

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE
ENGINEERING AND TECHNOLOGY

**ENERGY OPTIMIZED ELECTRIC VEHICLE LOCATION ROUTING
PROBLEM WITH INTERMEDIATE NODES**



M.Sc. THESIS

Selin HÜLAGÜ, M.Sc.

Department of Civil Engineering

Transportation Engineering Programme

JULY 2020

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**Selin HÜLAGÜ
(501171411)**

Department of Civil Engineering

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Thesis Advisor: Prof. Dr. Hilmi Berk ÇELİKOĞLU

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

**ENERJİ ENİYİLENMİŞ ELEKTRİKLİ ARAÇ ARA DÜĞÜM NOKTALI YER
ROTALAMA PROBLEMİ**

YÜKSEK LİSANS TEZİ

**Selin HÜLAGÜ
(501171411)**

İnşaat Mühendisliği Anabilim Dalı

Ulaştırma Mühendisliği Programı

Tez Danışmanı: Prof. Dr. Hilmi Berk ÇELİKOĞLU

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Selin Hülügü, a M.Sc student of İTÜ Graduate School of Science Engineering and Technology student ID 501171411, successfully defended the thesis entitled “Energy Optimized Electric Vehicle Location Routing Problem with Intermediate Nodes”, which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor : **Prof. Dr. Hilmi Berk ÇELİKOĞLU**
Istanbul Technical University

Jury Members : **Prof. Dr. Hande DEMİREL**
Istanbul Technical University

Prof. Dr. Mustafa KARAŞAHİN
Istanbul Gelişim University

Date of Submission : 02 June 2020
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Dedicated to my family,



FOREWORD

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ABBREVIATIONS

AFV	: Alternative Fuel Vehicle
EV	: Electric Vehicle
EVRP	: Electric Vehicle Routing Problem
EVRP-IN	: Electric Vehicle Routing Problem with Intermediate Nodes
GHGs	: Green House Gases
GVRP	: Green Vehicle Routing Problem
HVRP	: Heterogeneous Vehicle Routing Problem
ICEV	: Internal Combustion Engine Vehicle
ITU	: Technical University of Istanbul
LRP	: Location Routing Problem
mTSP	: Multiple Travelling Salesman Problem
PRP	: Pollution Routing Problem
SBRP	: School Bus Routing Problem
TSP	: Travelling Salesman Problem
VRP	: Vehicle Routing Problem

VRPTW : Vehicle Routing Problem with Time Windows



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ENERGY OPTIMIZED ELECTRIC VEHICLE LOCATION ROUTING PROBLEM WITH INTERMEDIATE NODES

SUMMARY

Considering the increasing concerns on the issues related to public health including air pollution, and climate change based on the greenhouse gas emissions, as externalities of transportation sector, where the sectoral contribution of transportation in total net anthropogenic warming has been estimated to increase up to 16% in 2050, the main feature initiating and supporting the introduction of alternative vehicle technologies including Hybrids and Electric Vehicles (EVs) to the vehicle market, which is dominated by Internal Combustion Engine Vehicles, have therefore been due to their reduced-emission or emission-free characteristics when they are in use. In this context, EVs are promising vehicle technologies to diminish the environmental effects of transportation by enabling the usage of renewable energy sources instead of fossil fuels and, ensure an emission-free operation according to the tank-to-wheel perspective in addition to the energy recovery potential in braking process via regenerative braking systems. However, due to both the battery and the recharging infrastructure technology in-develop in order to provide longer driving ranges and quicker recharging, EVs' market share is relatively low.

This study deals with the major challenges of using EVs in goods and/or people transport to: utilize effectively the limited driving range, and decide the optimal locations for the minimum number of recharging station within the context of determining battery discharging accurately. In this context, optimal routing plans, as well as the recharging station locations for EV fleets are obtained by introducing the Electric Vehicle Location Routing Problem with Intermediate Nodes (ELRP-IN) that considers actual battery discharging characteristics, which are determined respecting the vehicle motion dynamics in conjunction with 3-dimensional road geometry, passenger getting on and getting off demands, and the pre-defined speed profiles, where the network graph corresponding to the road network is extended with the explicit consideration of intersections. In order to provide a discussion on the impacts of the objective function to the routing plans and to the parameters including energy consumption, cost, traveled distance and travel time, the objective functions adopted are alternated within the proposed ELRP-IN formulation, where a number of numerical experiments are performed to evaluate the features of ELRP-IN using: (i) widely employed test instances; (ii) a medium-scale real case instance; and, (iii) a large-scale real case instance.

Network specific model based exact solutions are extracted and evaluated from varying perspectives including network characteristics, i.e., topology, node passenger demands, arc lengths, and arc grades, energy consumption, overall cost, i.e., energy cost, vehicle cost, and recharging station cost, traveled distance, and total time spent. Results reveal the importance of concentrating on the appropriate problem-specific objective where the routing plan, the number of recharging station assigned, and the

location of recharging stations as well as the energy consumption, cost, traveled distance, and travel time may vary according to the objective sought. Remarking the finding that energy is not recovered in all the sections with negative grade, the direct effect of the elevation on the energy consumption, and hence on the location of a recharging station, is revealed, where the limitation on the energy recovery due to the braking efficiency is discussed as well. By testing some instances both with and without their passenger demands, calculations on the energy consumptions are compared. The influence on introducing the intersection nodes to the road network graph is evaluated with respect to the total time spent, network consistency, and the centrality measure in order to both quantify and qualify the degree of nodes of the network.



ENERJİ ENİYİLENMİŞ ELEKTRİKLİ ARAÇ ARA DÜĞÜM NOKTALI YER SEÇİMİ ROTALAMA PROBLEMİ

ÖZET

İçten yanmalı motorlu taşıtların karayolu taşımacılığında baskın kullanımı, ulaştırma sektörünün dışsalılıklarından olan hava kirliliği ve sera gazı salımı kaynaklı iklim değişikliği gibi toplum sağlığını ilgilendiren konulardaki endişeleri arttırmaktadır. Bu bağlamda, 2000 yılında %9 olarak ölçülen ulaştırma sektörünün atmosferde insan kaynaklı ısınmaya olan katkısının 2050 yılında %16 değerine ulaşması beklenmektedir. Özellikle yenilenebilir olmayan enerji kaynaklarının tüketimine ve sera gazlarının etkilerine bağlı çevresel ve toplum sağlığı ile ilintili endişeler, işletim sürecindeki azaltılmış salım veya sıfır salım nitelikleri gözetildiğinde karma motorlu ve elektrikli araçlar gibi seçenek araç teknolojilerinin araç pazarına girişini tetiklemiştir.

Fosil yakıtlar yerine yenilenebilir enerji kaynaklarının kullanımına imkan sağlanması, ve içten yanmalı motorlu araçlarda ısı olarak kaybolan frenleme enerjisinin, geri kazanımlı frenleme ile yeniden pile yüklenebilmesi gibi özellikleri ile elektrikli araçlar ulaştırma sektörünün çevresel etkilerini azaltmada güçlü bir seçenek olarak araç pazarındaki yerini almıştır. Elektrikli araçların işletimindeki çevresel etkilerine bakıldığında, geleneksel içten yanmalı motorlu araçlardan farklı olarak egzoz gazı salımının olmaması bir getiriyken, pil dolumunun yapıldığı elektriğin kaynağı, elektrikli araçların yaşam döngüsü boyunca neden olduğu sera gazı salımının belirlenmesinde önemli rol oynamaktadır. Geleneksel içten yanmalı motorlu araçlara seçenek olarak geliştirilen elektrikli araçlar, kısıtlı menzilleri ve dolayısıyla gereksinim duydukları dolum istasyonu altyapısı gibi etmenler nedeniyle günümüzde henüz çok yaygınlaşamamıştır.

Seçenek (alternatif) yakıtlı araçlar için var olan söz konusu kısıtlar, araç rotalama problemi kapsamında ele alınarak, menzil kısıtlarına uygun rotalar ve dolum istasyonu yerleri belirlenebilmektedir. Araç rotalama problemi, coğrafi olarak saçılmış noktalar arasında mesafe, zaman gibi kısıtlara bağlı olarak araç sayısı kadar eniyilenmiş rota oluşturulmasını hedeflemektedir. Ele aldığı kısıtlara bağlı olarak Araç Rotalama Problemi yıllar içerisinde Zaman Pencere Araç Rotalama Problemi, Okul Servisi Rotalama Problemi, Yer Seçimi Rotalama Problemi gibi çeşitlenmeler göstermiştir. Bu kapsamda Yer Seçimi Rotalama Problemi kapsamında, eniyilenmiş rotanın yanında, depo, ara depo veya dolum istasyonu gibi rota üzerine yerleştirilmesi gereken düğüm noktalar için en iyi yere karar verilmektedir. Elektrikli Araç Rotama Problemi ise, yakıt tüketiminin çevresel kaygılar kaynaklı enküçüklenmeye çalışıldığı araç rotalama problemlerinden evrilmiş ve elektrikli araç kullanımına bağlı olarak ortaya çıkan mesafe kısıtı, pil dolum süresi gibi etmenleri dikkate alarak elektrikli araçların en kısa mesafe, en az maliyet, en az enerji tüketimi gibi amaçlar bağlamında eniyilenmiş rotalarda yolculuk etmesini hedeflemektedir.

Bu çalışmada, insan veya yük taşımacılığında elektrikli araçların yaygınlaşmasındaki zorluklar göz önünde bulundurularak, elektrikli araçların enerji tüketimlerinin

gerçekçi biçimde modellendiği, bu bağlamda kısıtlı menzillerinin verimli kullanıldığı rotalar ve söz konusu rotalar üzerinde enküçüklenmiş sayıdaki dolum istasyonları için en uygun yerlerin belirlenmesine odaklanılmıştır. Çalışma kapsamında, durak düğümlerine ek olarak yol ağındaki kavşakların da düğüm olarak ele alındığı ve araç hareket dinamiğinin üç boyutlu yol geometrisi, yolcuların düğüm noktası bazlı iniş ve biniş talepleri, ve önceden tanımlı hız profillerine bağlı olarak gözetilmesiyle enerji tüketiminin gerçekçi biçimde belirlendiği Ara Düğümlü Elektrikli Araç Yer Seçimi ve Rotalama Problemi tanımlanarak, elektrikli araçlar için dolum istasyonu yerlerinin belirlendiği rotaların önerilmesi amaçlanmıştır. Geliştirilen model kapsamında, rotalama ve dolum istasyonu yer seçiminde amaç fonksiyonunun önemine dikkat çekmek için enerji tüketimi, maliyet, rota uzunluğu ve yolculuk süresi olmak üzere farklı amaç fonksiyonları önerilmiştir. Literatürdeki Elektrikli Araç Yer Seçim Rotalama problemlerinde göz ardı edilen araç hareket dinamiği bazlı enerji tüketiminin dikkate alınmasıyla, yol geometrisi, araçların duraklara veya kavşaklara yaklaşırken hızlanma ve yavaşlanma davranışı, yolcu talebi gibi parametrelerin enerji tüketimine, dolayısıyla eniyi rota ve eniyi dolum istasyonu yerine etkisi değerlendirilmiştir.

Geliştirilen model, durak/kavşak/bağ sayısı, yolcu talebi, düğüm noktası yükseklik (kot) değerleri gibi özellikler ağ özelinde gözetilecek şekilde (i) sıklıkla kullanılan örnek ağlar; (ii) orta ölçekli gerçek bir ağ; ve (iii) büyük ölçekli gerçek bir ağ örnekleri için irdelenmiştir. Sıklıkla kullanılan örnek ağlar kapsamında Nguyen-Dupuis ve Sioux-Falls ağları mevcut başlangıç-bitiş talepleri ile, Sioux-Falls ağı için bağ eğim değerleriyle ele alınmıştır. Orta ölçekli gerçek ağ olarak İstanbul Teknik Üniversitesi Ayazağa Yerleşkesi yol ağı ele alınarak, söz konusu ağda günde sırasıyla 33 ve 43 çevrim yapan lojman ve öğrenci mekik servislerine odaklanılmıştır. Yeşil yerleşke vizyonuna sahip üniversitede mevcut koşullara uygun olacak şekilde mekik servislerinin elektrikli araçlarla yenilenebilmesi hedefiyle ağda bulunan mekik servis durakları için servis özelinde toplanan yolcu indi-bindi verileri kullanılarak, bağ eğimleri ile yerleşke içi trafik koşullarına göre hız profilleri belirlenmiştir. Büyük ölçekli gerçek ağ örneği olarak, ulaşımın faytonlar veya bisikletlerle sağlandığı Marmara Denizi'nde bulunan Büyükkada belirlenerek, önerilen modelin büyük bir ağdaki başarımlı değerlendirilmesini yapmanın yanında, ada içi ulaştırmasına sürdürülebilir ve çevre dostu bir öneride bulunmak amaçlanmıştır. Adalılar için günlük hayatı zorlaştırabilen Büyükkada'nın engebeli arazisinin geri kazanımlı frenleme, dolayısıyla enerji tüketimi üzerine etkisi ayrıca değerlendirilmiştir.

Bağ özelinde elde edilen kesin çözümler topolojik özellikler, düğüm yolcu talepleri, bağ eğimleri gibi ağ özellikleri, enerji tüketimi, araç, enerji ve dolum istasyonu maliyetlerini içeren toplam maliyet, rota uzunluğu ve yolculuk süresi gibi birçok açıdan değerlendirilmiştir. Bu kapsamda, farklı enküçükleme amaç fonksiyonlarına göre farklı rotalama ve dolum istasyonu yerleşimi sonuçları elde edilmesiyle, ele alınan örnek özelliklerine özgü uygun amaca odaklanmanın önemi vurgulanmıştır. Bağ eğim değerlerinin dikkate alınmadığı, dolayısıyla enerji tüketiminin katedilen mesafeye bağlı olduğu ve sonuç olarak tek bir enküçüklenmiş rota ve dolum istasyonu yerleşimi elde edilen Nguyen-Dupuis ağı dışındaki tüm örneklerde, enerji tüketimi ve toplam maliyeti enküçükleyen rota ile rota mesafesini ve yolculuk süresini enküçükleyen rota olmak üzere iki farklı orta ve dolum istasyonu yerleşim planı çözümü elde edilmiştir. Bu kapsamda önerilen söz konusu iki rota karşılaştırıldığında, enerji tüketiminin %24, toplam maliyetin %5, toplam rota mesafesinin %26 ve ağda geçirilen toplam sürenin %10 artabileceği ortaya konmuştur. Böylece enerji tüketimi

ve rota mesafesi arasında enerji tüketiminin küçüklenirken, katedilen mesafenin arttığı, dolayısıyla dolum istasyonu sayısı, söz konusu istasyonların yerleşimi ve söz konusu istasyonlardaki dolum miktarının değişiklik gösterdiği bir ödünleşim olduğuna dikkat çekilmiştir.

Tüketilen ve geri kazanılan enerjinin yükseklik (kot) değişimi, bir diğer deyişle bağ eğimleriyle doğrudan ilgili olduğu eklenik net enerji tüketimi çizelgeleriyle sunulurken, dolum istasyonu yerlerinin yükseklik (kot) değerindeki ve buna bağlı enerji tüketimindeki ani artıştan etkilendiği ortaya konmuştur. Elde edilen sonuçlar ışığında; azalan eğime sahip her bağda enerjinin geri kazanılmadığının, enerjinin geri kazanılabildiği bağlarda ise geri kazanım büyüklüğünün frenleme verimiyle sınırlandırıldığının altı çizilmiştir. Enerji tüketimi ve geri kazanımı eniyilenmiş rotalar özelinde incelendiğinde, enerji tüketiminin enküçüklendiği rotaların her zaman için enerji kazanımının en yüksek olduğu rotalar olmadığı, kimi örneklerde yüksek tepelerde yolculuk etmekten kaçınmayarak enerji kazanımının arttığı, buna bağlı olarak rota mesafesinin de kısaldığı, ancak enerji tüketiminin arttığı görülmüştür.

Araç ağırlığının araç hareket dinamiğine, bunun ardılı olarak enerji tüketimine etkisi göz önünde bulundurularak yolcuların inme ve binme taleplerine bağlı araç içi yolcu sayısının bağlardaki enerji tüketimine etkisinin ortaya konması amacıyla, orta ve büyük ölçekli örnek ağlarda yolcu taleplerinin dikkate alındığı ve göz ardı edildiği senaryolar için çözümler elde edilmiştir. Sonuçlar, net yolcu taleplerinin göz ardı edilmesiyle toplam ve bağ bazındaki enerji tüketim değerlerinin sırasıyla %10 ve %34 daha az hesaplandığını göstermiştir.

Durak noktaları gibi yalnızca uğranması zorunlu düğümlerin ele alındığı geleneksel araç rotalama problemlerinden farklı olarak, kavşak noktalarının da yol ağı kapsamında ele alınmasının toplam geçirilen süre, ağ tutarlılığı ve ağ grafiğinin merkezilik gibi topolojik özelliklerine etkisi incelenmiştir. Yoldaki kavşakların, dolayısıyla kavşak yaklaşımlarındaki hız azaltımının göz ardı edilmesiyle ağda geçirilen sürenin %10 daha az hesaplandığı ortaya konmuştur. Bununla birlikte kavşaklar göz ardı edilerek düğümler arası bağlantının basitleştirilmesiyle, gerçek ağ için uygun olmayan rota seçeneklerinin eniyilenmiş rota çözümü kapsamında sunulduğu görülmüştür. Ağdaki düğümleri nitelendirmek ve nicelendirmek adına özvektör merkeziliği değerleri karşılaştırıldığında, ağ grafiğindeki düğüm noktalarının özvektör merkezilik bağlamında azımsandığı veya çoğumsandığı, sonuç olarak ağın topolojik yapısının farklı ele alındığı orta konmuştur.

Araç rotalama problemleri kapsamında kavşak düğümlerinin de modellenmesi, trafik tıkanıklığını irdelemek ve trafik akımını akıllı denetim sistemleri ile yönetebilmek adına bir alan açmıştır. İlerleyen çalışmalarda Dinamik Rotalama Problemi'ne trafik ışık denetimli veya denetimsiz kavşaklar için trafik durumundaki değişim bağlamında odaklanılması öngörülmektedir. Ayrıca, hesaplama yükünün azaltılması amacıyla kesin çözüme ek olarak sezgisel yöntem ile çözüm geliştirilmesi de ilerleyen çalışma hedeflerindendir.



