electric vehicle energy consumption and range,” *IET Intelligent Transport Systems*, vol. 6, no. 1, pp. 29–35, 2012.

[91] E. Xydas, C. Marmaras, L. M. Cipcigan, A. Hassan, and N. Jenkins, “Forecasting electric vehicle charging demand using support vector machines,” in *2013 48th International Universities' Power Engineering Conference (UPEC).* IEEE, 2013, pp. 1–6.

[92] J. C. Ferreira, V. D. F. Monteiro, and J. L. Afonso, “Data mining approach for range prediction of electric vehicle,” in *Conference on Future Automotive Technology-Focus Electromobility*, 2012, pp. 1–15.

[93] C.-H. Lee and C.-H. Wu, “A novel big data modeling method for improving driving range estimation of evs,” *IEEE Access*, vol. 3, pp. 1980–1993, 2015.

[94] A. Montoya, C. Guéret, J. E. Mendoza, and J. Villegas, “The electric vehicle routing problem with partial charging and nonlinear charging function,” 2015.

[95] Á. Felipe, M. T. Ortuño, G. Righini, and G. Tirado, “A heuristic approach for the green vehicle routing problem with multiple technologies and partial recharges,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 71, pp. 111–128, 2014.

[96] B. Çatay and M. Keskin, “The impact of quick charging stations on the route planning of electric vehicles,” in *2017 IEEE Symposium on Computers and Communications (ISCC).* IEEE, 2017, pp. 152–157.

[97] S. Erdoğan and E. Miller-Hooks, "A green vehicle routing problem," *Transportation Research Part E: Logistics and Transportation Review*, vol. 48, no. 1, pp. 100–114, 2012.

[98] E. Labs, "Sviluppare la mobilità elettrica: tecnologie, ambiente, infrastrutture, mercato e regole." 2011.

[99] M. Keskin and B. Çatay, "Partial recharge strategies for the electric vehicle routing problem with time windows," *Transportation Research Part C: Emerging Technologies*, vol. 65, pp. 111–127, 2016.

[100] M. Schiffer and G. Walther, "The electric location routing problem with time windows and partial recharging," *European Journal of Operational Research*, vol. 260, no. 3, pp. 995–1013, 2017.

[101] G. Desaulniers, F. Errico, S. Irnich, and M. Schneider, "Exact algorithms for electric vehicle-routing problems with time windows," *Operations Research*, vol. 64, no. 6, pp. 1388–1405, 2016.

[102] M. Bruglieri, F. Pezzella, O. Pisacane, and S. Suraci, "A matheuristic for the electric vehicle routing problem with time windows," *arXiv preprint arXiv:1506.00211*, 2015.

[103] M. Keskin, G. Laporte, and B. Çatay, "Electric vehicle routing problem with time-dependent waiting times at recharging stations," *Computers & Operations Research*, vol. 107, pp. 77–94, 2019.

[104] H. Qin and W. Zhang, "Charging scheduling with minimal waiting in a network of electric vehicles and charging stations," in *Proceedings of the Eighth ACM international workshop on Vehicular inter-networking*. ACM, 2011, pp. 51–60.

[105] O. Worley, D. Klabjan, and T. M. Sweda, "Simultaneous vehicle routing and charging station siting for commercial electric vehicles," in *2012 IEEE International Electric Vehicle Conference*. IEEE, 2012, pp. 1–3.

[106] M. M. De Weerdt, S. Stein, E. H. Gerding, V. Robu, and N. R. Jennings, "Intention-aware routing of electric vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 5, pp. 1472–1482, 2015.

[107] G. B. Qiu, W. X. Liu, and J. H. Zhang, "Equipment optimization method of electric vehicle fast charging station based on queuing theory," in *Applied Mechanics and Materials*, vol. 291. Trans Tech Publ, 2013, pp. 872–877.

[108] A. Hess, F. Malandrino, M. B. Reinhardt, C. Casetti, K. A. Hummel, and J. M. Barceló-Ordinas, "Optimal deployment of charging stations for electric vehicular

networks," in *Proceedings of the first workshop on Urban networking.* ACM, 2012, pp. 1–6.

[109] M. Setak and A. Karimpour, "A mathematical model for the electric vehicle routing with time windows considering queuing system at charging stations and alternative paths," *Journal of Industrial and Systems Engineering*, vol. 12, no. 1, pp. 284–306, 2019.

[110] D. Said, S. Cherkaoui, and L. Khoukhi, "Queuing model for evs charging at public supply stations," in *2013 9th International Wireless Communications and Mobile Computing Conference (IWCMC).* IEEE, 2013, pp. 65–70.

[111] Z. Tian, T. Jung, Y. Wang, F. Zhang, L. Tu, C. Xu, C. Tian, and X.-Y. Li, "Real-time charging station recommendation system for electric-vehicle taxis," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 11, pp. 3098–3109, 2016.

[112] I. García-Magariño, G. Palacios-Navarro, R. Lacuesta, and J. Lloret, "Abscev: An agent-based simulation framework about smart transportation for reducing waiting times in charging electric vehicles," *Computer Networks*, vol. 138, pp. 119–135, 2018.

[113] S. Shao, W. Guan, B. Ran, Z. He, and J. Bi, "Electric vehicle routing problem with charging time and variable travel time," *Mathematical Problems in Engineering*, vol. 2017, 2017.

[114] A. R. Güner, A. Murat, and R. B. Chinnam, "Dynamic routing under recurrent and non-recurrent congestion using real-time its information," *Computers & Operations Research*, vol. 39, no. 2, pp. 358–373, 2012.

[115] S. Mirmohammadi, E. Babaee Tirkolaee, A. Goli, and S. Dehnavi-Arani, "The periodic green vehicle routing problem with considering of time-dependent urban traffic and time windows," *Iran University of Science & Technology*, vol. 7, no. 1, pp. 143–156, 2017.

[116] A. Omidvar and R. Tavakkoli-Moghaddam, "Sustainable vehicle routing: Strategies for congestion management and refueling scheduling," in *2012 IEEE international energy conference and exhibition (ENERGYCON).* IEEE, 2012, pp. 1089–1094.

[117] A. Haghani, G. M. Amoli, and M. Pternea, "Dynamic (time dependent) green vehicle routing problem," 2019.

[118] M. Lee, O. Aslam, B. Foster, D. Kathan, J. Kwok, L. Medearis, R. Palmer, P. Sporborg, and M. Tita, "Assessment of demand response and advanced metering," *Federal Energy Regulatory Commission, Tech. Rep*, 2013.

[119] Y. Cao, S. Tang, C. Li, P. Zhang, Y. Tan, Z. Zhang, and J. Li, "An optimized ev charging model considering tou price and soc curve," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 388–393, 2011.

[120] G. Ferro, M. Paolucci, and M. Robba, "An optimization model for electrical vehicles routing with time of use energy pricing and partial recharging," *IFAC-PapersOnLine*, vol. 51, no. 9, pp. 212–217, 2018.

[121] U. Breunig, R. Baldacci, R. F. Hartl, and T. Vidal, "The electric two-echelon vehicle routing problem," *Computers & Operations Research*, vol. 103, pp. 198–210, 2018.

[122] M. Schneider, A. Stenger, and J. Hof, "An adaptive vns algorithm for vehicle routing problems with intermediate stops," *Or Spectrum*, vol. 37, no. 2, pp. 353–387, 2015.

[123] O. Sassi and A. Oulamara, "Joint scheduling and optimal charging of electric vehicles problem," in *International Conference on Computational Science and Its Applications*. Springer, 2014, pp. 76–91.

[124] T. Abdallah, "The plug-in hybrid electric vehicle routing problem with time windows," Master's thesis, University of Waterloo, 2013.

[125] H. Yang, S. Yang, Y. Xu, E. Cao, M. Lai, and Z. Dong, "Electric vehicle route optimization considering time-of-use electricity price by learnable partheno-genetic algorithm," *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 657–666, 2015.

[126] A.-H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE transactions on Smart Grid*, vol. 1, no. 2, pp. 120–133, 2010.

[127] I. Roozbeh, "Heuristic solutions for electric vehicle routing problem with time windows and recharging stations," Master's thesis, Eastern Mediterranean University (EMU)-Doğu Akdeniz Üniversitesi (DAÜ), 2014.

[128] H.-J. Lee, H.-J. Cha, and D. Won, "Economic routing of electric vehicles using dynamic pricing in consideration of system voltage," *Applied Sciences*, vol. 9, no. 20, p. 4337, 2019.

[129] T. Wang, C. G. Cassandras, and S. Pourazarm, "Energy-aware vehicle routing in networks with charging nodes," *IFAC Proceedings Volumes*, vol. 47, no. 3, pp. 9611–9616, 2014.

[130] G. Kim, Y.-S. Ong, C. K. Heng, P. S. Tan, and N. A. Zhang, "City vehicle routing problem (city vrp): A review," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 4, pp. 1654–1666, 2015.

[131] J. Andelmin and E. Bartolini, "An exact algorithm for the green vehicle routing problem," *Transportation Science*, vol. 51, no. 4, pp. 1288–1303, 2017.

[132] T. Vidal, T. G. Crainic, M. Gendreau, and C. Prins, "Heuristics for multi-attribute vehicle routing problems: A survey and synthesis," *European Journal of Operational Research*, vol. 231, no. 1, pp. 1–21, 2013.

[133] S. Zhang, Y. Luo, and K. Li, "Multi-objective route search for electric vehicles using ant colony optimization," in *2016 American Control Conference (ACC)*. IEEE, 2016, pp. 637–642.

[134] H. Calik, A. Oulamara, C. Prodhon, and S. Salhi, "The electric location-routing problem: Formulation and benders decomposition approach," 2018.

[135] M. Schiffer and G. Walther, "An adaptive large neighborhood search for the location-routing problem with intra-route facilities," *Transportation Science*, vol. 52, no. 2, pp. 331–352, 2017.

[136] W. Li-ying and S. Yuan-bin, "Multiple charging station location-routing problem with time window of electric vehicle." *Journal of Engineering Science & Technology Review*, vol. 8, no. 5, 2015.

[137] J. Hof, M. Schneider, and D. Goeke, "Solving the battery swap station location-routing problem with capacitated electric vehicles using an avns algorithm for vehicle-routing problems with intermediate stops," *Transportation Research Part B: Methodological*, vol. 97, pp. 102–112, 2017.

[138] J. Yang and H. Sun, "Battery swap station location-routing problem with capacitated electric vehicles," *Computers & Operations Research*, vol. 55, pp. 217–232, 2015.