1. INTRODUCTION

The fact that road transportation is dominated by Internal Combustion Engine Vehicles (ICEVs) increases the concerns on the issues related the public health including air pollution, and climate change based on the greenhouse gas emissions, as externalities of transportation sector. The majority of environmental concerns due to transport is related to air pollution. Greenhouse gases that trap heat in the atmosphere, and, hence, contribute significantly to the global warming of the world are composed of Carbon Dioxide (CO₂), Methane (CH₄), Nitrous Oxide (N₂O), and fluorinated gasses. CO₂, as the primary greenhouse gas emitted through human activities by combustion of fossil fuels for energy and transportation, emitted by the transport sector accounts for around 34.2% of total emissions and around 27.7% of greenhouse gas emissions in US in the year 2017 (Url-1). Fig. 1 that shows the change in total Green House Gases (GHGs) emissions and the road transportation share in total between the years 1990-2017 in Europe, reveals the increment in the share of road transportation in terms of total GHGs emissions. Road transportation account for 19% of total GHGs emissions in 2017, although total GHGs emissions are decreased by 15% considering the year 1990 (Url-2). Regarding a study on estimating the global warming figures with future scenarios the sectoral contribution of transportation in total net anthropogenic warming in 2000 has been estimated to be around 9%, where the consequent future estimations have shown that the impact of GHGs may increase up to 16% and 20%, respectively in the years 2050 and 2100 (Skeie et al., 2009).

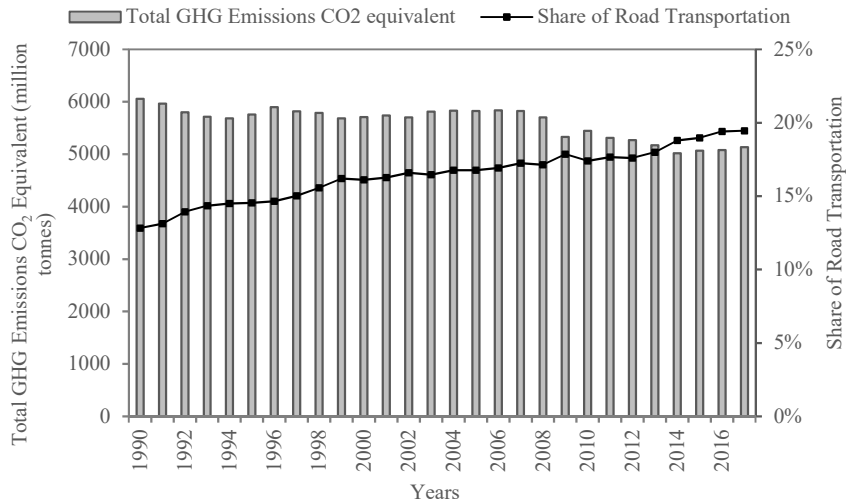


Figure 1.1 : Total GHG CO₂ equivalent and share of road transportation in total, between the years 1990- 2017 in Europe (Url-2).

In addition to the road transport's contribution to the environmental issues, the sector for transportation affects public health by increasing air pollution by burning of fossil fuels, which directly costs around 2 million premature deaths each year and indirectly affects soil, vegetation, and water resources (Uherek et al., 2010). Figures for the year 2017 reveal that the share of transportation in the total air pollution of Europe is around 17% due to the gases, including the Nitrogen Oxides (NOX), Non-Methane Volatile Organic Compounds (NMVOC), Particulate Matter 2.5 and 10 (PM2.5, PM10), Sulphur Oxides (SO_x), and Carbon Monoxide (CO) (Url-3).

Given the environmental concerns regarding especially the consumption of non-renewable energy sources and the effects of GHGs as summarized above, the main feature initiating and supporting the introduction of alternative vehicle technologies including Hybrids and Electric Vehicles to the market have therefore been due to their reduced-emission or emission-free characteristics when they are in use. Figure 1.2 shows the vehicle technologies on the purpose of reduce emissions, where the Internal Combustion Engine Vehicles as conventional vehicle type use fossil fuels; hybrids that enable to reduce emissions have an electric battery in addition to the internal combustion engine; and the electric vehicle types including pure electric vehicles and battery electric vehicles ensure an emission-free operation according to the tank-to-wheel perspective.

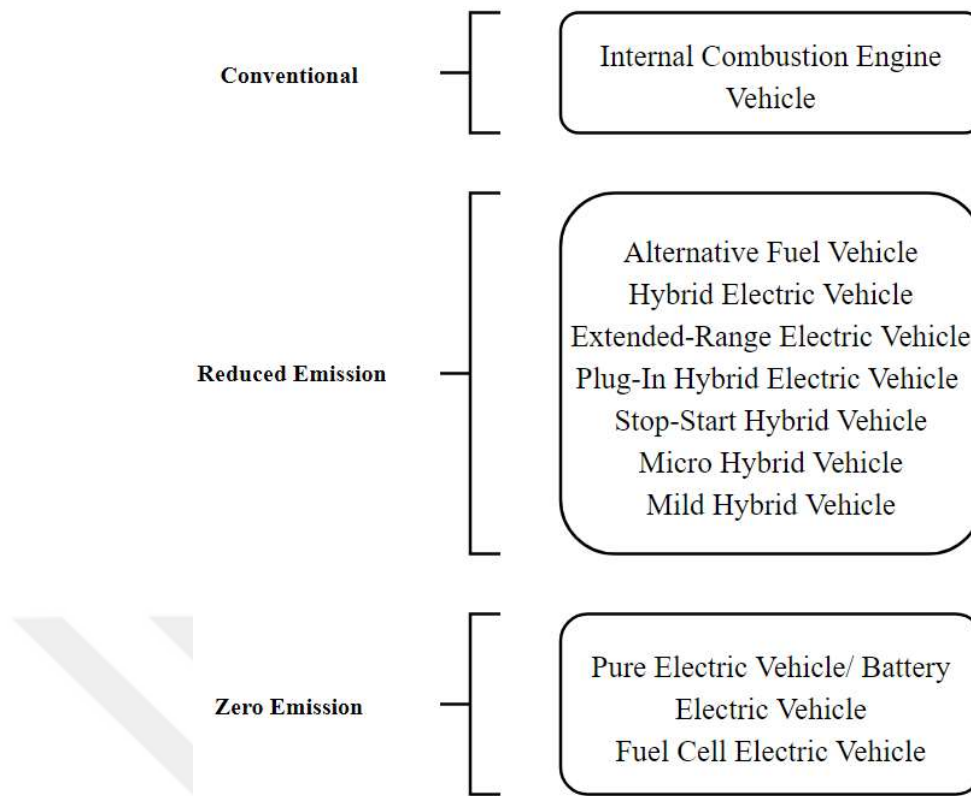


Figure 1.2 : Vehicle technologies on the purpose of reduce emissions.

Considering that the CO₂ emissions from EVs are highly related with the grid that vehicles are recharged at, the sources of cleaner energy are likely to result in more decarbonized transportation with EVs. However, EVs prevent the tailpipe emissions, at least, regardless of the electricity production process. Hence, in comparison to ICEVs that burn fossil fuels, such as coal, natural gas, and oil, the EVs can improve the local air quality, and specifically can reduce the well to wheel CO₂ emissions by around 50% using electricity as the fuel type (Denton, 2016). Additionally, the heat that is wasted during the braking process in ICEVs can be converted to electricity and stored in the battery using a regenerative braking systems in EVs.

1.1 Motivation of Research

Neglecting their relatively lower market share (IEA, 2017), and the battery infrastructure technology in-develop in order to provide longer driving range and quicker recharging, Electric Vehicles (EVs) are promising vehicle technologies to diminish the environmental effects of transportation by enabling the usage of renewable energy sources instead of fossil fuels. The issues related to electro-mobility (Liberto et al., 2018) in terms of longterm planning, face with the challenges on

infrastructure requirement considering the limited energy capacity of batteries and recharging rate of stations, according to the current technologies. In this context, the routing plan of EVs together with the settlement of recharging stations significantly affects the feasibility of preferring EVs. This study has consequently been motivated by the major challenges of using EVs in goods and/or people transport: to utilize effectively the limited driving range and decide the optimal locations for the minimum number of recharging station within the context of determining battery discharging accurately.

1.2 Research Objective

The present study aims to provide routing plans for Electric Vehicle (EV) fleets considering the actual battery discharging characteristics determined respecting to the vehicle motion dynamics cooperated with 3-dimensional road geometry, passenger getting on and getting off demands, and the pre-defined speed profiles, where the network graph expanded by explicit consideration of intersections. According to the different objective functions including minimizing energy consumption, cost, distance travel, and travel time, the significance of the objective to the routing and location decision is investigated. For this purpose, optimal routes and recharging station locations are sought for number of numerical instances including frequently employed test instances, a medium-scale real case instance, and a large-scale real case instance. Model-based exact solutions are evaluated in terms of battery discharging characteristics, road geometry, overall cost, and covered distance where the effects of the change in network topology by explicitly considering the intersection nodes is analyzed, as well, considering the travel time, network consistency and node centrality.

1.3 Scope of Thesis

Within the scope of this thesis, routing problem and location model is combined on the road network scanning all the intersections and their connectivity, considering the energy consumption and recovery characteristics of EVs. Regarding to the limitations on vehicle battery, vehicle passenger capacity, and, maximum travel time, figures including energy consumption, total cost, distance travel and travel time are obtained respecting to the routing solution. Exact solutions to the model formulation have further been obtained using set of instances that is designed for small, medium and

large-scale real networks, where the 3-dimensional road geometry, passenger getting on and getting off demands, average speed and acceleration values are determined network specific.

1.4 Organization of Thesis

This thesis is organized into six chapters starting with the definition of the motivation, objective and scope of this study in first chapter. Following chapter deals with two main sub-sections on the fundamentals of Vehicle Routing Problem and vehicle motion dynamics, where the characteristics Vehicle Routing Problem and its variants are explained in detail focusing on their mathematical background, and fuel/energy requirement of both internal combustion engine and electric vehicles are described together with the vehicle motion dynamics. Chapter 3 provides a general overview to evaluation of Electric Vehicle Routing Problem and discussion on the sub-problems of Electric Vehicle Routing Problem in terms of objective functions, and problem specific characteristics with the limitations and possible future researches. The description and the formulation of the proposed methodology together with the features of the instance sets where the optimal solutions are sought, is given in Chapter 4. Results from the solution of each instance sets are discussed separately in Section 5. Thesis is concluded with the findings and future research in the final section, 6.



2. FUNDAMENTALS OF VEHICLE ROUTING AND VEHICLE MOTION DYNAMICS

In order to meet the needs that have arisen with real life problems of passenger and goods transports, Vehicle Routing Problem (VRP) and its several variants have been proposed in conjunction with the advances in optimization. The vehicle fleet characteristics (Golden et al., 1984), the number of depots (Rego and Roucairol, 1995; Savelsbergh and Sol, 1998), the time-varying nature of routing (Letchford and Eglese, 1998; Frizzell and Griffin, 1995), time and loading constraints (Laporte et al., 1985; Desrochers et al., 1987), and the functional forms of specific objectives have been the primary features that the extensive number of VRP studies can be clustered around. Last decades, in order to improve the fuel economy and/or deal with the limited range of alternative fuel vehicles, vehicle motion dynamics are incorporated to the VRP studies, considering the hazardous impacts of road transportation on environment.

2.1 Definition and Evolution of Vehicle Routing Problem

Distribution management can be handled efficiently by considering strategic, tactical and operational aspects in decision-making. In this context various routing problems, including shortest path problem, Chinese postman problem, rural postman problem, dial-a-ride service route problem, arc routing problem, travelling salesman problem, and vehicle routing problem, are introduced to handle different cases (Bodin et al., 1983).

Basic routing problem can be defined to seek low-cost, feasible set of route/s for a given set of geographically scattered nodes (Figure 2.1(a)) and/or arcs that represent customers/cities to be serviced by a vehicle or a fleet of vehicles (Bodin et al., 1983). The basic vehicle routing problem is based on the Travelling Salesman Problem (TSP) and separated into variations according to the structure of the case handled, in terms of constraints, relaxations, parameters, and/or data type.

The TSP that is introduced by mathematician Karl Menger focuses on finding the minimum cost(/distance/time) tour that visits each node only once (Held et al., 1984). Therefore, for a given graph $G = (V, A)$, where $V = \{1, \dots, n\}$ and $A = \{(i, j): i, j \in V, i \neq j\}$ represent respectively the set of nodes and arcs, the TSP turns into seeking a single Hamiltonian cycle, by passing through each node $i \in V$ once, that minimizes

total cost/distance/time (Figure 2.1(b)) (Laporte, 1992). In the case that the TSP handles, there is a cost function involving c_{ij} , in usual corresponding to the cost of traveling from node i to j , which expresses the same trend as the variation of distance and/or time, where the travel speed is assumed to be constant, as usual, and, only one vehicle without a capacity restriction is considered (Figure 2.1(b)). The literature that focuses on TSP is well summarized by Laporte (1992), Held et al. (1984), Rego et al. (2011) and, a comprehensive survey on the cases, in which $c_{ij} \neq c_{ji}$ and called as Asymmetric Traveling Salesman Problem, is presented by Öncan et al. (2009). One of the first formulations of the TSP that is solved for a large-scale case as a pioneer, is established by Dantzig et al. (1954) and is given through (2.1) - (2.6), where the binary decision variable x_{ij} expresses whether arc (i,j) is traveled or not. The objective function (2.1) seeks the cost minimal cycle subject to the degree constraints (2.2) and (2.3) that ensure visiting each node $i \in V$. The assignment matrix X is defined with (2.4), in which the subset S of vertices is employed to prevent subtours where the possible alternatives are given by (i), (ii), and (iii).

$$(TSP) \quad \text{minimize } \sum_{i \neq j} c_{ij} \cdot x_{ij} \quad (2.1)$$

$$\text{subject to} \quad \sum_{j=1}^n x_{ij} = a_i = 1 \quad i=1, \dots, n \quad (2.2)$$

$$\sum_{i=1}^n x_{ij} = b_j = 1, \quad j=1, \dots, n \quad (2.3)$$

$$X = (x_{ij}) \in S \quad (2.4)$$

$$x_{ij} \in \{0,1\}, \quad i, j=1, \dots, n, \quad i \neq j \quad (2.6)$$

$$(i) \ S = \{(x_{ij}) : \sum_{i \in H} \sum_{j \notin H} x_{ij} \geq 1 \text{ for every nonempty proper subset } H \text{ of } V\}$$

$$(ii) \ S = \{(x_{ij}) : \sum_{i \in N} \sum_{j \in N} x_{ij} \leq |N| - 1 \text{ for every nonempty subset } N \text{ of } \{2, 3, \dots, n\}\}$$

$$(iii) \ S = \{(x_{ij}) : u_i - u_j + p \cdot x_{ij} \leq p - 1 \text{ for } 2 \leq i \neq j \leq n\}$$

Among the choices of S , (i) and (ii) consist of nearly 2^n subtour breaking constraints, in which the size of the problem increases exponentially, whereas (iii) that is proposed by Miller et al. (1960) contains only $n^2 - 3n + 2$ constraints, where u_i ($i=1, \dots, n$) is an arbitrary real number and, p represents the upper limit on the number of nodes to be visited (Golden et al., 1977).

Multiple Travelling Salesman Problem (mTSP) is a generalization of the TSP in which m salesmen/vehicles serve customers by starting and ending their tour in a specific

depot where each customer is visited only once by one vehicle and, the capacity of vehicles is neglected (Figure 2.1c). The mTSP can be obtained by considering $a_1=b_1=m$ and $a_i=b_j=1$ for $i \neq 1$ and $j \neq 1$ in the (TSP) formulation (Golden et al., 1977). In this context, considering the notation used in the model for the TSP an integer linear programming formulation for the mTSP is given through (2.7) to (2.13) as Bektas (2006) notes in a detailed review on mTSP (Bektas, 2006). The mTSP presented aims to find cost optimal m routes with the objective given in (2.7), by visiting each node, where $\{1\}$ is the depot node. Constraints (2.8) and (2.9) guarantee the assignment of m salesmen/vehicles starting from and ending at the depot, where (2.10) and (2.11) match respectively the constraints (2.2) and (2.3) that ensure each node is passed through once. (2.12) is given as the subtour elimination constraint as introduced by Miller et al. (1960).

$$(mTSP) \quad \text{minimize} \quad \sum_{i=1}^n \sum_{j=1}^n c_{ij} \cdot x_{ij} \quad (2.7)$$

$$\text{subject to} \quad \sum_{j=2}^n x_{1j} = m \quad (2.8)$$

$$\sum_{j=2}^n x_{j1} = m \quad (2.9)$$

$$\sum_{i=1}^n x_{ij} = 1, j=2, \dots, n \quad (2.10)$$

$$\sum_{i=1}^n x_{ij} = 1, j=2, \dots, n \quad (2.11)$$

$$u_i - u_j + p \cdot x_{ij} \leq p - 1 \quad \text{for } 2 \leq i \neq j \leq n \quad (2.12)$$

$$x_{ij} \in \{0, 1\}, \quad i, j = 1, \dots, n, \quad i \neq j \quad (2.13)$$

The classical Vehicle Routing Problem (VRP) is an NP-hard problem that generalizes the TSP, where unlimited capacitated vehicles are considered, so that, it requires considerably more computational efforts to be solved when compared to the TSP for the same problem size (Laporte, 2009). VRP can also be seen as a restricted version of the mTSP, by considering the capacity constraint for vehicles (Bektas, 2006). The VRP focuses on finding cost optimal m vehicle routes to serve geographically scattered cities or customers, satisfying some side constraints. As the side constraints increase, the VRP varies to branches (Figure 2.2). Classical VRP is set up in a framework, in which: (1) each route starts and ends in pre-specified depot/depots; (2) each city/customer is visited exactly by a single vehicle; (3) the total customer demand on a route does not exceed the vehicle capacity, Q ; and, (4) route lengths are in the range of distance limit, L (Figure 2.1(d)) (Laporte, 2009). The variations of the VRP with

only the capacity restriction and only the distance restriction are called respectively the Capacitated Vehicle Routing Problem (CVRP) and the Distance constraint Vehicle Routing Problem.