[139] NEO, "Vrp instances," http://neo.lcc.uma.es/vrp/vrp-instances/l, 2013, accessed January, 2020.

[140] S. Zhang, M. Chen, and W. Zhang, "A novel location-routing problem in electric vehicle transportation with stochastic demands," *Journal of Cleaner Production*, vol. 221, pp. 567–581, 2019.

[141] M. Wen, E. Linde, S. Ropke, P. Mirchandani, and A. Larsen, "An adaptive large neighborhood search heuristic for the electric vehicle scheduling problem," *Computers & Operations Research*, vol. 76, pp. 73–83, 2016.

[142] N. Sharmin and H. Lee, "Deadline-aware packet routing based on optimal charging schedule in electric vehicular networks," in *2016 International Conference on Information Networking (ICOIN)*. IEEE, 2016, pp. 172–177.

[143] H. Lee, "Greedy data transportation scheme with hard packet deadlines for wireless ad hoc networks," *The Scientific World Journal*, vol. 2014, 2014.

[144] R. Rana and S. Mishra, "Day-ahead scheduling of electric vehicles for overloading management in active distribution system via web-based application," *IEEE Systems Journal*, 2018.

[145] B. Yagcitekin and M. Uzunoglu, "A double-layer smart charging strategy of electric vehicles taking routing and charge scheduling into account," *Applied energy*, vol. 167, pp. 407–419, 2016.

[146] S. Pelletier, O. Jabali, and G. Laporte, "Charge scheduling for electric freight vehicles," *Transportation Research Part B: Methodological*, vol. 115, pp. 246–269, 2018.

[147] F. Alesiani and N. Maslekar, "Optimization of charging stops for fleet of electric vehicles: A genetic approach," *IEEE Intelligent transportation systems magazine*, vol. 6, no. 3, pp. 10–21, 2014.

[148] G. Zhenfeng, L. Yang, J. Xiaodan, and G. Sheng, "The electric vehicle routing problem with time windows using genetic algorithm," in *2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*. IEEE, 2017, pp. 635–639.

[149] S. Shao, W. Guan, and J. Bi, "Electric vehicle-routing problem with charging demands and energy consumption," *IET Intelligent Transport Systems*, vol. 12, no. 3, pp. 202–212, 2017.

[150] M. Mavrovouniotis, G. Ellinas, and M. Polycarpou, "Electric vehicle charging scheduling using ant colony system," in *2019 IEEE Congress on Evolutionary Computation (CEC)*. IEEE, 2019, pp. 2581–2588.

[151] K. Masliakova, "Optimal routing and charging procedures for electric buses," Master's thesis, UiT Norges arktiske universitet, 2016.

[152] R. Abousleiman and O. Rawashdeh, "An application of ant colony optimization to energy efficient routing for electric vehicles," SAE Technical Paper, Tech. Rep., 2013.

[153] U. F. Siddiqi, Y. Shiraishi, and S. M. Sait, "Multi-constrained route optimization for electric vehicles (evs) using particle swarm optimization (pso)," in *2011 11th International Conference on Intelligent Systems Design and Applications*. IEEE, 2011, pp. 391–396.

[154] R. Abousleiman and O. Rawashdeh, "Tabu search based solution to the electric vehicle energy efficient routing problem," in *2014 IEEE Transportation Electrification Conference and Expo (ITEC)*. IEEE, 2014, pp. 1–6.

[155] O. Sassi, W. R. Cherif-Khettaf, and A. Oulamara, "Multi-start iterated local search for the mixed fleet vehicle routing problem with heterogenous electric vehicles," in *European Conference on Evolutionary Computation in Combinatorial Optimization*. Springer, 2015, pp. 138–149.

[156] P. H. V. Penna, H. M. Afsar, C. Prins, and C. Prodhon, "A hybrid iterative local search algorithm for the electric fleet size and mix vehicle routing problem with time windows and recharging stations," *IFAC-PapersOnLine*, vol. 49, no. 12, pp. 955–960, 2016.

[157] M. Bruglieri, F. Pezzella, O. Pisacane, and S. Suraci, "A variable neighborhood search branching for the electric vehicle routing problem with time windows," *Electronic Notes in Discrete Mathematics*, vol. 47, pp. 221–228, 2015.

[158] S. Pourazarm, C. G. Cassandras, and A. Malikopoulos, "Optimal routing of electric vehicles in networks with charging nodes: A dynamic programming approach," in *2014 IEEE International Electric Vehicle Conference (IEVC)*. IEEE, 2014, pp. 1–7.

[159] G. Hiermann, J. Puchinger, S. Ropke, and R. F. Hartl, "The electric fleet size and mix vehicle routing problem with time windows and recharging stations," *European Journal of Operational Research*, vol. 252, no. 3, pp. 995–1018, 2016.

[160] F. Y. Vincent, A. P. Redi, Y. A. Hidayat, and O. J. Wibowo, "A simulated annealing heuristic for the hybrid vehicle routing problem," *Applied Soft Computing*, vol. 53, pp. 119–132, 2017.

[161] A. Froger, J. E. Mendoza, O. Jabali, and G. Laporte, "A matheuristic for the electric vehicle routing problem with capacitated charging stations," 2017.

[162] G. B. Dantzig and J. H. Ramser, "The truck dispatching problem," *Management science*, vol. 6, no. 1, pp. 80–91, 1959.

[163] F. Gonçalves, S. R. Cardoso, S. Relvas, and A. Barbosa-Póvoa, "Optimization of a distribution network using electric vehicles: A vrp problem," in *Proceedings of the IO2011-15 Congresso da associação Portuguesa de Investigação Operacional, Coimbra, Portugal*, 2011, pp. 18–20.

[164] G. Clarke and J. W. Wright, "Scheduling of vehicles from a central depot to a number of delivery points," *Operations research*, vol. 12, no. 4, pp. 568–581, 1964.

[165] J. K. Lenstra and A. R. Kan, "Complexity of vehicle routing and scheduling problems," *Networks*, vol. 11, no. 2, pp. 221–227, 1981.

[166] W. Feng and M. Figliozzi, "An economic and technological analysis of the key factors affecting the competitiveness of electric commercial vehicles: A case study from the usa market," *Transportation Research Part C: Emerging Technologies*, vol. 26, pp. 135–145, 2013.

[167] K. Young, C. Wang, K. Strunz *et al.*, "Electric vehicle battery technologies," in *Electric vehicle integration into modern power networks*. Springer, 2013, pp. 15–56.

[168] D. Efthymiou, K. Chrysostomou, M. Morfoulaki, and G. Aifantopoulou, "Electric vehicles charging infrastructure location: a genetic algorithm approach," *European Transport Research Review*, vol. 9, no. 2, pp. 1–9, 2017.

[169] S. Pelletier, O. Jabali, and G. Laporte, "50th anniversary invited article—goods distribution with electric vehicles: review and research perspectives," *Transportation Science*, vol. 50, no. 1, pp. 3–22, 2016.

[170] A. A. Juan, C. A. Mendez, J. Faulin, J. De Armas, and S. E. Grasman, "Electric vehicles in logistics and transportation: A survey on emerging environmental, strategic, and operational challenges," *Energies*, vol. 9, no. 2, p. 86, 2016.

[171] D. Margaritis, A. Anagnostopoulou, A. Tromaras, and M. Boile, "Electric commercial vehicles: Practical perspectives and future research directions," *Research in transportation business & management*, vol. 18, pp. 4–10, 2016.

[172] A. Bourass, S. Cherkaoui, and L. Khoukhi, "Secure optimal itinerary planning for electric vehicles in the smart grid," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 6, pp. 3236–3245, 2017.

[173] R. Basso, B. Kulcsár, and I. Sanchez-Diaz, "Electric vehicle routing problem with machine learning for energy prediction," *Transportation Research Part B: Methodological*, vol. 145, pp. 24–55, 2021.

[174] X. Chen, J. Xue, X. Qian, J. Suarez, and S. V. Ukkusuri, "Online energy-optimal routing for electric vehicles with combinatorial multi-arm semi-bandit," in *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, 2020, pp. 1–6.

[175] J. Zhang, Z. Wang, P. Liu, and Z. Zhang, "Energy consumption analysis and prediction of electric vehicles based on real-world driving data," *Applied Energy*, vol. 275, p. 115408, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S030626192030920X

[176] X. Tang, T. Jia, X. Hu, Y. Huang, Z. Deng, and H. Pu, "Naturalistic data-driven predictive energy management for plug-in hybrid electric vehicles," *IEEE Transactions on Transportation Electrification*, vol. 7, no. 2, pp. 497–508, 2020.

[177] J. Hu, F. Xiao, B. Mei, Z. Lin, and C. Fu, "Optimal energy efficient control of pure electric vehicle power system based on dynamic traffic information flow," *IEEE Transactions on Transportation Electrification*, 2021.

[178] M. Granada-Echeverri, L. Cubides, and J. Bustamante, "The electric vehicle routing problem with backhauls," *International Journal of Industrial Engineering Computations*, vol. 11, no. 1, pp. 131–152, 2020.

[179] P. Toth and D. Vigo, "An exact algorithm for the vehicle routing problem with backhauls," *Transportation science*, vol. 31, no. 4, pp. 372–385, 1997.

[180] M. Goetschalckx and C. Jacobs-Blecha, "The vehicle routing problem with backhauls," *European Journal of Operational Research*, vol. 42, no. 1, pp. 39–51, 1989.

[181] L. C. Cubides, A. Arias Londoño, and M. Granada Echeverri, "Electric vehicle routing problem with backhauls considering the location of charging stations and the operation of the electric power distribution system," *TecnoLógicas*, vol. 22, no. 44, pp. 3–22, 2019.

[182] G. Laporte, "The vehicle routing problem: An overview of exact and approximate algorithms," *European journal of operational research*, vol. 59, no. 3, pp. 345–358, 1992.

[183] I. Sbai and S. Krichen, "An adaptive genetic algorithm for dynamic vehicle routing problem with backhaul and two-dimensional loading constraints," in *2020 International Multi-Conference on:"Organization of Knowledge and Advanced Technologies"(OCTA)*. IEEE, 2020, pp. 1–7.

[184] H. A. Daham and H. J. Mohammed, "An evolutionary algorithm approach for vehicle routing problems with backhauls," *Materials Today: Proceedings*, 2021.