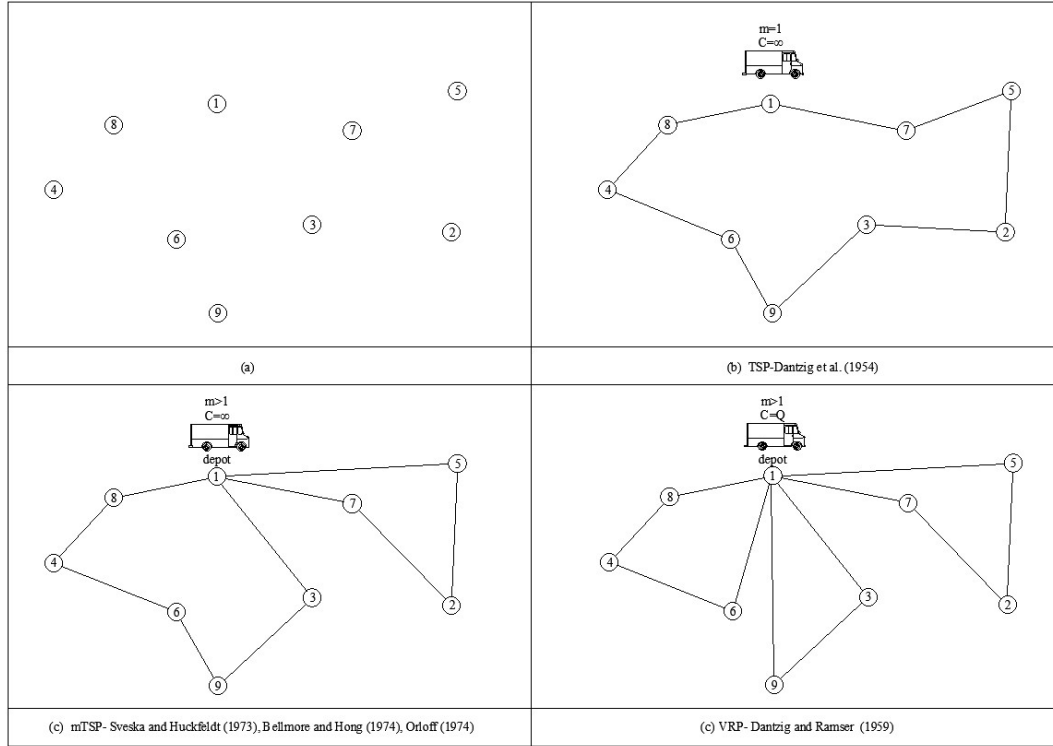


Figure 2.1 : (a) Set of nodes to be visited, (b) Illustration of TSP, (c) Illustration of mTSP, (d) Illustration of VRP.

VRP existed for the first time in the optimization literature as the “Truck Dispatching Problem” as introduced by Dantzig and Ramser (1959) where Clarke and Wright (1964) are the first who have handled more than one vehicle in the routing problem (Eksioglu et al., 2009). Several variants of VRP have been introduced in years considering different constraints, parameters, and data types that can be found in the taxonomic review of Eksioglu et al. (2009), and where the feature and variations of the VRP are well summarized by Cordeau et al. (2007), Laporte (2009), and Laporte (1992b) as well. Figure 2.2 summarizes the evolution of the VRP by focusing especially on the variants that are related to this study. Consideration of visiting customer nodes within a time-window and different types of vehicles are incorporated respectively to VRP with Time Windows and Heterogeneous VRP formulations. School Bus Routing Problem differs from the VRP, where ending a route at a depot is not restricted. The location of depot(s) is sought in Location Routing Problem and, the

fuel consumption of a vehicle is analyzed in details by Pollution Routing Problem formulations in order to minimize the emission effects of transportation.

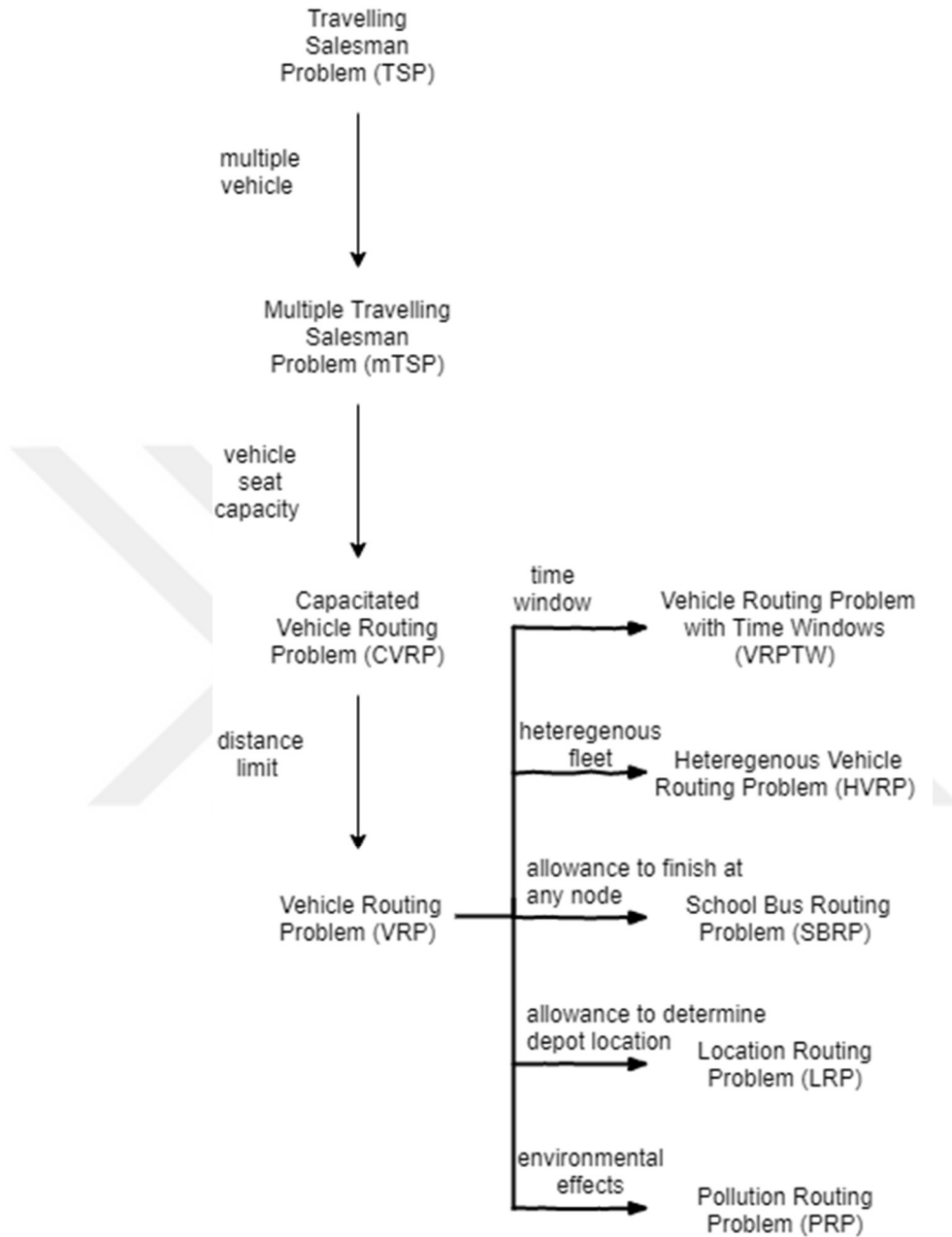


Figure 2.2 : Basis and variants of VRP.

VRP can be generalized with the formulation proposed by Golden et al. (1977) that specifies the vehicle routed on (i,j) among m vehicles by developing three-index vehicle routing model, considering the vehicle capacity, and the route length limit. The VRP can be defined using graph theory, i.e., by $G=(V,A)$, that is introduced previously in this chapter. Customer demand at each node $i \in V$, and the capacity of each vehicle

$k \in K = \{1, \dots, m\}$ are denoted respectively by d_i and Q_k . The route length is limited with the maximum travel time of vehicle $k \in K$, T_k , by tracking the travel time of the vehicle between nodes (i to j), t_{ij}^k , and the service time of vehicle to deliver/collect at node $i \in V$, s_i^k . VRP seeks to minimize total distance cost, as given by (2.14) using the decision variable x_{ij}^k in order to decide whether vehicle k travels from node i to j or not. (2.15) and (2.16) are the assignment constraints that ensure each customer is visited once, and only once. The flow conservation is provided using (2.18), where the constraint (2.19) guarantees that the vehicle capacity is never exceeded by customer visits. Constraint (2.20) controls the maximum allowable travel time, where (2.21) and (2.22) ensure that the available number of is not exceeded. Subtour elimination constraint (2.23) can be specified using any of the choices, i.e., (i), (ii), or (iii), that are mentioned above. Golden et al. (1977) also have remarked that constraints (2.16) and (2.22) are redundant because of the constraint (2.15) with (2.18) and (2.18) with (2.21), respectively, and, hence can be removed from the formulation.

$$\text{(VRP)} \quad \text{minimize} \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^m c_{ij} \cdot x_{ij}^k \quad (2.14)$$

$$\text{subject to} \quad \sum_{i=1}^n \sum_{k=1}^m x_{ij}^k = 1 \quad j=2, \dots, n \quad (2.15)$$

$$\sum_{j=1}^n \sum_{k=1}^m x_{ij}^k = 1 \quad i=2, \dots, n \quad (2.16)$$

$$\sum_{i=1}^n x_{ip}^k - \sum_{j=1}^n x_{pj}^k = 0 \quad k=1, \dots, m, p = 1, \dots, n \quad (2.18)$$

$$\sum_{i=1}^n d_i \cdot \left(\sum_{j=1}^n x_{ij}^k \right) \leq Q_k \quad k=1, \dots, m \quad (2.19)$$

$$\sum_{i=1}^n s_i^k \cdot \sum_{j=1}^n x_{ij}^k + \sum_{i=1}^n \sum_{j=1}^n t_{ij}^k \cdot x_{ij}^k \leq T_k \quad k=1, \dots, m \quad (2.20)$$

$$\sum_{j=2}^n x_{1j}^k \leq 1 \quad k=1, \dots, m \quad (2.21)$$

$$\sum_{i=2}^n x_{i1}^k \leq 1 \quad k=1, \dots, m \quad (2.22)$$

$$X = (x_{ij}) \in S \quad (2.23)$$

$$x_{ij}^k \in \{0, 1\} \quad \text{for all } i, j = 1, \dots, n, k = 1, \dots, m \quad (2.24)$$

Problems in vehicle routing involve not only determining the paths of a vehicle fleet but also deciding the fleet size with vehicles of different capacities and cost values, referred to as Mixed Fleet VRP or Heterogeneous Fleet VRP (HVRP). HVRP as an extension of the VRP, in which the fleet composition is decided, is well summarized in a review paper by Koç et al. (2016). Among the variations that consider different

fleet sizes, as limited/unlimited, fixed costs, and routing costs, HVRP can be generalized with the following formulation as Baldaci et al. (2008) proposed that is originated from the formulation of Gheysens et al. (1984) (Baldaci et al., 2008; Koç et al., 2016). Considering the set of vehicle types as $H=\{1,\dots,l\}$, the HVRP is defined as a variant of the VRP. The fixed purchasing cost, traveling cost, and the capacity of each vehicle type $h \in H$ are denoted respectively with f^h , c_{ij}^h , and Q^h . The number of vehicles for each type $h \in H$ is represented by m_h , where the decision variables are introduced to decide whether a vehicle type h travels from i to j with x_{ij}^h or not, and to trace the flow of goods from i to j , with S_{ij} . Using an HVRP formulation, minimization of the overall costs composed by fixed vehicle purchasing and traveling costs (2.25) are aimed. Constraints (2.26) and (2.27) guarantee to serve each customer exactly once while respecting the flow conservation. Fleet size is considered using the constraint (2.28) Constraint (2.29) tracks the flow of goods satisfying the customer demands and, constraint (2.30) controls the vehicle capacity.

$$(HVRP) \quad \text{minimize} \quad \sum_{h=1}^l f^h \cdot \sum_{j=1}^n x_{1j}^h + \sum_{h=1}^l \sum_{i=1}^n \sum_{j=1}^n c_{ij}^h \cdot x_{ij}^h \quad (2.25)$$

$$\text{subject to} \quad \sum_{h=1}^l \sum_{i=1}^n x_{ij}^h = 1 \quad (j=2,\dots,n) \quad (2.26)$$

$$\sum_{i=1}^n x_{ip}^h - \sum_{j=1}^n x_{pj}^h = 0 \quad (h=1,\dots,l; p=2,\dots,n) \quad (2.27)$$

$$\sum_{j=2}^n x_{1j}^h \leq m_h \quad (h=1,\dots,l) \quad (2.28)$$

$$\sum_{i=1}^n y_{ij} - \sum_{i=1}^n y_{ji} = d_j \quad (j=2,\dots,n) \quad (2.29)$$

$$d_j \cdot x_{ij}^h \leq y_{ij} \leq (Q^h - d_i) \cdot x_{ij}^h \quad (i,j=1,\dots,n), (h=1,\dots,l), i \neq j \quad (2.30)$$

$$y_{ij} \geq 0 \quad (i=1,\dots,n), (j=1,\dots,n), i \neq j \quad (2.31)$$

$$x_{ij}^h \in \{0,1\} \text{ for } \forall i,j,h, i \neq j \quad (2.32)$$

In order to ensure visiting each customer $i \in V$ within a pre-defined time interval $[a_i, b_i]$ that is bounded by the earliest (a) and the latest (b) times for serving to a present customer, the time window constraint is added to the VRP formulation, where $a_i=0$ and $b_i=\infty$, and Vehicle Routing Problem with Time Window (VRPTW) is introduced, as summarized in (Baldacci, 2012; Cordeau, 2007; Braysy and Genreau, 2005). The following constraints given through (2.33) to (2.35) can be incorporated to the VRP formulation in order to add time window restriction to the vehicle dispatching problem (Bodin et al. 1983), where t_i represents the arrival time at node i . (2.33) links the arrival

time at a customer node to the service time at the previous customer location to determine the travel time between customers, where (2.34) starts the timer from zero. Time window constraint is imposed to the problem by (2.35).

(VRPTW)

(VRP) +

$$t_j = \sum_{k=1}^v \sum_{i=1}^n (t_i + s_i^k + t_{ij}^k) \quad (j=1, \dots, n) \quad (2.33)$$

$$t_1 = 0 \quad (2.34)$$

$$a_j \leq t_j \leq b_j \quad (j=2, \dots, n) \quad (2.35)$$

The school bus routing problem (SBRP), which is evolved from the traveling salesman problem and is a variant of the CVRP with no necessity for tours to end at the origin node, is an NP-hard optimization problem as well. In this context, SBRP optimization seeks the cost optimal paths, rather than tours, and hence is accepted as a version of the open vehicle routing problem (Bektaş and Elmastaş, 2007). Studies concentrating on the SBRP that date back to fifties have been initiated with the motivation of solving a real life problem and are pioneered with article of Newton and Thomas (1969). SBRP that is well discussed in (Park and Kim, 2010) can simply be formulated to optimize the route planning and/or the scheduling for a fleet of busses to pick-up users from various stops and to deliver them to their destinations subject to a number of constraints, including bus capacities, route lengths, traveling times, allocation of bus stops to routes, and etc. An integer programming formulation that is proposed by Bektaş and Elmastaş (2007) for the SBRP is presented below through (2.36) to (2.46). SBRP is defined where graph G is expanded to $G' = (V', A')$, in which the set V' is composed of the set V , and the dummy node d to represent an arriving node for all paths connected with ($V' = V \cup \{d\}$). Objective function (2.36) seeks the minimal-cost path that is composed of travel and vehicle costs. Constraints (2.37) and (2.38) limit the number of vehicles assigned, and (2.39) and (2.40) ensure that each stop node is visited exactly once. Considering vehicle seat capacity is incorporated using constraints through (2.41) to (2.43), where subtour elimination is ensured by (2.41). The maximum allowable travel length is controlled with constraints through (2.44) to (2.46).

$$(SBRP) \quad \text{minimize } \sum_{i \in V'} \sum_{j \in V'} c_{ij} \cdot x_{ij} + f \cdot m \quad (2.36)$$

$$\text{subject to} \quad \sum_{i \in V \setminus \{0\}} x_{1i} \leq m \quad (2.37)$$

$$\sum_{i \in V \setminus \{0\}} x_{id} \leq m \quad (2.38)$$

$$\sum_{j \in V \setminus \{0\} \cup d} x_{ij} = 1 \quad i = 2, \dots, n \quad (2.39)$$

$$\sum_{i \in V} x_{ij} = 1 \quad j = 2, \dots, n \quad (2.40)$$

$$u_i - u_j + Q \cdot x_{ij} + (Q - d_i - d_j) \cdot x_{ji} \leq Q - d_j \quad i, j = 2, \dots, n, i \neq j \quad (2.41)$$

$$u_i \geq d_i \quad i = 2, \dots, n \quad (2.42)$$

$$u_i - d_i \cdot x_{li} + Q \cdot x_{li} \leq Q \quad i = 2, \dots, n \quad (2.43)$$

$$v_i - v_j + (L - d_{id} - d_{lj} + d_{ij}) \cdot x_{ij} + (L - d_{id} - d_{lj} - d_{ij}) \cdot x_{ji} \leq T - d_{id} - d_{lj} \quad i, j = 2, \dots, n, i \neq j \quad (2.44)$$

$$v_i - d_{li} \cdot x_{li} \geq 0 \quad i = 2, \dots, n \quad (2.45)$$

$$v_i - d_{li} \cdot x_{li} + L \cdot x_{li} \leq L \quad i = 2, \dots, n \quad (2.46)$$

$$x_{ij} \in \{0, 1\} \quad \forall i, j \in V' \quad (2.47)$$

The Location routing problem (LRP) combines the standard location problem, where the optimal depot location to serve all customers is sought, and the VRP, with the purpose of not only planning the path to visit/serve all the customers, but also finding the departure node/s for the paths. A comprehensive review on the LRP is presented by Nagy and Salhi (2007). An LRP formulation that aims to find the optimal depot location and the routing of m vehicles to serve, in a cost minimized way, is adopted from Laporte and Nobert (1981) and given in the following.

$$(LRP) \quad \text{minimize } \sum_{i < j} \sum d_{ij} \cdot x_{ij} + \sum_{k=1}^n f_k \cdot y_k \quad (2.48)$$

$$\text{subject to} \quad \sum_{k=1}^n y_k = 1 \quad (2.49)$$

$$\sum_{i < k} x_{ik} + \sum_{j > k} x_{kj} = 2 + 2(m-1) \cdot y_k \quad k = 1, \dots, n \quad (2.50)$$

$$\sum_{\substack{i < j, \\ i, j \in S}} x_{ij} \leq |S| - 1 + (m-1) \cdot \sum_{k \in S} y_k \quad \forall S \subseteq \{1, \dots, n\} \text{ and } 2 \leq |S| \leq n-2 \quad (2.51)$$

$$x_{ij} = 0, 1, 2 \quad \forall i < j; y_k = 0, 1 \quad \forall k = \{1, \dots, n\} \quad (2.52)$$

Due to the increasing concerns on the hazardous impacts of road transportation on environment, which is discussed in details in Section 1.1, researches involving VRP show tendency on environmentally-friendly options to route vehicle fleets. Kara et al. (2007) attracted attention on the fuel consumption, and, hence the cost differences between two nodes and proposed an integer programming formulation for an energy

minimized VRP by simply relating the fuel consumption with the weight of the vehicle that changes by loading/unloading at customer nodes.

Jabali et al. (2012) focus to the VRP over an environmental point of view as well, and introduce Emissions-based Time-Dependent Vehicle Routing Problem formulation that seeks to minimize CO₂ emissions in instead of travel times or distance. The cost externalities of transportation considering the fuel consumption is handled as well by Bektaş and Laporte (2011) by developing an energy based model for vehicle routing that is referred to as the Pollution Routing Problem (PRP), in which cost of GHG emissions as well as the operational costs composed of drivers' wages and fuel consumptions are aimed to be minimized.

2.2 Vehicle Motion Dynamics

The power and energy required to drive a vehicle is associated with the tractive force, which refers to the force from propulsion unit, i.e., electric motor for EVs (Iqbal, 2010). The tractive force produced, F_{tr} , depends on the resisting forces against motion, F_{rm} , including the ones sourced from the resistances of rolling, aerodynamics, and grading. A vehicle can only propel at a desired speed when the traction force overcomes to the resistances against motion. According to Newton's Second Law of Motion involving the change in the momentum, the speed, and hence the acceleration of a vehicle, can be obtained as a function of the tractive force and the resistances against motion. As Newton's Second Law implies, change in vehicle speed, V , over time t , so-called acceleration, a , depends on convenient power corresponding to the net force acting on the vehicle (Iqbal, 2010). Equation (2.53) can be used to obtain the speed differentiation of a vehicle with the mass m with respect to time, where there exists rotational inertia due to the internal rotating elements of the vehicle and, is incorporated to the formulation by ξ .

$$\frac{dV}{dt} = \frac{\sum F_{tr} - \sum F_{rm}}{m + \xi} \quad (2.53)$$

Given the fact that the resistive effects of horizontal maneuvering especially in cases of low speeds can be neglected (Iqbal, 2010), the acting forces on a vehicle are taken into consideration as if the vehicle moves on a straight road section during its entire

tour, where the resistances against the motion, i.e., rolling, aerodynamics, and grade, are represented respectively with F_r , F_a , and F_g as shown in Figure 2.3.

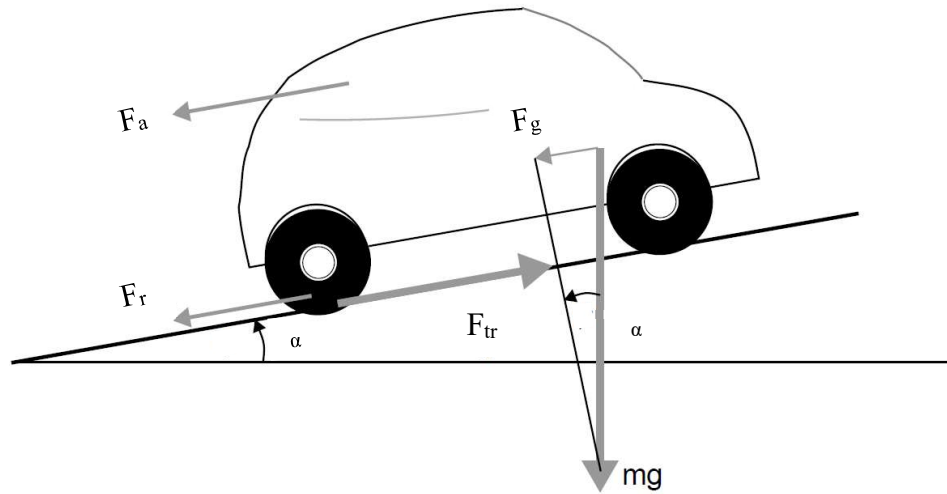


Figure 2.3 : Forces acting on vehicle (Larminie and Lowry, 2003).

Figure 2.2(2) shows the misalignment, a , between the weight on wheel and the normal force occurred in the center of rotation, where these forces are in balance in a perfectly rounded tire (Iqbal, 2010). As vehicle's is deflected along the contact surface on the road, as being flattened, a moment by the rolling resistance is produced due to the displacement of the normal force in the rolling direction considering the asymmetric load distribution on the contact surface as shown in Figure 2.4. (Wong, 2001). A horizontal force, namely the rolling resistance force, F_r , exists in order to provide a balance to rolling resistance moment for a free-rolling tire.

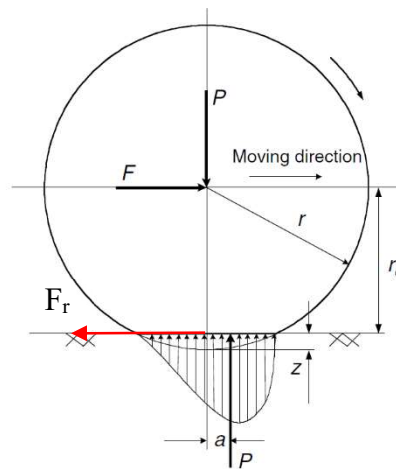


Figure 2.4 : Rolling resistance on wheels (Ehsani et al., 2005).

The rolling resistance force, F_r , can be obtained as a function of the normal force, P , shifting distance, a , and effective radius of tire, r : $F_r = (P \cdot a)/r$. The ratio of F_r to P , in other words of a to r , is referred to as the coefficient of rolling resistance, μ_r . The rolling resistance that a vehicle with the weight m [kg] is exposed to on a road with the slope $\tan(\alpha)$ can be obtained by Equation (2.54), where $\cos(\alpha)$ may be assumed as 1 for small angles and, g represents the gravitational acceleration [m/s^2].

$$F_r = m \cdot g \cdot \mu_r \cdot \cos \alpha \quad (2.54)$$

The coefficient of rolling resistance coefficient, and hence the rolling resistance, is affected by many parameters that can be grouped into two considering the: (i) structure of tire including its construction and materials; and, (ii) operating conditions including the material of the surface material, vehicle speed, and temperature. Since the tire construction is an important determinant of rolling resistance (Wong, 2001), and hence the fuel consumption, remarkable number of researches have focused on developing low-resistance tire structure in terms of both material and surface type in recent years (Ehsani et al., 2005). The deflection of the tire decreases as the inflation pressure of the tire increases and hence, the rolling resistance decreases (Figure 2.5 (a)). Considering the roughness of the road surface, rolling resistance increases from: smooth to rough, in terms of surface material; and, dry to wet in terms of surface condition. In addition, as a significant parameter, the increase on speed results in the increase in rolling resistance (Figure 2.5(b)) (Gillespie, 1992). Because of the complexity from the number of parameters affecting, and as well their joint effects on the coefficient of rolling resistance, empirical models have been proposed to figure out their relationship rather than analytical ones (Wong, 2001).

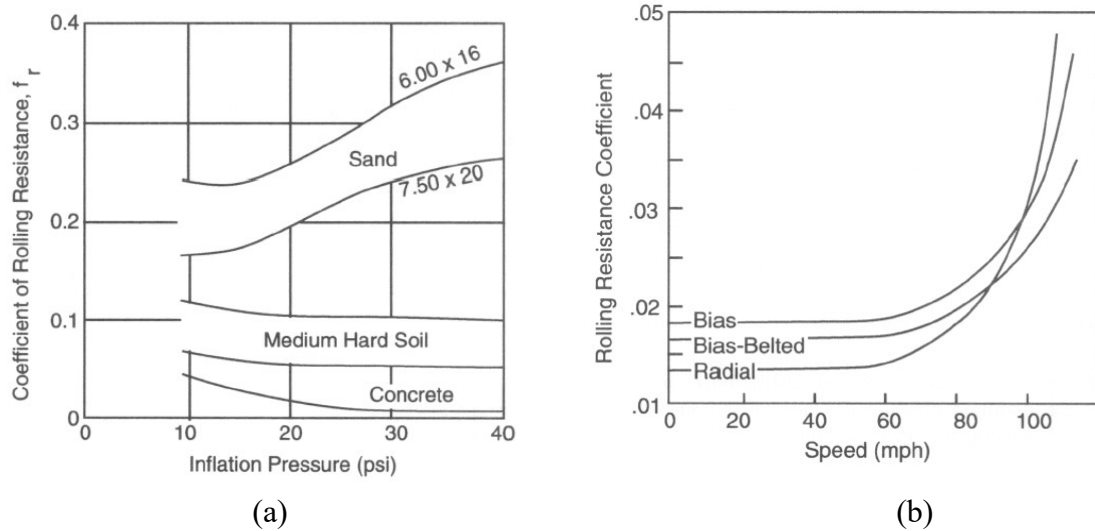


Figure 2.5 : Rolling resistance coefficient changes with (a) inflation pressure and (b) speed (1 mph= 1.609 km/h, 1 psi= 6.895 kPa) (Gillespie, 1992).

The empirical relationships derived to incorporate the effects of driving speed on the coefficient of rolling resistance specific to types of road surface and tire construction are given in Table 2.1.

Table 2.1 : Empirical Relationships between Driving Speed and Coefficient of Rolling Resistance (Wong, 2001).

Rolling resistance coefficient, μ_r	Road and tire type
$0.0136 + 0.40 \cdot 10^{-7} \cdot V^2$	For radial-ply passenger car tires on smooth road ($V < 150 \text{ km/h}$)
$0.0169 + 0.19 \cdot 10^{-6} \cdot V^2$	For bias-ply passenger car tires on smooth road ($V < 150 \text{ km/h}$)
$0.006 + 0.23 \cdot 10^{-6} \cdot V^2$	For radial-ply truck tires on smooth road ($V < 100 \text{ km/h}$)
$0.007 + 0.45 \cdot 10^{-6} \cdot V^2$	For bias-ply truck tires ($V < 100 \text{ km/h}$)
$0.01 \cdot \left(1 + \frac{V}{100}\right)$	For passenger car on concrete road ($V < 128 \text{ km/h}$)

The rolling resistance can be assumed as the resistance for the wheel by neglecting some other parameters' effects on the wheel, especially the resistance that affects driving through a curved section in horizontal geometry of a road (Mitschke, 1972).

More than 90% of the resistance of aerodynamics that a vehicle in motion is exposed to is composed of drag pressure and skin friction (Wong, 2001). The high pressure and low pressure zones that are created by the moving vehicle as shown in Figure 2.6, result in vehicle's being pushed and pulled respectively in forward and backward

directions (Ehsani et al., 2005) that are defined as pressure drag and shape drag. Although pressure drag is much more effective than the skid friction, skid resistance becomes significant when compared to the friction produced by the speed differences between the air close to and far from the skin of a long-bodied vehicle.

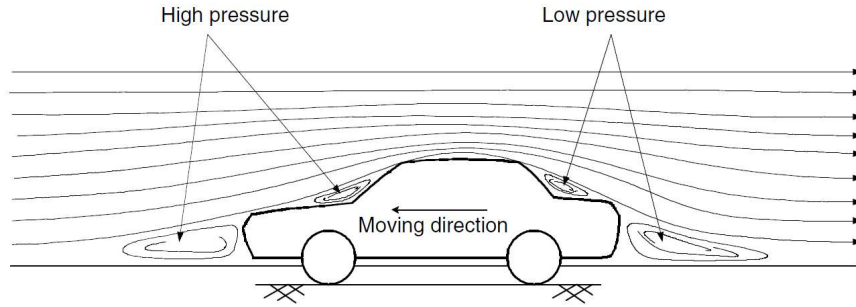


Figure 2.6 : The high pressure and low pressure zones that are created by the moving vehicle (Ehsani et al. 2005).

Expressing the combined effects of aerodynamic movements using the coefficient of aerodynamics resistance, μ_a , the aerodynamic resistance can be obtained using is defined with Equation (2.55), where ρ symbolizes the mass density of air [$\text{kg}\cdot\text{m}^{-3}$], A the projected area on the plane perpendicular to the direction of the movement of the vehicle, and v_r the speed of the vehicle relative to the wind speed.

$$F_a = \frac{1}{2} \cdot \rho \cdot \mu_a \cdot A \cdot v_r^2 \quad (2.55)$$

From Equation (2.55) it is obvious that vehicle speed highly affects the aerodynamics resistance, and hence, the power required where they are proportional to respectively the square and the cube of the speed. Considering the dependence on the air density, temperature and elevation are some other parameters that affect aerodynamics resistance, as well (Wong, 2001). Variation in the coefficient of aerodynamics resistance, μ_a , specific to a number of vehicle types is listed in Table 2.2 (Ehsani et al., 2005). It is useful to note that there is an opportunity in electric vehicles to reduce the μ_a value due to flexibility in locating its major components (Larmin and Lowry, 2003).

Table 2.2 : Coefficient of aerodynamic resistance specific to vehicle types (Ehsani et al., 2005).

Rolling resistance coefficient, μ_r	Road and tire type
Trucks	0.8-1.5
Buses	0.6-0.7
Streamlined buses	0.3-0.4
Motorcycles	0.6-0.7

On a graded section, the horizontal component of a vehicle's weight creates respectively the effects of facilitating and challenging on climbing and descending in a road section. The resultant grade resistance can be obtained by Equation (2.56).

$$F_g = m \cdot g \cdot \sin \alpha \quad (2.56)$$

The overall resisting force against the motion of a vehicle on low graded roads, F_{rm} , can be expressed by Equation (2.57).

$$F_{rm} = \frac{1}{2} \cdot \rho \cdot \mu_a \cdot A \cdot v_r^2 + m \cdot g \cdot (\mu_r + \sin \alpha) \quad (2.57)$$

Considering Equation (2.53), the tractive force that is required in order to overcome the driving resistances for an accelerating vehicle, with the rate of acceleration a , can be obtained using Equation (2.58).

$$F_{tr} = F_{rm} + (m + \xi) \frac{dv}{dt} \quad (2.58)$$

For vehicles with internal combustion engine, the instantaneous tractive power demand [W], P_{tr}^{ic} , to propel the vehicle forward can further be calculated with Equation (2.59), where η_i refers to the driveline efficiency for internal combustion engine vehicles in order to incorporate the effect of losses from the power plant to the wheels.

$$P_{tr}^{ic} = \frac{v \cdot F_{tr}}{\eta_i} \quad (2.59)$$

Considering the travel by an ICEV on an arc (i, j) while accelerating its speed from v_i to v_j in the time interval $t_j - t_i$, the energy consumption corresponding to the motion on the specific arc (i, j), E_{ij}^{ic} , can be determined using Equation (2.60).

$$E_{ij}^{ic} = \int_{t=t_i}^{t=t_j} P_{tr}^i dt = \int_{t=t_i}^{t=t_j} \left((m+\xi) \frac{dv}{dt} + F_g + F_r + F_a \right) \cdot v \cdot \eta_i^{-1} dt =$$

$$\left((m+\xi) \int_{v=v_i}^{v=v_j} v \cdot dv + m \cdot g \int_{t=t_i}^{t=t_j} v \cdot \sin \alpha dt + \int_{t=t_i}^{t=t_j} (F_r + F_a) \cdot v dt \right) \cdot \eta_i^{-1} \quad (2.60)$$

By employing the variations, that are represented with (2.61) and (2.62), the type of the energy can be identified using Equation (2.60), as kinetic and potential energy (Iqbal, 2010, and Mitschke, 1972), where h_i represents the grade elevation of node i .

$$(m+\xi) \int_{v=v_i}^{v=v_j} v dv = \frac{1}{2} \cdot (m+\xi) \cdot (v_j^2 - v_i^2) \quad (2.61)$$

$$m \cdot g \int_{t=t_i}^{t=t_j} \sin \alpha dt = m \cdot g \int_{h=h_i}^{h=h_j} dt = m \cdot g \cdot (h_j - h_i) \quad (2.62)$$

Therefore, Equation (2.60) can be converted to Equation (2.63) (Iqbal, 2010, and Mitschke, 1972), where $\bar{v}$ denotes the average driving speed between i to j .

$$E_{ij}^{ic} = \left(\frac{1}{2} \cdot (m+\xi) \cdot (v_j^2 - v_i^2) + m \cdot g \cdot (h_j - h_i) + \int_{t=t_i}^{t=t_j} (F_r + F_a) \cdot \bar{v} dt \right) \cdot \eta_i^{-1} \quad (2.63)$$

Denoting the energy losses due to the rolling and air resistances in Equation (2.63) by E_{loss} , the energy consumed on an arc (i, j) can be expressed as a function of the kinetic and potential energy changes together with the losses as given by (2.64) (Iqbal, 2010).

$$E_{ij}^{ic} = \Delta^{ij}(\text{kinetic energy}) + \Delta^{ij}(\text{potential energy}) + E_{loss} \quad (2.64)$$

Note that the auxiliary energy consumption, which is neglected in the present study, needs to be included in E_{loss} for the cases where auxiliary energy consumption is high.

Energy consumption by EVs can be mainly differentiated from ICEVs in terms of the potential they possess for energy recuperation from surplus kinetic or potential energy. On one hand, for the cases where the kinetic or/and potential energy is increased as a result of respectively accelerating and uphill traveling, tractive energy is required in order to meet the energy demand. On the other hand, for the cases where the kinetic or/and potential energy is decreased as a result of respectively decelerating and downhill traveling, the surplus energy will be converted to the heat energy when a braking force is applied by ICEVs if the surplus energy is not recovered. However, for the EV case, using the regenerative braking system, the surplus energy can be converted to electrical energy in order to be stored in the battery and utilized. Considering the share of wasted energy during the braking by ICEVs, which corresponds to around 30% to 50% (Saffaran et al., 2016), the potential of energy recuperation from braking by EVs is a significant feature to consider in order to deal

with their limited driving ranges. During the braking phase of motion for EVs and HEVs, the braking energy can only be recuperated on the driven axle and, the portion of the braking energy existing on non-driven axle(s) is lost inevitably, due to the friction (Gao et al. 1999). In fact, the potential regenerated energy is dissipated during the energy recovering process and, the potential energy recuperation for EVs is dependent on many factors including vehicle speed, acceleration rate, and braking friction (Yang et al., 2014). Figure 2.7 shows a sample variation of the energy that can be recuperated by EV motors with respect to the changes in speed and braking friction.

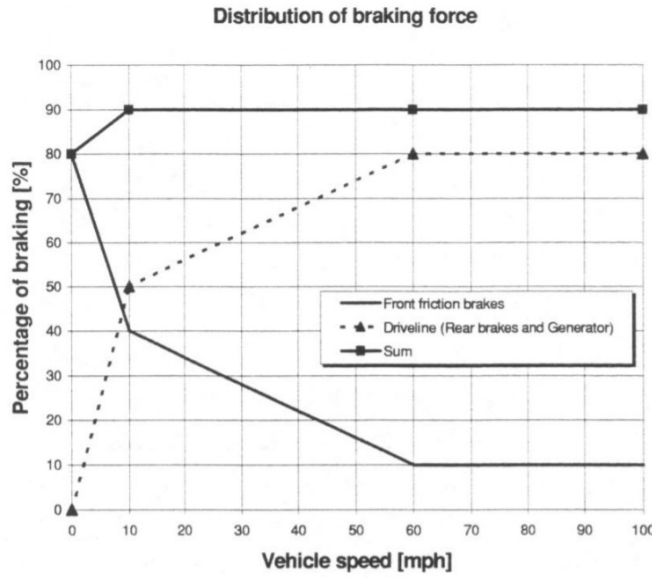


Figure 2.7 : Changes in energy can be recovered by motor with speed (Panagiotidis et al., 2000).