[185] S. Yang, L. Ning, L. C. Tong, and P. Shang, "Optimizing electric vehicle routing problems with mixed backhauls and recharging strategies in multi-dimensional representation network," *Expert Systems with Applications*, vol. 176, p. 114804, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417421002451

[186] S. Afshar, P. Macedo, F. Mohamed, and V. Disfani, "A literature review on mobile charging station technology for electric vehicles," in *2020 IEEE Transportation Electrification Conference & Expo (ITEC)*. IEEE, 2020, pp. 1184–1190.

[187] M. Brenna, F. Foiadelli, C. Leone, and M. Longo, "Electric vehicles charging technology review and optimal size estimation," *Journal of Electrical Engineering & Technology*, pp. 1–14, 2020.

[188] Q.-S. Jia and T. Long, "A review on charging behavior of electric vehicles: data, model, and control," *Control Theory and Technology*, vol. 18, no. 3, pp. 217–230, 2020.

[189] T. U. Solanke, V. K. Ramachandaramurthy, J. Y. Yong, J. Pasupuleti, P. Kasinathan, and A. Rajagopalan, "A review of strategic charging–discharging control of grid-connected electric vehicles," *Journal of Energy Storage*, vol. 28, p. 101193, 2020.

[190] B. Vu, J. M. González-González, V. Pickert, M. Dahidah, and A. Trivino, "A hybrid charger of conductive and inductive modes for electric vehicles," *IEEE Transactions on Industrial Electronics*, 2020.

[191] S. Hulagu and H. B. Celikoglu, "An electric vehicle routing problem with intermediate nodes for shuttle fleets," *IEEE Transactions on Intelligent Transportation Systems*, 2020.

[192] H. Li, Z. Li, L. Cao, R. Wang, and M. Ren, "Research on optimization of electric vehicle routing problem with time window," *IEEE Access*, vol. 8, pp. 146 707–146 718, 2020.

[193] J. Lin and W. Zhou, "Important factors to daily vehicle routing cost of battery electric delivery trucks," *International Journal of Sustainable Transportation*, vol. 15, no. 7, pp. 541–558, 2021.

[194] S. Karakatič, "Optimizing nonlinear charging times of electric vehicle routing with genetic algorithm," *Expert Systems with Applications*, vol. 164, p. 114039, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417420308083

[195] U. Bac and M. Erdem, "Optimization of electric vehicle recharge schedule and routing problem with time windows and partial recharge: A comparative study for an urban logistics fleet," *Sustainable Cities and Society*, vol. 70, p. 102883, 2021.

[196] "Optimization of electric vehicle recharge schedule and routing problem with time windows and partial recharge: A comparative study for an urban logistics fleet," *Sustainable Cities and Society*, vol. 70, p. 102883, 2021.

[197] D. Gong, M. Tang, B. Buchmeister, and H. Zhang, "Solving location problem for electric vehicle charging stations—a sharing charging model," *IEEE Access*, vol. 7, pp. 138 391–138 402, 2019.

[198] S. Goel, R. Kumar, A. Kumar, and R. Malhotra, "S^{3}A: Smart station search assistance for electric vehicle—a step toward smart city," *IEEE Consumer Electronics Magazine*, vol. 9, no. 4, pp. 27–33, 2020.

[199] G. Ferro, M. Paolucci, and M. Robba, "Optimal charging and routing of electric vehicles with power constraints and time-of-use energy prices," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 12, pp. 14 436–14 447, 2020.

[200] T. Arora and R. Dhir, "Correlation-based feature selection and classification via regression of segmented chromosomes using geometric features," *Medical & biological engineering & computing*, vol. 55, no. 5, pp. 733–745, 2017.

[201] C. Iwendi, A. K. Bashir, A. Peshkar, R. Sujatha, J. M. Chatterjee, S. Pasupuleti, R. Mishra, S. Pillai, and O. Jo, "Covid-19 patient health prediction using boosted random forest algorithm," *Frontiers in public health*, vol. 8, p. 357, 2020.

[202] C. Iwendi, P. K. R. Maddikunta, T. R. Gadekallu, K. Lakshmanna, A. K. Bashir, and M. J. Piran, "A metaheuristic optimization approach for energy efficiency in the iot networks," *Software: Practice and Experience*, vol. 51, no. 12, pp. 2558–2571, 2021.

[203] S. Pan, W. Zhou, S. Piramuthu, V. Giannikas, and C. Chen, "Smart city for sustainable urban freight logistics," pp. 2079–2089, 2021.

[204] E. Katiyar, J. Singh, V. Gupta, R. Tulasyan, N. Auluck, and M. Pandey, "A multiobjective genetic algorithm to improve power and performance of heterogeneous multiprocessors," 2021.

[205] A. Kumar, R. Kumar, and A. Aggarwal, "S2rc: A multi-objective route planning and charging slot reservation approach for electric vehicles considering state of traffic and charging station," *Journal of King Saud University-Computer and Information Sciences*, vol. 34, no. 5, pp. 2192–2206, 2022.

[206] X. Dong, Y. Mu, X. Xu, H. Jia, J. Wu, X. Yu, and Y. Qi, "A charging pricing strategy of electric vehicle fast charging stations for the voltage control of electricity distribution networks," *Applied energy*, vol. 225, pp. 857–868, 2018.

[207] H. Liu, W. Yin, X. Yuan, and M. Niu, "Reserving charging decision-making model and route plan for electric vehicles considering information of traffic and charging station," *Sustainability*, vol. 10, no. 5, p. 1324, 2018.

[208] T. Chen, B. Zhang, H. Pourbabak, A. Kavousi-Fard, and W. Su, "Optimal routing and charging of an electric vehicle fleet for high-efficiency dynamic transit systems," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3563–3572, 2016.

[209] P. K. Gupta, R. Rana, and S. Mishra, "Multi priority-queuing algorithm for real time charge scheduling of electric vehicles on highways based on time allotment," in *2020 IEEE International Conference on Power Electronics, Smart Grid and Renewable Energy (PESGRE2020)*, 2020, pp. 1–5.

[210] E.-F. Ibrahim, K. Driss, and A. Rachid, "Framework for optimizing the charging time of electric vehicles in public supply station deployed in smart cities," in *2018 IEEE 5th International Congress on Information Science and Technology (CiSt)*, 2018, pp. 537–541.

[211] Z. Moghaddam, I. Ahmad, D. Habibi, and Q. V. Phung, "Smart charging strategy for electric vehicle charging stations," *IEEE Transactions on Transportation Electrification*, vol. 4, no. 1, pp. 76–88, 2018.

[212] Q. Tang, K. Wang, Y. Song, F. Li, and J. H. Park, "Waiting time minimized charging and discharging strategy based on mobile edge computing supported by software-defined network," *IEEE Internet of Things Journal*, vol. 7, no. 7, pp. 6088–6101, 2020.

[213] F. Morlock, B. Rolle, M. Bauer, and O. Sawodny, "Forecasts of electric vehicle energy consumption based on characteristic speed profiles and real-time traffic data," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 2, pp. 1404–1418, 2019.

[214] X. Bi and W. K. Tang, "Logistical planning for electric vehicles under time-dependent stochastic traffic," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 10, pp. 3771–3781, 2018.

[215] B. Yu, J. Xin, and A. D 'Ariano, "Route planning of a sanitation vehicle in a dynamic traffic environment," in *2019 Chinese Automation Congress (CAC)*, 2019, pp. 2898–2903.

[216] R. Zhang, J. Guo, and J. Wang, "A time-dependent electric vehicle routing problem with congestion tolls," *IEEE Transactions on Engineering Management*, 2020.

[217] O. Fallah-Mehrjardi, M. H. Yaghmaee, and A. Leon-Garcia, "Charge scheduling of electric vehicles in smart parking-lot under future demands uncertainty," *IEEE Transactions on Smart Grid*, vol. 11, no. 6, pp. 4949–4959, 2020.

[218] N. Tucker, B. Turan, and M. Alizadeh, "Online charge scheduling for electric vehicles in autonomous mobility on demand fleets," in *2019 IEEE Intelligent Transportation Systems Conference (ITSC)*. IEEE, 2019, pp. 226–231.

[219] N. T. Milas, D. A. Mourtzis, P. I. Giotakos, and E. C. Tatakis, "Two-layer genetic algorithm for the charge scheduling of electric vehicles," in *2020 22nd European*

Conference on Power Electronics and Applications (EPE'20 ECCE Europe). IEEE, 2020, pp. P–1.

[220] M. Elmehdi and M. Abdelilah, "Genetic algorithm for optimal charge scheduling of electric vehicle fleet," in *Proceedings of the 2nd International Conference on Networking, Information Systems & Security*, 2019, pp. 1–7.

[221] A. Triviño-Cabrera, J. A. Aguado, and S. de la Torre, "Joint routing and scheduling for electric vehicles in smart grids with v2g," *Energy*, vol. 175, pp. 113–122, 2019.

[222] Y. Cui, Z. Hu, and H. Luo, "Optimal day-ahead charging and frequency reserve scheduling of electric vehicles considering the regulation signal uncertainty," *IEEE Transactions on Industry Applications*, vol. 56, no. 5, pp. 5824–5835, 2020.

[223] N. Mhaisen, N. Fetais, and A. Massoud, "Real-time scheduling for electric vehicles charging/discharging using reinforcement learning," in *2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT)*. IEEE, 2020, pp. 1–6.

[224] B. Li, M. Niu, H. Wu, M. Zou, Y. Zhang, D. Liu, S. Shang, L. Wang, T. Zhang, and M. Liu, "Incentive strategies for responders of electric vehicle virtual energy storage based on comprehensive contribution evaluation," in *IOP Conference Series: Earth and Environmental Science*, vol. 647, no. 1. IOP Publishing, 2021, p. 012147.

[225] B. Sohet, Y. Hayel, O. Beaude, and A. Jeandin, "Coupled charging-and-driving incentives design for electric vehicles in urban networks," *IEEE Transactions on Intelligent Transportation Systems*, 2020.

[226] G. Wang, Z. Fang, X. Xie, S. Wang, H. Sun, F. Zhang, Y. Liu, and D. Zhang, "Pricing-aware real-time charging scheduling and charging station expansion for large-scale electric buses," *ACM Transactions on Intelligent Systems and Technology (TIST)*, vol. 12, no. 1, pp. 1–26, 2020.

[227] C. Zhang, Y. Zhao, and L. Leng, "A hyper-heuristic algorithm for time-dependent green location routing problem with time windows," *IEEE Access*, vol. 8, pp. 83 092–83 104, 2020.