The energy consumed by an EV while traveling on an arc (i, j) can then be determined as E_{ij}^e , using Equation (2.65). As a difference with respect to ICEVs, one needs to determine whether the electric motor requires energy to drive or tends to recover energy. In this context, the propulsion energy required, E_{ij}^{pr} , is calculated by Equation (2.66) when $E_{ij}^e > 0$ or alternatively, the regenerative energy, E_{ij}^{rg} , is calculated by Equation (2.67) when $E_{ij}^e < 0$.

$$E_{ij}^e = \left(\frac{1}{2} \cdot (m + \xi) \cdot (v_j^2 - v_i^2) + m \cdot g \cdot (h_j - h_i) + \int_{t=t_i}^{t=t_j} (F_r + F_a) \cdot v \, dt \right) \quad (2.65)$$

$$E_{ij}^{pr} = E_{ij}^e \cdot \eta_e^{-1} \quad (2.66)$$

$$E_{ij}^{rg} = E_{ij}^e \cdot \eta_{rg} \quad (2.67)$$



3. RELATED RESEARCH

Although electric vehicles (EVs) possess a number of common features with internal combustion engine vehicles (ICEVs) in terms of vehicle dynamics, autonomy, and seat or payload capacity, the relatively more restricted availability of charging stations and longer charging times for EVs but with the possibilities of being partially charged at nodes served and making use of regenerative energy in comparison to options and times of refueling for ICEVs highlight the energy-based distinction that is fundamental to the formulation of vehicle routing problems involving such vehicles. The need to determine both the location and the amount of time for charging complicates the traditional problem structure of vehicle routing: assigning nodes to be visited by the vehicles and the sequence of node visits by each single vehicle in the fleet. In the following, a detailed review on the vehicle routing problem involving variants of EVs and varying characteristics of the problem in terms of objectives and constraints is presented.

3.1 A General Overview to Variants of Vehicle Routing Studies

The formulation for the Vehicle Routing Problem (VRP), which is evolved from the traveling salesman problem, seeks the minimization of the entire routing cost while serving to a set of nodes using a fleet of vehicles. Dantzig and Ramser (1959) proposed the pioneering formulation for the VRP, in which a fleet of trucks with limited capacities is routed from a depot to serve a set of customers so that demands of customers are met and the total distance traveled is minimized. Real-world problems involving either varying constraints or different objectives with varying functional forms have induced the development of variants of the VRP since then. Thorough reviews on either formulations or solution approaches to the VRP are published by Toth and Vigo (2002), Golden et al. (2008), and, Laporte (2009).

As a number of features of EVs, including the need to visit charging stations and the variation of the driving range due to being recharged, and etc., do exist the traditional form of distance constrained VRP is not appropriate completely for routing and/or scheduling problems involving EVs. The specialization of the problem formulation has therefore been initially sought to take into account the effects of refueling needs. Ichimori et al. (1981, 1983) have been the first to consider refueling stations at specific

locations aiming to find the minimum distance needed to serve all customers and return to the depot without refueling during the trip through a formulation based on distance limitations. While Ichimori et al. (1983) have focused on avoiding to run out of fuel, Crevier et al. (2007) have extended the VRP formulation by adding intermediate depots to reload goods, where intermediate depots can be further handled as recharging/refueling stations for distance limited vehicles. In this context, focusing on rechargeable vehicles, i.e., variants of EVs, Conrad and Figliozzi (2011) have introduced the Recharging Vehicle Routing Problem (RVRP) that enables vehicles with limited ranges to be recharged during their trips by considering fixed charging time at customer nodes, which are considered as recharging stations as well. In addition to the standard VRP formulation that is presented in Section 2.1 in details, Conrad and Figliozzi (2011) have proposed a new set of constraint in order to determine the remaining battery load, required battery load to travel, and the recharger location. Using the notations given in Table 3.1, the sub-problems as variants of Electric Vehicle Routing Problem (EVRP) are defined in Section 3.1 in details.

Table 3.1: Notation frequently used.

Sets	
$\{0\}$	Depot node
V	Set of all vertices ($\{0\} \cup C \cup R$)
C	Set of all customers
R	Set of all recharging/refueling stations
S	Set of all dummy vertices
K	Set of vehicles
V'	$V \cup S$
R'	$R \cup S$
Decision variables	
x_{ij}	Binary, arc (i,j) is traversed or not
τ_i	Arrival time at node i
u_i	Demand at node i
w_i	Amount recharged [kWh]
y_i	Binary, node i is with a recharging station or not

Decision variables	
q_i	Battery load left when arrived at node i
Y_i	Battery load present while departing from node i
m	Number of vehicles assigned
Parameters	
d_{ij}	Distance between node i and j
t_{ij}	Driving time from node i to j
s_i	Service time at node i
e_i	Earliest time of arrival allowed at node i
l_i	Latest time of arrival allowed at node i
a_i	Customer demand
f	Vehicle purchasing cost
T	Maximum duration for a tour
h	Recharging rate
r	Energy consumption rate
Q	Battery capacity
K	Vehicle loading/passenger capacity
c^d	Travel cost
c^s	Charging station cost

Instead of considering all/some customer nodes as charging/re-fueling stations, Erdoğan and Miller-Hooks (2012) have considered particular nodes for charging stations and, introduced the Green Vehicle Routing Problem (GVRP) as an extension to the multi-depot VRP with inter-depot routes to minimize total distance by incorporating the possibility of re-fueling at a certain station. It is demonstrated that the location of the recharging station has a greater effect on shortening the distance traveled, rather than increasing the number of recharging stations arbitrarily. The GVRP formulation introduced by Erdoğan and Miller-Hooks (2012) is given through the equations (3.1) – (3.13). The GVRP is defined on an undirected and complete graph $G = (V, A)$, where V is a set for all nodes including the depot, $\{0\}$, the customer set, C , and set of recharging/refueling stations, R . A set of dummy nodes, S , is used to

allow multiple visits, and hence graph G is augmented to $G' = (V', A')$. The GVRP seeks the minimum of the total distance traveled by a fleet within a specified time limit, T , through the objective function given in equation (3.1) that is subject to the constraints given through (3.2) to (3.13), where d_{ij} represents the distance between nodes i and j . Constraint (3.2) ensures that each customer is visited exactly one, where with Constraint (3.3) recharging station visits are relaxed and, the flow conservation is guaranteed with Constraint (3.4). The decision on the number of vehicles employed, m , is restricted with the arcs sinking to and sourcing from the depot respectively by the constraints (3.5) and (3.6). Time related constraints are listed through Constraint (3.7) to (3.9) by introducing the arrival time at each node $i \in V'$, τ_i , the driving time between nodes, t_{ij} , and the service time at nodes $\forall i \in V' \setminus \{0\}$, s_i , considering T . The level of fuel left in a vehicle is determined with constraint (3.10) depending on the distance traveled between two nodes and the recharging rate, r , which is set as constant. Constraint (3.11) guarantees that a vehicle re-fuels to its capacity, Q , when re-fueling, where Constraint (3.12) ensures that each vehicle completes its tour without running out of fuel. Binary variable x_{ij} that shows whether an arc is traveled from i to j is represented by (3.13).

$$\text{minimize} \quad \sum_{i,j \in V', i \neq j} d_{ij} \cdot x_{ij} \quad (3.1)$$

subject to

$$\sum_{j \in V', j \neq i} x_{ij} = 1, \quad \forall i \in C \quad (3.2)$$

$$\sum_{j \in V', j \neq i} x_{ij} \leq 1, \quad \forall i \in v_0 \cup R' \quad (3.3)$$

$$\sum_{i \in V', j \neq i} x_{ji} - \sum_{i \in V', j \neq i} x_{ij} = 0, \quad \forall j \in V' \quad (3.4)$$

$$\sum_{j \in V' \setminus \{0\}} x_{j0} \leq m \quad (3.5)$$

$$\sum_{j \in V' \setminus \{0\}} x_{0j} \leq m \quad (3.6)$$

$$\tau_j \geq \tau_i + (t_{ij} + s_j) \cdot x_{ij} - T \cdot (1 - x_{ij}), \quad i \in V', \forall j \in V' \setminus \{0\} \text{ and } i \neq j \quad (3.7)$$

$$0 \leq \tau_0 \leq T \quad (3.8)$$

$$t_{0j} \leq \tau_j \leq T - (t_{j0} + s_j), \quad \forall j \in V' \setminus \{0\} \quad (3.9)$$

$$q_j \leq q_i - r \cdot d_{ij} \cdot x_{ij} + Q \cdot (1 - x_{ij}), \quad \forall j \in C \text{ and } i \in V', i \neq j \quad (3.10)$$

$$q_j = Q, \quad \forall i \in R' \cup \{0\} \quad (3.11)$$

$$q_j \geq \min\{r \cdot d_{j0}, r \cdot (d_{j1} + d_{l0})\}, \quad \forall j \in C, \forall l \in R' \quad (3.12)$$

$$x_{ij} \in \{0,1\} \quad \forall i,j \in V \quad (3.13)$$

Although the GVRP is improved in order to increase the computational efficiency of solution, i.e., in Koç and Karaoğlu, 2016, Leggieri and Haouari, 2017, and Mancini, 2017, it involves a number of assumptions including constant refueling time, unlimited resources in re-fueling stations, re-fueling to the capacity and neglecting the time window, and vehicle and battery capacities, all of which do not match with real-world conditions.

In order to propose relatively a more realistic formulation to route EVs, Schneider et al. (2014) have introduced the Electric Vehicle Routing Problem with Time Windows and Recharging Stations (E-VRPTW) by considering vehicle capacity, customer time windows, and specifically the recharging times. The E-VRPTW aims to minimize the total distance traveled by a homogenous EV fleet, in which the battery characteristics of all the vehicles are identical. In this context Schneider et al. (2014) have improved the GVRP by adding a time window $[e_i, l_i]$ to represent the earliest (e) and latest (l) times to serve a customer, a new variable that shows the remaining cargo, u_i , in order to track the vehicle occupancy, and a recharging rate (r) to determine the time spent for recharging. Objective function of the E-VRPTW is identical to that of the GVRP's, (3.1), and is constrained with the identical constraints (3.2), (3.3), (3.4), and (3.10). The time constraints of the E-VRPTW differ from GVRP's to prevent sub tours together, as shown through (3.14)-(3.16). Time feasibility is ensured by constraints (3.14) and (3.15) respectively for arcs leaving from customers and depot nodes, and recharging visits considering the recharging rate, h, while constraint (3.16) guarantees that each visit is finished within its specific time window. Constraints (3.17) and (3.18) ensure the demand satisfaction while limiting the cargo load with vehicle payload capacity. Schneider et al. (2014) have introduced constraint (3.19) to alternate constraint (3.12).

$$\tau_j \geq \tau_i + (t_{ij} + s_i) \cdot x_{ij} - T \cdot (1 - x_{ij}), \quad \forall i \in C \cup \{0\}, \forall j \in C \cup R' \cup \{0\} \text{ and } i \neq j \quad (3.14)$$

$$\tau_j \geq \tau_i + t_{ij} \cdot x_{ij} - h \cdot (Q - q_i) - (T + h \cdot Q) \cdot (1 - x_{ij}), \forall i \in R', \forall j \in C \cup R' \cup \{0\} \text{ and } i \neq j \quad (3.15)$$

$$e_j \leq \tau_j \leq l_j \quad \forall j \in \{0\} \cup C \cup R' \quad (3.16)$$

$$0 \leq u_j \leq u_i - a_i \cdot x_{ij} + K \cdot (1 - x_{ij}) \quad \forall i, \forall j \in \{0\} \cup C \cup R' \text{ and } i \neq j \quad (3.17)$$

$$0 \leq u_0 \leq K \quad (3.18)$$

$$q_j \leq Q - (r \cdot d_{ij}) \cdot x_{ij} \quad \forall j \in \{0\} \cup C \cup R', \forall i \in R' \cup \{0\}, i \neq j \quad (3.19)$$

In order to minimize both the total cost and the total distance traveled, Hiermann et al. (2016) have introduced the Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations (E-FSMFTW) as an extension of E-VRPTW, in which a heterogeneous fleet with varying battery and purchasing cost characteristics are considered. Taking into account the variety in EVs in terms of range, capacity, and price, an economical optimization to compose and route an EV fleet is obtained with the solution to the E-FSMFTW. In this context, authors define a new set, K , to represent the vehicle types and, build a cost optimal objective function related with the purchasing cost of vehicle type k (f_k) and the distance cost (c_{ij}), as given by (3.20). Objective of the E-FSMFTW is subject to the constraints given through (3.21) to (3.31) as an extension of E-VRPTW, where the superscript k is used to convert the variables and parameters to stand for different types of vehicles.

$$\min \sum_{k \in K} \sum_{j \in C \cup R'} f^k \cdot x_{0j}^k + \sum_{k \in K} \sum_{i \in C \cup R' \cup \{0\}, j \in C \cup R' \cup \{0\}, i \neq j} c_{ij}^k \cdot x_{ij}^k \quad (3.20)$$

$$\sum_{k \in K} \sum_{j \in V', j \neq i} x_{ij}^k = 1, \quad \forall i \in C \quad (3.21)$$

$$\sum_{k \in K} \sum_{j \in V', j \neq i} x_{ij}^k \leq 1, \quad \forall i \in \{0\} \cup R' \quad (3.22)$$

$$\sum_{i \in V', j \neq i} x_{ji}^k - \sum_{i \in V', j \neq i} x_{ij}^k = 0, \quad \forall j \in V', \forall k \in K \quad (3.23)$$

$$e_j \leq \tau_j \leq l_j \quad \forall j \in \{0\} \cup C \cup R' \quad (3.24)$$

$$\tau_j \geq \tau_i + (t_{ij} + s_j) x_{ij}^k - T \cdot (1 - x_{ij}^k), \quad i \in V', \forall j \in V' \setminus \{0\} \text{ and } i \neq j, \forall k \in K \quad (3.25)$$

$$\tau_j \geq \tau_i + t_{ij} \cdot x_{ij}^k - h^k \cdot (Q^k - q_i^k) - (T + h^k \cdot Q^k) \cdot (1 - x_{ij}^k), \quad \forall i \in R', \forall j \in C \cup R' \cup \{0\} \text{ and } i \neq j, \forall k \in K \quad (3.26)$$

$$0 \leq u_j \leq u_i - a_i \cdot x_{ij}^k + K^k \cdot (1 - x_{ij}^k) \quad \forall i, \forall j \in \{0\} \cup C \cup R' \text{ and } i \neq j \quad (3.27)$$

$$0 \leq u_j^k \leq K^k \quad \forall j \in V, \forall k \in K \quad (3.28)$$

$$q_j^k \leq q_i^k - r^k \cdot d_{ij} \cdot x_{ij}^k + Q^k \cdot (1 - x_{ij}^k), \quad \forall j \in C \text{ and } i \in V', i \neq j, \forall k \in K \quad (3.29)$$

$$q_j^k \leq Q^k - (r^k \cdot d_{ij}) \cdot x_{ij}^k \quad \forall j \in \{0\} \cup C \cup R', \forall i \in R' \cup \{0\}, i \neq j, \forall k \in K \quad (3.30)$$

$$q_0^k = Q^k, \quad \forall i \in R' \cup 0, \forall k \in K \quad (3.31)$$

$$x_{ij}^k \in \{0,1\} \quad \forall i,j, \forall k \in K \quad (3.32)$$

In the studies summarized above it is assumed that vehicle's fuel tank/battery is filled/charged to its capacity when the refueling is undertaken and, the battery lifespan, which allows a limited number of charging cycle, is neglected. Felipe et al. (2014) have relaxed the full recharging limitation that is represented by equations (3.11) and (3.15) to the partial recharging. Aiming to minimize the total recharging cost considering different recharging technologies including plug-in or wireless charging, Felipe et al. (2014) have introduced the Green Vehicle Routing Problem with Multiple Technologies and Partial Recharges (GVRP-MTRP), where the recharging time-window is neglected. In this context, Keskin and Çatay (2016) consider the time-window and propose the EVRPTW with Partial Recharging (EVRPTW-PR) by extending the EVRPTW formulation. In addition to the variable q_i that represents the remaining battery load on arrival to node i , Keskin and Çatay (2016) introduce Y_i as a new decision variable to represent the battery load on departure from node i to take into consideration the partial recharge, that is limited with the battery capacity as implied with constraint (3.33). Regarding to the objective function given by (3.1), the EVRPTW-PR comprises the constraints considered in the EVRPTW, i.e., (3.2), (3.3), (3.4), (3.10), (3.13), (3.14), (3.16), (3.17), (3.18), and (3.19), and additionally the constraints (3.33), (3.34), and (3.35) Note that instead of constraint (3.15), where full recharge at recharging stations is restricted with $(Q-q_i)$, Keskin and Çatay (2016) define (3.34) in order to impose the partial recharging.

$$q_i \leq Y_i \leq Q \quad (3.33)$$

$$\tau_j \geq \tau_i + t_{ij} \cdot x_{ij} - h \cdot (Y_i - q_i) - (T + h \cdot Q) \cdot (1 - x_{ij}), \quad \forall i \in R', \forall j \in C \cup R' \cup \{0\} \text{ and } i \neq j \quad (3.34)$$

$$q_j \leq Y_i - r \cdot d_{ij} x_{ij} + Q \cdot (1 - x_{ij}), \quad \forall j \in C \text{ and } i \in V', i \neq j \quad (3.35)$$

Aiming minimize both the number of vehicles operated and the overall recharging costs, Keskin and Çatay (2018) extended the EVRPTW-PR by considering different

types of recharging system in terms of the recharging speed, such as quick and normal, for pre-defined recharging station locations.