[228] M. Mazini, B. Shirazi, and I. Mahdavi, "Anomaly network-based intrusion detection system using a reliable hybrid artificial bee colony and adaboost algorithms," *Journal of King Saud University-Computer and Information Sciences*, vol. 31, no. 4, pp. 541–553, 2019.

[229] M. Mavrovouniotis, G. Ellinas, and M. Polycarpou, "Ant colony optimization for the electric vehicle routing problem," in *2018 IEEE Symposium Series on Computational Intelligence (SSCI)*, 2018, pp. 1234–1241.

[230] M. Mavrovouniotis, C. Menelaou, S. Timotheou, G. Ellinas, C. Panayiotou, and M. Polycarpou, "A benchmark test suite for the electric capacitated vehicle routing problem," in *2020 IEEE Congress on Evolutionary Computation (CEC)*. IEEE, 2020, pp. 1–8.

[231] O. Tremblay, L.-A. Dessaint, and A.-I. Dekkiche, "A generic battery model for the dynamic simulation of hybrid electric vehicles," in *2007 IEEE Vehicle Power and Propulsion Conference*, 2007, pp. 284–289.

[232] M. P. Kazmierkowski, *Advanced Electric Drive Vehicles*, 2015, vol. 9, no. 4.

[233] X. Tang, S. Bi, and Y.-J. A. Zhang, "Distributed routing and charging scheduling optimization for internet of electric vehicles," *IEEE Internet of Things Journal*, vol. 6, no. 1, pp. 136–148, 2019.

[234] J. J. Q. Yu, "Two-stage request scheduling for autonomous vehicle logistic system," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 5, pp. 1917–1929, 2019.

[235] S. Pourazarm and C. G. Cassandras, "Optimal routing of energy-aware vehicles in transportation networks with inhomogeneous charging nodes," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 8, pp. 2515–2527, 2018.

[236] Nissan, "Ev parameters," Available:http://www.nissan.co.uk/, 2017, accessed June, 2020.

[237] G. Zhu and S. Kwong, "Gbest-guided artificial bee colony algorithm for numerical function optimization," *Applied mathematics and computation*, vol. 217, no. 7, pp. 3166–3173, 2010.

[238] J. Eisner, S. Funke, and S. Storandt, "Optimal route planning for electric vehicles in large networks," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 25, no. 1, 2011.

[239] A. Sitchin, "Acquisition of transient tire force and moment data for dynamic vehicle handling simulations," *SAE Transactions*, pp. 1098–1110, 1983.

[240] I. Tiseo, "Breakdown of co2 emissions in the transportation sector," https://www.statista.com/statistics/, 2020, accessed july, 2021.

[241] UN, "Emissions gap report," https://www.unep.org/, 2019, accessed july, 2021.

[242] ICCT, "Air pollution in india," https://theicct.org/india, 2021, accessed may, 2021.

[243] N. Aayog, "India's energy and emissions outlook," https://niti.gov.in/, 2019, accessed may, 2021.

[244] E. Commission, "Mobility and transport," https://ec.europa.eu/transport, 2011, accessed may, 2021.

[245] H. Joo and Y. Lim, "Ant colony optimized routing strategy for electric vehicles," *Journal of Advanced Transportation*, vol. 2018, 2018.

[246] L. Guzzella and A. Sciarretta, "Electric and hybrid-electric propulsion systems," in *Vehicle Propulsion Systems*. Springer, 2013, pp. 67–162.

[247] L. Guzzella, A. Sciarretta *et al.*, *Vehicle propulsion systems*. Springer, 2007, vol. 1.

[248] G. Laporte, "Fifty years of vehicle routing," *Transportation science*, vol. 43, no. 4, pp. 408–416, 2009.

[249] T. Erdelić and T. Carić, "A survey on the electric vehicle routing problem: variants and solution approaches," *Journal of Advanced Transportation*, vol. 2019, 2019.

[250] G. Macrina, L. D. P. Pugliese, and F. Guerriero, "The green-vehicle routing problem: A survey," in *Modeling and Optimization in Green Logistics*. Springer, 2020, pp. 1–26.

[251] R. G. Conrad and M. A. Figliozzi, "The recharging vehicle routing problem," in *Proceedings of the 2011 industrial engineering research conference*. IISE Norcross, GA, 2011, p. 8.

[252] S. Zhang, Y. Gajpal, S. Appadoo, and M. Abdulkader, "Electric vehicle routing problem with recharging stations for minimizing energy consumption," *International Journal of Production Economics*, vol. 203, pp. 404–413, 2018.

[253] M. Keskin, G. Laporte, and B. Çatay, "Electric vehicle routing problem with time-dependent waiting times at recharging stations," *Computers & Operations Research*, vol. 107, pp. 77–94, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S030505481930053X

[254] M. Mavrovouniotis, C. Li, G. Ellinas, and M. Polycarpou, "Parallel ant colony optimization for the electric vehicle routing problem," in *2019 IEEE Symposium Series on Computational Intelligence (SSCI)*, 2019, pp. 1660–1667.

[255] H. Mao, J. Shi, Y. Zhou, and G. Zhang, "The electric vehicle routing problem with time windows and multiple recharging options," *IEEE Access*, vol. 8, pp. 114 864–114 875, 2020.