Instead of assuming a linear relationship between the distance traveled and the energy consumed in the routing of EVs, Preis et al. (2014) have introduced the energy-optimized EVRP (Energy-optimizing-VRP) formulation by defining an EV energy model taking into account the driving resistances. In this context Preis et al. (2014) subdivide the energy consumption into two, while driving with an empty vehicle and a loaded vehicle. The E_{ij}^F is used to determine the energy consumption for an empty vehicle with the mass m_F as having traversed a section with the distance d_{ij} and elevation difference h_{ij} as given by (3.36), where aerodynamic drag coefficient, frontal area, driving velocity, air density, coefficient of friction, and gravitational acceleration are represented respectively with c_w , A , v , p , μ , and g . Specific energy consumption per kilogram for a loaded vehicle (E_{ij}^L) is calculated using (3.37) Energy consumption equations given by (3.36) and (3.37) are incorporated to the objective function, (3.40), by using (3.38) and (3.39), where β represents the recuperation factor in cases of driving towards downhill road sections (Preis et al., 2014). In order to find the optimal route, driving through which corresponds to the minimum energy consumption subject to the constraints given through (3.41) to (3.48) in addition to (3.2), (3.3), (3.4), (3.14), and (3.16), Preis et al. (2014) have introduced u_{ij} to represent arc-based loading weight rather than handling the allocated loading weight through a node-based approach.

$$E_{ij}^F = m_F \cdot g \cdot (h_{ij} + d_{ij} \cdot \mu) \frac{1}{2} \cdot \sqrt{h_{ij}^2 + d_{ij}^2} \cdot c_w \cdot A \cdot p \cdot v^2 \quad (3.36)$$

$$E_{ij}^L = g \cdot (h_{ij} + d_{ij} \cdot \mu) \quad (3.37)$$

$$c_{ij}^F = \max(E_{ij}^F, \beta \cdot E_{ij}^F) \quad (3.38)$$

$$c_{ij}^L = \max(E_{ij}^L, \beta \cdot E_{ij}^L) \quad (3.39)$$

$$\text{minimize } \sum_{i \in V} \sum_{j \in V} (c_{ij}^F \cdot x_{ij} + c_{ij}^L \cdot m_{ij}) \quad (3.40)$$

$$\sum_{i \in V' \setminus j \neq i} u_{ij} - \sum_{i \in V' \setminus j \neq i} u_{ji} = a_j, \quad \forall j \in V' \quad (3.41)$$

$$0 \leq u_{ij} \leq K \cdot x_{ij} \quad (3.42)$$

$$t_i + (s_i + t_{i0}) \cdot x_{i0} \leq T \quad (3.43)$$

$$q_j \leq q_i - c_{ij}^F \cdot x_{ij} - c_{ij}^L \cdot u_{ij} + Q \cdot (1 - x_{ij}) \quad (3.44)$$

$$q_j \leq Q - c_{ij}^F \cdot x_{ij} - c_{ij}^L \cdot u_{ij} \quad (3.45)$$

$$0 \leq q_i \leq Q \quad (3.46)$$

Frank et al. (2014) further improved their Energy-optimizing-VRP model by conceding the actual locations of charging stations as a novel approach rather than considering charging stations through dummy sets. A realistic energy consumption model is used by Goeke and Schneider (2015) as well, where the driving resistances, including air, rolling, grade, and acceleration/deceleration, in which the mass of a vehicle is a variable that changes with the cargo load, and the regenerative energy are considered. The Mixed Integer Program (MIP) proposed by Goeke and Schneider (2015) have sought to minimize the traveled distance and cost for a fleet that is composed of ICEVs and EVs, subject to battery energy constraints within the energy consumption model considered in addition to the routing, fleet, and time related constraints that are commonly considered in EVRP studies. Lin et al. (2016) have handled heterogeneous electric fleet routing problem and provide a linear programming formulation by considering driving resistances affecting the battery load, especially focusing on the effects of changes in vehicle payload to the energy consumption in EVs. In order to achieve optimal driving paths with the optimal recharging plan, Shao et al. (2018) have tested with data of a large-scale real case their EVRP model including an energy consumption model, solution of which varies with all driving resistances and the regenerated energy, and considers varying travel speeds dependent on the travel speed of each link. Instead of assuming constant values for parameters, Pelletier et al. (2019) have handled the energy consumption uncertainties in EVs, including aerodynamic drag coefficient, rolling friction coefficient, air density, driveline efficiency, auxiliary power required, and etc.

Considering the recharging requirements of EVs in accordance with their limited driving ranges, one significant decision is to determine the location of recharging infrastructure in order to operate a vehicle fleet efficiently. In this context many location models are proposed considering demand is originated either from nodes or paths (e.g. Riemann et al., 2015; He et al., 2013; Ghamami et al., 2016; Wang and Lin, 2009; Wen et al. 2014). However, studies on recharging station location models neglect the interdependency between the recharging station location decision and EV routing as it is neglected in EVRP studies as well, where the optimal solution may differ in terms of routing plan and location decision (Salhi and Rand, 1989). In this

context, a model for the location routing problem needs to capture the interdependency between the decision on the recharging station location and the EV routing.

Worley et al. (2012) have focused on simultaneous and direct locating problem of recharging/refueling stations for a vehicle fleet composed of ICEVs and EVs. Aiming to minimize the total cost including the costs of travel and recharging/refueling station, Worley et al. (2012) neglect the recharging/refueling time. Yang and Sun (2015), have concentrated on EV routing as a location-routing problem, and sought the optimal locations of Battery Swap Stations (BSSs) and routing plans for the vehicles, which are determined simultaneously in order to minimize overall costs. Electric Vehicles Battery Swap Location Routing Problem (BSS-EV-LRP) that is introduced by Yang and Sun (2015) neglects the time windows as well as recharging-replenishment time. In this context, focusing on plug-in recharging stations, Schiffer and Walther (2017) have proposed a formulation that allows recharging at customer sites while considering time-window constraint and partially recharge option and, introduced Electric Location Routing Problem with Time Window and Partial Recharging (ELRP-TWPR). Schiffer and Walther (2017) have provided five different objective functions that are given by (3.1), (3.47), (3.48), (3.49), and (3.50), which aim to minimize respectively the number of vehicles assigned, number of recharging stations sited, combined number of vehicles and recharging station considering as a long-term decision, and overall costs subject to the identical constraint sets defined through (3.2) to (3.4), (3.6), (3.14), (3.16), (3.17), (3.18), and (3.51) to (3.59). A decision variable on mounting a recharging station at node i , y_i , is defined with the variable w_i as well to represent the amount of recharging at node i .

$$\text{minimize } \sum_{j \in V} x_{0j} \quad (3.47)$$

$$\text{minimize } \sum_{i \in V} y_i \quad (3.48)$$

$$\text{minimize } (1-\alpha) \sum_{j \in V} x_{0j} + \alpha \cdot \sum_{i \in V} y_i \quad (3.49)$$

$$\text{minimize } f \cdot \sum_{j \in V} x_{0j} + c^d \cdot \sum_{i,j \in V} d_{ij} \cdot x_{ij} + c^s \sum_{i \in V} y_i \quad (3.50)$$

$$w_i \leq Q y_i \quad \forall j \in V' \quad (3.51)$$

$$y_i \leq w_i \quad \forall j \in S \quad (3.52)$$

$$\sum_{i \in V \setminus S} y_i \leq n \quad (3.53)$$

$$y_i \geq y_j \quad \forall j \in V \setminus S \quad (3.54)$$

$$q_j \leq q_0 - r \cdot d_{0j} \cdot x_{0j} + Q \cdot (1 - x_{0j}) \quad \forall j \in V'_{n+1} \quad (3.55)$$

$$q_j \leq q_i + w_i - r \cdot d_{ij} \cdot x_{ij} + Q \cdot (1 - x_{ij}) \quad \forall i \in V', \forall j \in V'_{n+1} \quad (3.56)$$

$$0 \leq q_0 \leq Q \quad (3.57)$$

$$0 \leq q_i + w_i \leq Q \quad \forall i \in V' \quad (3.58)$$

$$y_i \in \{0,1\} \quad \forall i \in V \quad (3.59)$$

A general overview to the variants of the Electric Vehicle Routing Problem (EVRP) involving the model characteristics is presented by Table 3.2. The sub-problem classification of the EVRP presented in Table 3.2 is done mainly according to the: time-window, fleet characteristics, and the partial recharging considerations as well as battery discharging characteristics, and decision on recharging station location.

Table 3.2 : A general overview to evaluation of Electric Vehicle Routing Problem.

Sub-problem	Definition	Reference	Model
GVRP	Green Vehicle Routing Problem	Erdoğan and Miller Hooks (2012)	(3.1) to (3.13)
EVRPTW	Electric Vehicle Routing Problem with Time Windows	Schneider et al. (2014)	(3.1) to (3.4), (3.10), (3.13) to (3.19)
EFSMFTW	Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations	Hiermann et al. (2016)	(3.20) to (3.32)
EVRPTWPR	Electric Vehicle Routing Problem with Time Windows and Partial Recharges	Keskin and Çatay (2016)	(3.1) to (3.4), (3.10), (3.13), (3.14), (3.16) to (3.19), (3.33) to (3.35)
Energy-optimizing-VRP	Energy optimized vehicle routing problem	Preis et al. (2014)	(3.2), (3.3), (3.4), (3.14), (3.16), (3.36) to (3.46)

Table 3.2 (continued) : A general overview to evaluation of Electric Vehicle Routing Problem.

Sub-problem	Definition	Reference	Model
ELRP-TWPR	Electric location routing problem with time window and partial recharging	Schiffer and Walther (2017)	(3.1) to (3.4), (3.6), (3.14) to (3.18), (3.47) to (3.59),

3.2 Discussion

The recent review on researches concentrating on the VRP as summarized in the previous sub-sections highlights an evolution of the problem towards the involvement of alternative vehicles focusing mainly on their limited driving ranges, longer refueling durations, and the additional infrastructure requirements. The routing of alternative vehicles, referred to as the GVRP or EVRP, involves a wide range of objective functions as minimizing: (i) total traveled distance (e.g.: Erdoğan and Miller-Hooks, 2012; Schneider et al., 2014; Keskin and Çatay, 2016; Schiffer and Walther, 2017; and, Zuo et al., 2017); (ii) total elapsed time (e.g.: Wang et al., 2014; Pourazarm and Cassandras, 2018; and, Montoya et al., 2017); (iii) number of vehicle assigned (e.g.: Conrad and Figliozzi, 2011; Bruglieri et al., 2015; Schiffer and Walther, 2017; and, Hiermann et al., 2016); (iv) cost (e.g.: Sassi et al., 2014; Goeke and Schneider, 2015; Shao et al., 2017; Felipe et al., 2014; Schiffer and Walther, 2017; Keskin and Çatay, 2018; and, Hiermann et al., 2016); (v) energy consumption (e.g.: Preis et al., 2014; and, Ziebuhr et al., 2017); and, (vi) number of recharging stations (e.g.: Schiffer and Walther, 2017).

Based on the technology differences between ICEVs and EVs, the EVRP has different aspects to consider when compared to the classical VRP that focuses mainly on ICEVs. Required fuel type is one of the main differences that necessitates formulating the EVRP based on the time constraints, considering that refueling duration is much longer in EVs in comparison to ICEVs. The requirement of time control in an EVRP is imposed by the time-window constraint, as employed in Conrad and Figliozzi (2011), and Schneider et al. (2014) as the very first examples, that ensures a time-window composed of an early and a late leaving time to and from the routing points. Such a

time-window prevents an excessive time spent at nodes because of recharging, or at arcs because of the long traveling time that may exist due to traffic congestion and/or long distances. The total elapsed time for recharging may be formulated considering the time spent on the recharging stations due to the recharging process (e.g. Schneider et al., 2014; Felipe et al., 2014; Goeke and Schneider, 2015; and, Shiffer and Walther, 2017) and the queueing conditions (e.g. Shao et. al., 2017; and, Hausler et al., 2014) as well, where the trade-off between the total distance traveled and the customer waiting time can be remarked as done by Shi et al. (2018) for a ride-share service composed of EVs. The attempts to impose the effects of time-varying characteristics of traffic congestion into routing optimization have been studied in dynamic programming approach within the context of Dynamic VRP formulations, including Kim et al. (2005a), Kim et al. (2005b), and, Kim et al. (2016) in addition to ones that concentrate on the features of the EVRP (e.g. Bi and Tang, 2019; and, Pourazarm and Cassandras, 2014a). The traffic congestion at each link is considered as well by Pourazarm and Cassandras (2014a), and as an extension, the computational challenges of real-time application is met with the dynamic programming approach (Pourazarm and Cassandras, 2014b). The traffic conditions are handled by Bi and Tang (2019) to optimize the total service duration, where the time-dependent stochastic nature of traffic is considered to propose a system optimal solution for the Dynamic EVRP that is represented as a finite-horizon Markovian decision process for a single EV.

Some researches have focused on taking the advantage of considering various types of vehicles in terms of capacity, driving range, and purchasing price, which may consequently offer a better solution for decision makers in composing vehicle fleets as done by Hiermann et al. (2016), Goeke and Schneider (2015), and Zuo et al. (2018). In this context, researches considering heterogeneous fleets that involve generally the EVs and ICEVs, called as well the “mix fleet” (e.g. Sassi et al., 2014; Goeke and, Schneider, 2015), and different types of EVs in terms of both passenger and battery capacity (e.g. Hiermann et al., 2016; Ziebuhr et al., 2017; and, Zuo et al., 2017) or solely passenger capacity (e.g. Worley et al., 2012; and, Yang and Sun, 2015), have been conducted in order to meet the needs of demand in VRPs. Therefore, a great majority of the researches involving the EVRP have focused on customer demands at each node with the restriction of vehicle capacity, and considered the change in the total load for load distribution or collection (e.g. Schneider et al., 2014; Keskin and

Çatay, 2018; and, Conrad and Figliozzi, 2011).

The battery recharging process is imposed to the EVRP formulations within various aspects in terms of the recharging rate, i.e., linear or nonlinear in time, recharging amount, i.e., partially or full, and recharging station type, i.e., monotype recharging stations or heterogeneous recharging stations based on price and/or recharging rate. The actual nonlinear characteristics of EV battery recharging is assumed to be linear in most of the studies while the nonlinearity, that arises especially when the battery is being recharged from 80 percent to its capacity (Montoya et al., 2017), is considered specifically in (Montoya et al. 2017) employing piecewise linear functions, and in (Bi and Tang 2019), in which an analytical battery model is incorporated. Battery recharging characteristics is handled from another point of view as well in a number of studies (e.g. Felipe et al., 2014; Sassi et al., 2014; Bruglieri et al., 2015; Desaulniers et al., 2016; Keskin and Catay, 2016; and, Schiffer and Walther 2017), where partial recharging is allowed to relax the constraint that necessitates a full recharge up to battery's capacity, which may yield to waste of both time and cost due to the redundant energy loading. As the pioneer, Felipe et al. (2014) have aimed to reveal the impact of relaxing the full recharging constraint to partial with the consideration of different recharging technologies. Keskin and Çatay (2018) have extended their study, in which they allow partial recharging (Keskin and Çatay, 2016), by considering three levels of recharging station option at pre-defined nodes to minimize the total costs. Different recharging technologies in terms of recharging rate, and consequently in purchasing price, have been explicitly considered by Felipe et al. (2014), Sassi et al. (2014), and Pourazarm and Cassandras (2014a), as well, where different focuses in terms of the objective have been made, such as the cost (e.g. Felipe et al., 2014; and, Keskin and Çatay, 2018) or the total elapsed time (Pourazarm and Cassandras, 2014a) considering the variations in recharging station prices and recharging rates.

In addition to the sub-problem in (Felipe et al. 2014) on “how much” to recharge, some researchers have focused on both “how much” and “where” to recharge by formulating a Location Routing Problem considering EVs (e.g. Yang and Sun, 2015; Schiffer and Walther, 2017; and, Schiffer et al. 2018). The energy replenishment station is handled either as a Battery Swap Station (BSS) (e.g. Yang and Sun, 2015; Hof et al., 2017; and, Zhang et al., 2019) or plug-in recharging station (Schiffer and Walther, 2017a; and, Schiffer et al., 2018), where the time losses in recharging process are neglected

in case of the BSS. Energy replenishment stations are handled as intermediate facilities to stop during the path as well (e.g. Hof et al., 2017; Schiffer and Walther, 2017b; and, Schiffer et al. 2018), by extending the model introduced by Schneider et al. (2015), which is called VRP with intermediate stops (VRPIS), to the LRP Intra-route Facilities (LRPIF). Imposing the time-dependency in recharging and the partially recharge availability in recharging stations, Schiffer and Walther (2017a) have proposed the Electric Vehicle Routing Problem with Time Window and Partial Recharging (ELRP-TW) model and, discussed the set of optimal solutions that comprises of for different objectives to be minimized including the number of recharging stations, distance traveled, and total costs. Uncertainties in customer demands (e.g. Zhang et al., 2018; and, Schiffer and Walther, 2018) as well as customer locations (e.g. Schiffer and Walther, 2018) are studied in the related literature as well, in order to propose a robust solution to the ELRP. In addition to locating the replenishment stations, optimal depot locations for an EV fleet are sought considering multi-depots cases (e.g. Almouhanna et al., 2020).

Instead of considering the battery discharging characteristics as a linear function of traveled distance, the battery load is determined in a more accurate manner in a number of studies by imposing the effects of the resistances against the motion and/or traffic congestion. In this context, the energy consumption when traversing an arc bounded by two subsequent nodes is calculated considering the features involving the dynamics of vehicles, and the traffic, such as: the traffic conditions and the two-dimensional road geometry parameters including the vehicle speed and mass (e.g. Wang et al., 2014; and, Pourazarm and Cassandras, 2014a); and, the three-dimensional road geometry to determine driving resistance (e.g. Preis et al., 2014; Goeke and Schneider, 2015; and, Shao et al., 2018; and, Zhang et al., 2018). Realistic energy consumption models, as in the forms of an MIP and MILP as well as a dynamic model, are incorporated to the formulations respectively in (Goeke and Schneider, 2015), (Lin et al. 2016), and (Bi and Tang 2018), where the driving resistances including air, rolling, grade, and acceleration/deceleration in which the vehicle mass is a variable that changes with the cargo load, and the regenerative energy are considered. In order to achieve optimal driving paths with the optimal recharging plan with energy consumption concerns, a large-scale real world case is tested using the EVRP model provided in (Shao et al., 2018). Yi and Bauer (2018) have remarked the randomness in energy consumption of

EVs considering the dynamic nature of environmental parameters such as wind and temperature, and proposed a stochastic decision model to seek the minimum energy path, where Pelletier et al. (2019) have focused on the energy consumption uncertainties in EVs, including aerodynamic drag coefficient, rolling friction coefficient, air density, driveline efficiency, auxiliary power required, and etc.

Studies on the Electric Vehicle Routing Problem, which are summarized in details in the preceding sections, are classified in Table 3.3 according mainly to the: problem type, objectives, constraints, vehicle types, recharging station (RS) types, discharging and recharging characteristics of the battery, battery recharging time, recharging station locations, mixed fleet existence, and traffic. In classification, objective functions are mainly decomposed considering seven minimization criteria, i.e., total traveled distance (TTD), total elapse time (TTE), total cost (TC), customer waiting time (CWT), energy usage (E), number of vehicle assigned (NV), and number of recharging station sited (NS). The constraints considered are: vehicle freight capacity (VFC); vehicle battery capacity (VBC); maximum riding time (MRT); time window (TW); maximum number of vehicles assigned (MNV); and, maximum number of recharging stations (MNS). The type of vehicle and RS is classified as homogeneous (HO) or heterogeneous (HT), where battery discharging is grouped into three assuming that it is: a linear function of distance traveled (D); affected by driving resistances (R); or, traffic congestion (T). Battery recharging time is classified into two, i.e., linear (L) or nonlinear (NL). Partial and full recharging characteristics are denoted respectively by (PR) and (FR). The RS location is grouped into two, i.e., fixed location (F) and simultaneous siting decision (S). are differed in RS location column. The references reviewed are analyzed in terms of mixed fleet and traffic congestion as well, to figure out whether the parameters are considered or not.

Despite the fact that researches involving the EVRP are getting widespread, there are still some gaps in the literature that obstruct to evaluate accurately the requirements for increasing the use of EVs. Although the energy consumption of EVs is incorporated to models through various formulations as mentioned above in preceding sections in details, a number of issues regarding especially the vehicle motion dynamics and vehicle vs. road interaction in the formulation of the EVRP still do exist to be researched, as, for example, some of the resistances against the motion are neglected, including inertia and curb resistances. Additionally, the interdependency between the

recharging station location and EV routing has not been addressed yet by considering a realistic battery discharging model. The actual recharging characteristics need to be incorporated to the formulations as well, in order to evaluate the nonlinearity in the form of the recharging function.



Table 3.3: Related literature on EVRP.

Reference	Problem class	Objective(s)	Constraints	Vehicle type	RS type	Battery discharging	Battery recharging time	Recharging characteristic	RS location	Mixed fleet	Traffic
Conrad and Figliozzi, 2011	RVRP	NV, TTD+ST+RC	VFC, VBC, TW	HO	HO	D	Constant	PR	S		
Worley et al. , 2012	ELRP	TC	VFC, VBC	HT (cap)	HO	D	Not considered	FR *	S		
Erdoğan and Miller-Hooks, 2012	GVRP	TTD	VBC, MRT, MNV	HO	HO	D	Not considered	FR	F		
Albert and Pudney, 2013	ELRP	TET	VBC, MRT, MNV	HO	HO	D	L	PR	F		
Felipe et al., 2014	GVRP	TC/RC+BT	VFC, VBC, MRT	HO	HT	D	L	PR	F		
Schneider et al., 2014	EVRPTW	TTD	VFC, VBC, TW	HO	HO	D	L	FR	F		
Ziebuhr et al. 2017	GVRP	E	VFC	HT	No recharging.	Load-dependent	No recharging	No recharging	No recharging.		
Schiffer and Walther, 2017b	ELRP	TC	VFC, VBC, TW, MNV, MNS	HO	HO	D	L	PR	S		
Schiffer et al., 2018	ELRP	TC	VFC, VBC, TW	HO	HO	D	L	PR	S		
Goeke and Schneider, 2015	Energy-optimizing VRP	TTD, TC	VFC, VBC, TW, MNV	HO	HO	R	L	FR	F	x	
Bruglieri et al., 2015	EVRPTWPR	NV+TET	VFC, VBC, TW	HO	HO	D	L	PR	F		
Keskin and Çatay, 2016	EVRPTWPR	TTD	VFC, VBC, TW	HO	HO	D	L	PR	F		
Hiermann et al., 2016	EFSMFTW	TC	VFC, VBC, TW	HT	HO	D	L	FR	F		
Schiffer and Walther, 2017	ELRPTWPR	TTD, NV, NS, TC	VFC, VBC, TW, MNV, MNS	HO	HO	D	L	PR	S		
Yang and Sun, 2015	ELRP	TC	VFC, VBC, MNV	HT (cap)	HO	D	Not considered	FR	S		
Pelletier et al., 2019	Energy-optimizing VRP	TC	VFC, VBC,	HO	No recharging	R	No recharging	No recharging	No recharging		x

Table 3.3 (continued) : Related literature on EVRP.

Reference	Problem class	Objective(s)	Constraints	Vehicle type	RS type	Battery discharging	Battery recharging time	Recharging characteristic	RS location	Mixed fleet	Traffic
Sassi et al., 2014	E-VRPTWPR	TC	VFC, VBC, MNV, TW	HT	HT	D	L	PR	F	x	
Preis et al., 2014	Energy-optimizing VRP	E	VFC, VBC, TW, MRT	HO	HO	R	Constant	FR	F		
Montoya et al., 2017	EVRP	TET	MRT, VBC	HO	HT	D	NL	PR	F		
Shao et al., 2017	Energy-optimizing VRP	TC	VFC, VBC	HO	HO	R	Constant	FR	F		
Zuo et al., 2017	ELRP	TTD	VFC, VBC	HT	HO	D	Not considered	FR	S		
Pourazarm and Cassandras, 2018		TET	VBC	HO	HT	D,T	L	PR	F		x
Schiffer and Walther, 2018	ELRPTWPR	TC	VFC, VBC, TW	HO	HO	D	L	PR	S		Customer uncertainty
Keskin and Çatay, 2018	EVRPTWPR	TC	VFC, VBC, TW	HO	HT	D	L	PR	F		
Shi et al. , 2018	EVRP	TC, CWT	VBC, MRT	HO	HO	D	L	PR	F		



4. PROBLEM DESCRIPTION AND FORMULATION

The problem described questions in general the optimal routing of vehicles given a number of energy-consumption characteristics with Mixed Integer Linear Programming Formulation (MILP). In this context, considering the fact that there may be multiple choices to be made to travel between any nodes using the actual intersections in a real road network, graph of the conventional VRP is expanded with intersection nodes, and Electric Vehicle Location Routing Problem with Intermediate Nodes (ELRP-IN) is defined, in which routing of vehicles and location of recharging stations are sought, where the battery discharging is determined realistically considering different objective functions as explained in detail in sub-sections of section 4.

4.1 Definition and Formulation

ELRP-IN can be defined using an undirected and complete graph, $G=(N,A)$, with the set of all nodes, N , and the set of all arcs $(i, j) \in A$. The set of nodes, $N=\{1,2..n+1\}$, includes the sourcing, N_d , and the sinking, N_a , depots, and the two subsets, N_s and N_i , that represent respectively the set of bus stop nodes and the set of intersection nodes. The set N_i is defined in order to handle the whole road network with all its connections instead of focusing only on the nodes that should be visited, including the bus stop and/or customer nodes, and the air distances among them. Regardless of the computational issues, such an approach that incorporates the actual features of the road network certainly provides a more realistic formulation of the real life problem due to the fact that there can be multiple choices to travel between two subsequent bus stops, $i \in N_s$ and $j \in N_s$, depending on the bi-directional characteristics of arcs and the intersections that exist in-between subsequent bus stops. Figure 4.1 provides an example that emphasizes the importance of taking into account the arcs and nodes of a whole road network. An illustration of a real road network of Sioux-Falls city is given in Figure 4.1(a) assuming that a vehicle is supposed to travel from node 1 to node 4 by visiting nodes 2 and 3. As it is clear from Figure 4.1(b)-(h) there are various route options that may vary in time as well in order to complete the tour successfully. Any of the routing options shown in part in Figure 4.1 may offer the optimal solution according to the objective sought.

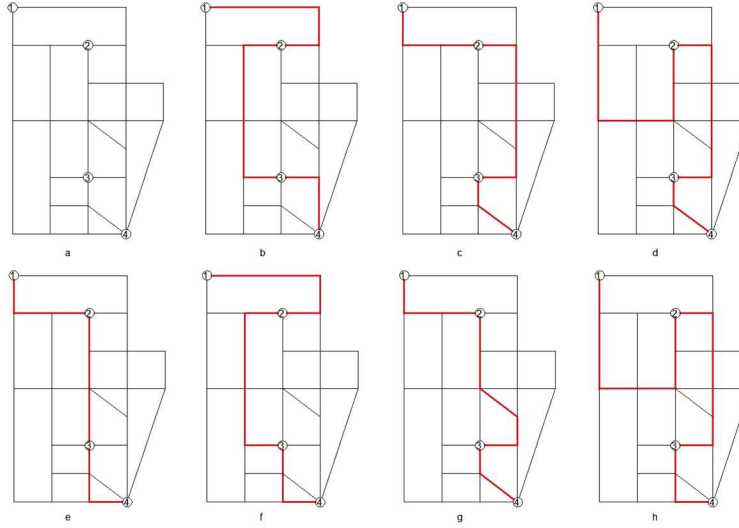


Figure 4.1 : Examples on the route options between nodes $\{1\}$ to $\{4\}$ by visiting nodes $\{2\}$ and $\{3\}$.

Researches that handle air distance or shortest distance as the distance between two nodes can offer good solutions according to their objectives, but, may not offer the optimal solution. The optimality of the solution lies down on the small differences in route options between two nodes, which can vary in terms of several parameters, such as the distance based cost/fee, the slope of the arcs composing the route, the traffic demanding to flow and conflicting at intersections, and etc., that can affect the total travel time, the total energy consumption, and the total cost or the total distance traveled as the objective function in the studies involving EVRP, as discussed in details in Section 3.3. One may think that shortest path algorithms, such Dijkstra's algorithm (Dijkstra, 1959), can be applied to the network in order to determine the shortest route between two subsequent stops and, then its output can be incorporated as an input parameter to the mathematical model in order to avoid introducing intersection nodes. This approach can also be used in seeking the least energy consuming route by weighting arcs according to the energy consumption values instead of distance (Shao et al., 2018; Artmeier, 2010). However, considering that there may be various parameters, such as travel time, energy consumption, travel distance, and etc., all of which are sought to be minimized to fit an overall objective and the fact that such parameters affect each other in real life, focusing on a single parameter may result in unrealistic solutions. Assume that one wants to travel between i and j on a network given in Figure 4.2 through a route that minimizes its total travel costs including the cost equivalent of travel time (c_t) and energy consumption (c_e). Considering the arc

related c_t and c_e figures in Figure 4.2, the outcomes of least travel time and the least energy consumption algorithms will lead to a non-optimal solution in terms of the overall cost. In addition, the routing of a vehicle, which is determined using a mathematical model, will affect the arc weights regardless of the weight parameter, i.e., distance, time, and energy consumption. For instance the total mass of a vehicle that varies according to the path tracked in terms of pick-up and deliveries affects the energy consumption of that vehicle or the speed, hence the travel time, of that vehicle.

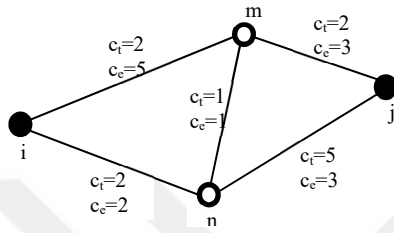


Figure 4.2 : A sample network.

Table 4.1 : Unit cost for route options
(*Optimal solution)

Route	Time Cost	Energy Cost	Total Cost
i-m-j	4*	8	12
i-m-n-j	8	9	17
i-n-j	7	5*	12
i-n-m-j	5	6	11*

Apart from the effects on the optimal solution, modeling intersection nodes on a road network in routing problems is essential to open up a space in order to analyze and incorporate the effects of the traffic congestion due to the interruption of flows conflicting at intersections, and to manage the conflicting flows at intersections given the priorities from the VRP formulation. In addition, real-time routing information involving intersection nodes can offer a full and realistic navigation to drivers.

As reasoned above, in this study the set of nodes is divided into two subsets, as bus stop and intersection nodes, where each node $i \in N_s$ has to be visited exactly once, while $i \in N_i$ does not necessarily have to be visited once, but can be visited multiple times. Recharging is allowed at each node $i \in N_s$ considering the time-windows at bus stops. Battery discharging is calculated considering the resistances to the motion. Recharging speed of a battery is assumed to be linear. The speed of a vehicle is set adopting a pre-defined speed profile, as explained in Section 4.1.1.

Despite the fact that the explicit consideration of intermediate nodes increases the problem size, the overall computational load tends to decrease by limiting the number of connections among nodes in a realistic manner while respecting the actual road network topology. For example, considering 30 customers to be served via a graph with the conventional VRP approach where there is an arc between any nodes, there are 870 and 29 arcs respectively in total and for each customer when the self-

connections are removed. However, for the same case, assuming there are 70 additional intermediate nodes each with a node degree of 4, composed of sources and sinks, there exist 340 feasible arcs to be considered, which increases the computational capability of exact solutions.

4.1.1 Energy consumption

In order to incorporate the energy consumption effects of vehicle types to the problem formulation, the motion, and hence the traction, characteristics are considered. In addition to the opportunities that vehicular technology possess with the advances in traction by and/or recuperation of electrical energy, considering the fact that service vehicles tend to have similar acceleration and deceleration behavior while riding through two subsequent nodes, where first they accelerate while departing from a subsequent node to a desired speed and, then the speed is decelerated to 0 with the stop at the following subsequent node, a train's-like speed profile is adopted instead of a speed profile with fully constant speed. Examples of train's-like speed profile are illustrated in Figure 4.1.1(2), where a vehicle travels from node i to node j . According to the acceleration rate, γ_a , the vehicle accelerates from node i for t_a seconds in phase I until it reaches to a desired speed, V , at the time instant that corresponds to node i_1 . Following the phase (II) that the vehicle is driven with a constant speed for t_c seconds from i_1 to i_2 it reaches to the subsequent node j from node i_2 by decelerating with the deceleration rate, γ_d , for t_d seconds in phase III. In this study, the nodes that the road intersections correspond to are considered as intermediate nodes, where vehicles are supposed to decelerate to a certain extent in order to safely approach to the area of conflicting movements. Therefore, the speed profile adopted for a ride between two stop nodes is adopted for rides between two intermediate nodes as well. Although rides involving approaching to and departing from two subsequent nodes containing bus stop and intersection and vice versa have the similar trend in terms of their speed profile, the desired speeds considered for intermediate nodes and bus stop nodes differ, respectively as $V_i \in N_i$ and V_s , where $V_s=0$ as a vehicle needs to stop in order to serve customers/passengers at a bus stop node. The desired speed for decelerating a ride while approaching to intermediate nodes may differ for each node $i \in N_i$ considering the traffic conditions and the cases where intersections are controlled by signalization. In such cases may be defined with a desired speed matrix V_i , $i \in N_i$, can be defined to account for the variation in desired speeds. Given the feature of the real case handled

in this study does not involve any signal control at intersections and, a relatively lower speed limit, 30-40 km/h, is posted for the entire traffic flowing throughout the campus area, the required deceleration hence the desired speed while driving through intersections is assumed to be fixed. Considering all the possible travels between two subsequent nodes in terms of their types, i.e., from stop to stop, from stop to intersection, from intersection to stop, and from intersection to intersection, the speed profiles are illustrated in Figure 4.3 (a)-(d).

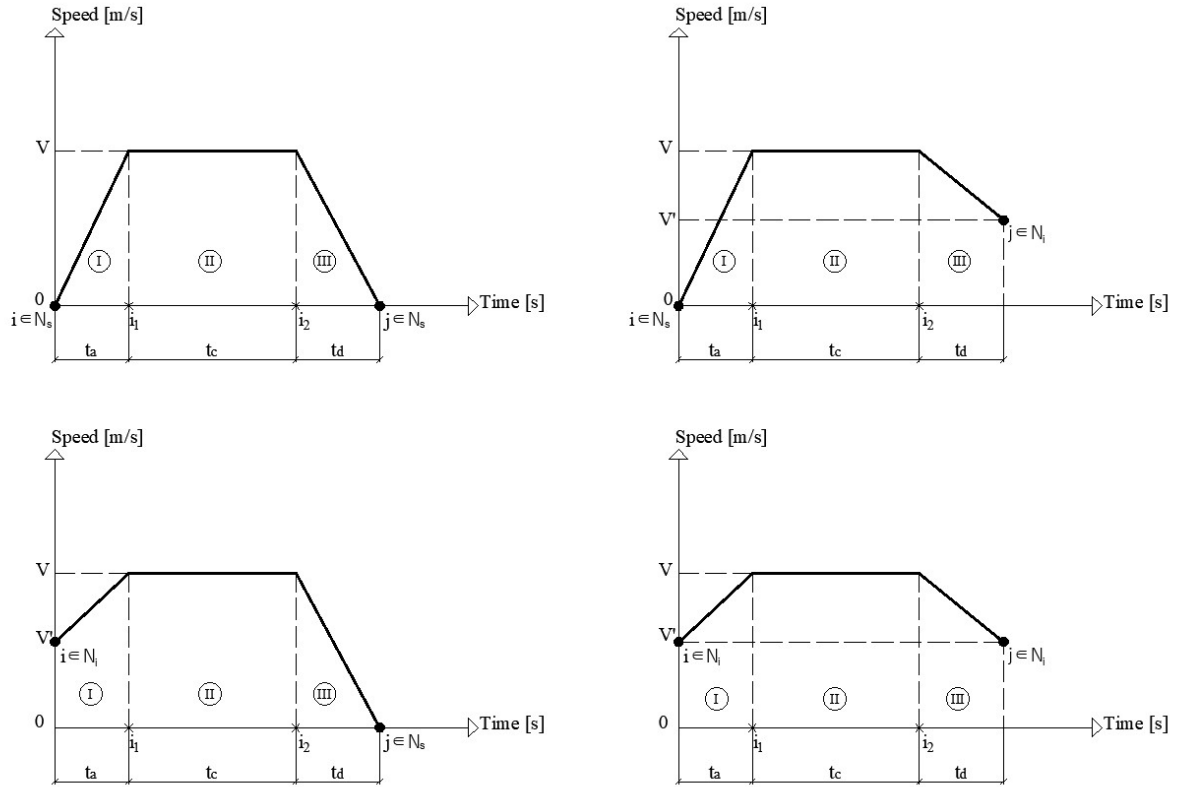


Figure 4.3 : Speed profiles adopted dependent on type of sourcing and sinking node pairs: (a) stop to stop; (b) stop to intersection; (c) intersection to stop; and, (d) intersection to intersection.

The underlying idea in handling an arc (i,j) by decomposing it into three sections is to incorporate to the problem formulation the actual features by tracking the changes that affect the energy consumption and energy recuperation of vehicles including speed, rates of acceleration and deceleration, and road geometry along a travel. Obviously the more the arc (i,j) is segmented into pieces, the more the realistic energy consumption/recuperation figures are obtained. However, in order to trade-off the computational load due to the exact solution of the problem each arc of the road network is assumed to be composed of 3 sections, that each of which correspond to a phase of

acceleration, cruising, and deceleration, in which the requirements for the braking energy, as well as the propulsion energy are evaluated. Therefore, the changes in the propulsion required in cases of varying resistances to the motion can be figured out in conjunction with the consideration of energy recuperation possibilities.