[256] S. Shao, W. Guan, and J. Bi, "Electric vehicle-routing problem with charging demands and energy consumption," *IET Intelligent Transport Systems*, vol. 12, no. 3, pp. 202–212, 2018.

[257] R. Basso, B. Kulcsár, B. Egardt, P. Lindroth, and I. Sanchez-Diaz, "Energy consumption estimation integrated into the electric vehicle routing problem," *Transportation Research Part D: Transport and Environment*, vol. 69, pp. 141–167, 2019.

[258] K. N. Genikomsakis and G. Mitrentsis, "A computationally efficient simulation model for estimating energy consumption of electric vehicles in the context of route planning applications," *Transportation Research Part D: Transport and Environment*, vol. 50, pp. 98–118, 2017.

[259] H. Liu, W. Yin, X. Yuan, and M. Niu, "Reserving charging decision-making model and route plan for electric vehicles considering information of traffic and charging station," *Sustainability*, vol. 10, no. 5, 2018.

[260] X. Dong, Y. Mu, X. Xu, H. Jia, J. Wu, X. Yu, and Y. Qi, "A charging pricing strategy of electric vehicle fast charging stations for the voltage control of electricity distribution networks," *Applied Energy*, vol. 225, pp. 857–868, 2018.

[261] A. Ham and M.-J. Park, "Electric vehicle route optimization under time-of-use electricity pricing," *IEEE Access*, vol. 9, pp. 37 220–37 228, 2021.

[262] B. Lin, B. Ghaddar, and J. Nathwani, "Electric vehicle routing with charging/discharging under time-variant electricity prices," *Transportation Research Part C: Emerging Technologies*, vol. 130, p. 103285, 2021.

[263] A. Moradipari and M. Alizadeh, "Pricing and routing mechanisms for differentiated services in an electric vehicle public charging station network," *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1489–1499, 2020.

[264] T. Chen, B. Zhang, H. Pourbabak, A. Kavousi-Fard, and W. Su, "Optimal routing and charging of an electric vehicle fleet for high-efficiency dynamic transit systems," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3563–3572, 2018.

[265] S. Pelletier, O. Jabali, G. Laporte, and M. Veneroni, "Battery degradation and behaviour for electric vehicles: Review and numerical analyses of several models," *Transportation Research Part B: Methodological*, vol. 103, pp. 158–187, 2017, green Urban Transportation.

[266] G. Macrina, L. Di Puglia Pugliese, F. Guerriero, and G. Laporte, "The green mixed fleet vehicle routing problem with partial battery recharging and time windows," *Computers & Operations Research*, vol. 101, pp. 183–199, 2019.

[267] C. Li, T. Ding, X. Liu, and C. Huang, "An electric vehicle routing optimization model with hybrid plug-in and wireless charging systems," *IEEE Access*, vol. 6, pp. 27 569–27 578, 2018.

[268] M. Mavrovouniotis, G. Ellinas, and M. Polycarpou, “Ant colony optimization for the electric vehicle routing problem,” in *2018 IEEE Symposium Series on Computational Intelligence (SSCI)*, 2018, pp. 1234–1241.

[269] A. Eslaminia and P. Azimi, “Solving the electric vehicle routing problem considering the vehicle volume limitation using a simulated annealing algorithm,” *Journal of Industrial Management Perspective*, vol. 9, no. 4, pp. 165–188, 2020.

[270] R. Basso, B. Kulcsár, and I. Sanchez-Diaz, “Electric vehicle routing problem with machine learning for energy prediction,” *Transportation Research Part B: Methodological*, vol. 145, pp. 24–55, 2021.

[271] J. Wang, I. Besselink, and H. Nijmeijer, “Battery electric vehicle energy consumption prediction for a trip based on route information,” *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, vol. 232, no. 11, pp. 1528–1542, 2018.

[272] W. Zhou and L. Wang, “The energy-efficient dynamic route planning for electric vehicles,” *Journal of Advanced Transportation*, vol. 2019, 2019.

[273] M. Neaimeh, G. A. Hill, Y. Hübner, and P. T. Blythe, “Routing systems to extend the driving range of electric vehicles,” *IET Intelligent Transport Systems*, vol. 7, no. 3, pp. 327–336, 2013.

[274] H. Eldem and E. Ülker, “The application of ant colony optimization in the solution of 3d traveling salesman problem on a sphere,” *Engineering Science and Technology, an International Journal*, vol. 20, no. 4, pp. 1242–1248, 2017.

[275] E. S. Rigas, S. D. Ramchurn, and N. Bassiliades, “Managing electric vehicles in the smart grid using artificial intelligence: A survey,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 4, pp. 1619–1635, 2015.

[276] MoI, “Chandigarh road map,” https://www.mapsofindia.com/maps/chandigarh/road.html, 2021, accessed june, 2021.

[277] S. Goel, R. Kumar, A. Kumar, and R. Malhotra, “S^3A: Smart station search assistance for electric vehicle—a step toward smart city,” *IEEE Consumer Electronics Magazine*, vol. 9, no. 4, pp. 27–33, 2020.

[278] Z. Gu, S. Sharma, D. A. Riley, M. V. Pantawane, S. S. Joshi, S. Fu, and N. B. Dahotre, “A universal predictor-based machine learning model for optimal process maps in laser powder bed fusion process,” *Journal of Intelligent Manufacturing*, pp. 1–23, 2022.