The driving resistances against the motion differ from phase to phase while the resistances of rolling, aerodynamics, and grade are assumed to be fixed within a phase, where phase I and phase III additionally involves respectively the resistances of acceleration and deceleration.

The energy required to travel, called the energy consumption, is considered as the total battery power demand during the time of a travel, where the minimum required time to travel between i and j with a constant speed V is denoted by $t_{ij,min}$. As Figure 4.3 implies, a vehicle needs t_a and t_d hours respectively to accelerate and decelerate, which differ according to the states of departing from and arriving to nodes. Let 1, 2, 3, and 4 express the counters respectively for the subsequent node pairs, i.e., from stop to stop, from stop to intersection, from intersection to stop, and from intersection to intersection. The cruising time is different for each arc (i, j) given the travel distance between i and j , d_{ij} . The time required to accelerate, t_a , and decelerate, t_d , as well as the cruising time, $t_{c,ij}$, is defined for each type of speed profile below.

For stop to stop

$$t_{a,1} = \int_{V=0}^{V=V} \frac{1}{\gamma_a} dv \quad (4.1)$$

$$t_{c,1}^{ij} = t_{ij,min} - \frac{\int_{V=0}^{V=V} \frac{1}{2} dv + \left| \int_{V=V}^{V=0} \frac{1}{2} dv \right|}{V} \quad \forall i,j \in N_s \quad (4.2)$$

$$t_{d,1} = \left| \int_{V=V}^{V=0} \frac{1}{\gamma_d} dv \right| \quad (4.3)$$

$$t_{ij,1} = t_{a,1} + t_{c,1}^{ij} + t_{d,1} \quad \forall i,j \in N_s \quad (4.4)$$

For stop to intersection

$$t_{a,2} = t_{a,1} = \int_{V=0}^{V=V} \frac{1}{\gamma_a} dv \quad (4.5)$$

$$t_{c,2}^{ij} = t_{ij,min} - \frac{\int_{V=0}^{V=V} \frac{1}{2} dv + \left| \int_{V=V}^{V=V'} \frac{1}{2} dv \right| + \int_{V=0}^{V=V'} t_{d,2} dv}{V} \quad \forall i \in N_s, \forall j \in N_i \quad (4.6)$$

$$t_{d,2} = \left| \int_{V=V}^{V=V'} \frac{1}{\gamma_d} dv \right| \quad (4.7)$$

$$t_{ij,2} = t_{a,1} + t_{c,2}^{ij} + t_{d,2} \quad \forall i \in N_s, \forall j \in N_i \quad (4.8)$$

For intersection to stop

$$t_{a,3} = \int_{V=V'}^{V=V} \frac{1}{\gamma_a} dv \quad (4.9)$$

$$t_{c,3}^{ij} = t_{ij,min} - \frac{\int_{V=V'}^{V=V} \frac{t_{a,3}}{2} dv + \int_{V=0}^{V=V'} t_{a,3} dv + \left| \int_{V=V}^{V=0} \frac{t_{d,3}}{2} dv \right|}{V} \quad \forall i \in N_i, \forall j \in N_s \quad (4.10)$$

$$t_{d,3} = t_{d,1} = \left| \int_{V=V}^{V=0} \frac{1}{\gamma_d} dv \right| \quad (4.11)$$

$$t_{ij,3} = t_{a,3} + t_{c,3}^{ij} + t_{d,1} \quad \forall i \in N_i, \forall j \in N_s \quad (4.12)$$

For intersection to intersection

$$t_{a,4} = t_{a,3} = \int_{V=V'}^{V=V} \frac{1}{\gamma_a} dv \quad (4.13)$$

$$t_{c,4}^{ij} = t_{ij,min} - \frac{\int_{V=V'}^{V=V} \frac{t_{a,4}}{2} dv + \int_{V=0}^{V=V'} t_{a,4} dv + \left| \int_{V=V}^{V=V'} \frac{t_{d,4}}{2} dv \right| + \int_{V=0}^{V=V'} t_{d,4} dv}{V} \quad \forall i, j \in N_i \quad (4.14)$$

$$t_{d,4} = t_{d,2} = \left| \int_{V=V}^{V=V'} \frac{1}{\gamma_d} dv \right| \quad (4.15)$$

$$t_{ij,4} = t_{a,3} + t_{c,4}^{ij} + t_{d,2} \quad \forall i, j \in N_i \quad (4.16)$$

Figure 4.4 shows a sample of the change in the elevation of nodes of an arc (i, j), where there is an uphill travel. It is assumed that the elevation on grade line increases or decreases linearly for all arcs. Therefore, given the grade elevation for node i and node j respectively with h_i and h_j , and the distance between them, d_{ij} , the elevations of the nodes that help to bound the phases of a speed profile, i_1 and i_2 , are determined considering the grade of arc (i,j), g_{ij} , (Equation 4.17), using Equation (4.18) and Equation (4.19).

$$g_{ij} = \frac{h_j - h_i}{d_{ij}} \quad (4.17)$$

$$h_{i_1} = h_i + g_{ij} \cdot d_{i,i_1} \quad (4.18)$$

$$h_{i_{12}} = h_i + g_{ij} \cdot d_{i,i_2} \quad (4.19)$$

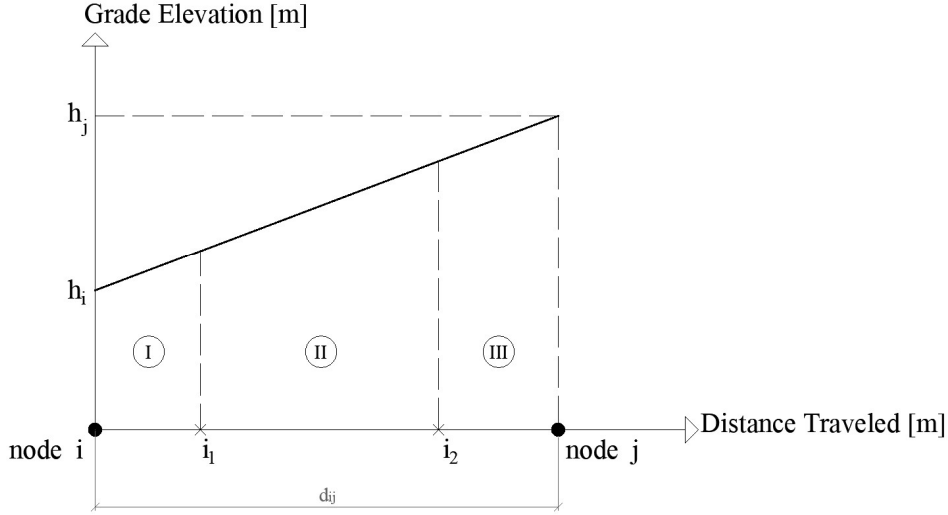


Figure 4.4: Sample of change in the elevation of nodes of an arc (i, j).

Given the features of driving and road geometry, the energy required can then be determined upon the principle of energy conservation by evaluating the motion dynamics regarding the kinetic energy, potential energy, and the energy losses for each phase for each speed profile, i.e., acceleration, abbreviated as ‘acc’, cruising, abbreviated as ‘cru’, and deceleration, abbreviated as ‘dec’, as shown in Figure 4.3. The changes in overall mass of the vehicle due to changes in the cumulative passenger load at each node $i \in N_s$, p_i , is considered as well with the parameter ϕ that defines the mass of a unit passenger. Average speeds in phases of acceleration and deceleration are denoted by $\bar{V}$ and $\bar{V}'$ respectively to represent the speed changes (0-V) or (V-0), and (V-V') or (V'-V).

Considering the energy Equation (2.65) that is explained in details in Section 2, the change in tractive energy in acceleration phase is calculated using Equation (4.20) and Equation (4.21) respectively for subsequent node pairs, i.e., from stop $i \in N_s$ to intermediate (i_1) and from intermediate (i_1) to intermediate (i_2), where E_{ij}^{acc} depends on the features at the departing node regardless of the arrival node.

$$E_{ij}^1 = \frac{1}{2} \cdot (m + \phi \cdot p_i + \xi) \cdot (V^2 - 0) + (m + \phi \cdot p_i) \cdot g \cdot (h_{i_1} - h_i) + \int_{t=0}^{t=t_{a,1}} (F_r + F_a) \cdot \bar{V} dt \quad \forall i \in N_s, \forall j \in N \quad (4.20)$$

$$E_{ij}^1 = \frac{1}{2} \cdot (m + \phi \cdot p_i + \xi) \cdot (V'^2 - 0) + (m + \phi \cdot p_i) \cdot g \cdot (h_{i_1} - h_i) + \int_{t=0}^{t=t_{a,1}} (F_r + F_a) \cdot \bar{V}' dt \quad \forall i \in N_s, \forall j \in N \quad (4.21)$$

Equations given through (4.22) to (4.25) are used to determine the change in the energy required for the cruising phase of each of the speed profiles, where the kinetic energy is excluded as there is no change in it due to the constant cruising speed during the phase.

$$E_{ij}^2 = (m + \phi \cdot p_i) \cdot g \cdot (h_{i_2} - h_{i_1}) + \int_{t=t_{a,1}}^{t=t_{c,1}^{ij} + t_{a,1}} (F_r + F_a) \cdot V \, dt \quad \forall i, j \in N_s \quad (4.22)$$

$$E_{ij}^2 = (m + \phi \cdot p_i) \cdot g \cdot (h_{i_2} - h_{i_1}) + \int_{t=t_{a,2}}^{t=t_{c,2}^{ij} + t_{a,2}} (F_r + F_a) \cdot V \, dt \quad \forall i \in N_s, \forall j \in N_i \quad (4.23)$$

$$E_{ij}^2 = (m + \phi \cdot p_i) \cdot g \cdot (h_{i_2} - h_{i_1}) + \int_{t=t_{a,3}}^{t=t_{c,3}^{ij} + t_{a,3}} (F_r + F_a) \cdot V \, dt \quad \forall i \in N_i, \forall j \in N_s \quad (4.24)$$

$$E_{ij}^2 = (m + \phi \cdot p_i) \cdot g \cdot (h_{i_2} - h_{i_1}) + \int_{t=t_{a,4}}^{t=t_{c,4}^{ij} + t_{a,4}} (F_r + F_a) \cdot V \, dt \quad \forall i, j \in N_i \quad (4.25)$$

The change in the kinetic energy in cases of deceleration is obtained using Equation (4.26), Equation (4.27), Equation (4.28), and Equation (4.29) respectively for subsequent node pairs, i.e., from stop to stop $j \in N_s$ or to intermediate $j \in N_i$ and from intermediate to stop $j \in N_s$ or to intermediate $j \in N_i$ to intermediate.

$$E_{ij}^3 = \frac{1}{2} \cdot (m + \phi \cdot p_i + \xi) \cdot (V^2 - 0) + (m + \phi \cdot p_i) \cdot g \cdot (h_j - h_{i_2}) + \int_{t=t_{a,1} + t_{c,1}^{ij} + t_{d,1}}^{t=t_{a,1} + t_{c,1}^{ij} + t_{d,1}} (F_r + F_a) \cdot \bar{V} \, dt \quad \forall i \in N_s, \forall j \in N_s \quad (4.26)$$

$$E_{ij}^3 = \frac{1}{2} \cdot (m + \phi \cdot p_i + \xi) \cdot (V^2 - V^2) + (m + \phi \cdot p_i) \cdot g \cdot (h_j - h_{i_2}) + \int_{t=t_{a,2} + t_{c,2}^{ij} + t_{d,2}}^{t=t_{a,2} + t_{c,2}^{ij} + t_{d,2}} (F_r + F_a) \cdot \bar{V} \, dt \quad \forall i \in N_s, \forall j \in N_i \quad (4.27)$$

$$E_{ij}^3 = \frac{1}{2} \cdot (m + \phi \cdot p_i + \xi) \cdot (V^2 - 0) + (m + \phi \cdot p_i) \cdot g \cdot (h_j - h_{i_2}) + \int_{t=t_{c,3}^{ij} + t_{a,3}}^{t=t_{c,3}^{ij} + t_{a,3} + t_{d,3}} (F_r + F_a) \cdot \bar{V} \, dt \quad \forall i \in N_i, \forall j \in N_s \quad (4.28)$$

$$E_{ij}^3 = \frac{1}{2} \cdot (m + \phi \cdot p_i + \xi) \cdot (V^2 - V^2) + (m + \phi \cdot p_i) \cdot g \cdot (h_j - h_{i_2}) + \int_{t=t_{a,4} + t_{c,4}^{ij} + t_{d,4}}^{t=t_{a,4} + t_{c,4}^{ij} + t_{d,4}} (F_r + F_a) \cdot \bar{V} \, dt \quad \forall i \in N_i, \forall j \in N_i \quad (4.29)$$

Finally, the energy in terms of kWh required to move a vehicle with the passenger load p_i from node i to j , E_{ij} , is determined using (4.30) considering the travel times in the phases of motion on arc (i, j) . Note that a conversion from kWsec to kWh is needed.

$$E_{ij} = \sum_{k=1}^3 E_{ij}^k \quad \forall i,j \in N \quad (4.30)$$

In order to write a general formulation of the energy requirement for both ICEVs and EVs, the efficiency constants are neglected in Equation (4.30) at first hand. In this context, the extensions explained below need to be incorporated to formulation specific to the vehicle types

For the routing of electric vehicles; the energy change in each phase is evaluated in order to determine if there is a traction or braking force needed. Therefore, the recuperated and/or the consumed energy can be identified. In this context, subject to the phase of motion, k , the Equation (4.31) implies that: in cases where energy is required ($E_{ij}^k > 0$), the propulsion efficiency; and, in cases where there is surplus energy that needs to be covered by braking energy ($E_{ij}^k < 0$), the regenerative braking efficiency is to be considered.

$$E_{ij}^k = \begin{cases} E_{ij}^k \cdot \eta_e^{-1} & \text{if } E_{ij}^k > 0 \\ 0 & \text{if } E_{ij}^k = 0 \\ E_{ij}^k \cdot \eta_{rg} & \text{if } E_{ij}^k < 0 \end{cases} \quad k=1,2,3, \forall i,j \in N \quad (4.31)$$

For the routing of internal combustion engine vehicles; as the braking energy is converted to the heat, the required energy can be calculated using Equation (4.32).

$$E_{ij}^k = \begin{cases} E_{ij}^k \cdot \eta_i^{-1} & \text{if } E_{ij}^k > 0 \\ 0 & \text{if } E_{ij}^k \leq 0 \end{cases} \quad k=1,2,3, \forall i,j \in N \quad (4.32)$$

In this study, it is assumed that the refueling is available only for EVs considering their limited driving ranges. The amount of recharging energy required from a recharging station i , E_{grid}^i , is calculated according to the energy required, q_i , and the energy efficiency of the recharging, n_g , as given by Equation (4.33).

$$E_{grid}^i = \frac{q_i}{n_g} \quad (4.33)$$

In order to increase the computational efficiency of the proposed methodology, a number assumptions, regarding the motion and the corresponding energy needs, made are listed in the following:

- Regenerated energy is assumed to be utilized instantaneously as it is recuperated.

- Parameters that affect the tractive force, and hence the energy consumption along a road section are assumed to be fixed.
- Influence of temperature on battery is assumed to be neglected.
- Rates of acceleration and deceleration are assumed to be constant.

4.1.2 Decision variables

Table 4.2 shows the seven decision variables considered in this study. Regarding the nature of vehicle routing, the binary decision variable x_{ij} is used to decide whether the arc between i to j is traversed or not. As important aspects of electric vehicle routing: the locations of recharging stations; the amount of energy charged; and, the battery load are determined respectively by the binary decision variables y_i , b_i , and q_i . The total time spent to reach node $i \in N$ and the vehicle passenger load at node $i \in N$ are represented respectively with τ_i and p_i . The variable that is used to determine the energy consumption between two subsequent nodes, E_{ij} , is explained in Section 4.1.1.

Table 4.2: Notations of decision variables.

Notation	Decision variable
x_{ij}	Arc (i,j) is traveled or not, binary
y_i	Recharging station is sited at node i or not, binary
τ_i	Total time spent to reach node i [sec]
b_i	Battery load at node i [kWh]
q_i	Amount of energy required from recharging station at node i [kWh]
p_i	Passenger load of vehicle as it arrives at node i .
E_{ij}	Energy consumption between i and j [kWh]

4.1.3 Parameters

Some of the parameters are defined as given in Table 4.3. The cost parameters analyzed are decided taking into account four aspects as the cost of: vehicle purchasing (c_v); energy consumption (c_e), recharging station (c_s), and distance related operational tasks (c_d). A cost parameter β is defined in order to incorporate together the effects of long-term investments, such as vehicle and recharging station purchasing, with the daily expenses including fuel consumption and operational costs. The stopping time at

each node $i \in N_s$ is determined using the service time (s_i), which equals zero at each $i \in N_i$. The passenger load at each $j \in N$ is calculated in a cumulative fashion as a difference of the numbers of passengers getting on (n_i) and off (m_i) at each $i \in N_s$. Battery and passenger capacity of a vehicle are represented respectively with Q and K , where the time limit is represented with T . The recharging rate at a station is denoted by o , where Y stands for the maximum number of recharging stations.

Table 4.3 : Notation of parameters.

Notation	Parameter
d_{ij}	Distance between i and j [m]
Q	Battery capacity [kWh]
c_e	Energy cost [€/kWh]
c_s	Recharging station cost [€/unit]
c_v	Vehicle purchasing cost [€/unit]
c_d	Distance cost [€/m]
β	Cost coefficient for purchasing costs
o	Recharging rate [s/kWh]
T	Upper limit on time to complete a tour [s]
s_i	Service duration at node i [s]
m_i	Number of getting off passengers at node i [persons]
n_i	Number of getting on passengers at node i [persons]
K	Passenger capacity of vehicle [persons]
Y	Maximum number of recharging stations [unit]
n_g	Energy efficiency of recharging
$t_{ij,1}$	Travel time from $i \in N_s$ to $j \in N_s$
$t_{ij,2}$	Travel time from $i \in N_s$ to $j \in N_i$
$t_{ij,3}$	Travel time from $i \in N_i$ to $j \in N_s$
$t_{ij,4}$	Travel time from $i \in N_i$ to $j \in N_i$

4.1.4 Constraints

ELRP-IN proposed is restricted with number of constraints as listed through (4.34) to (4.54) considering the limitations in operating electric vehicles and the necessities of routing problems. The routing constraints are given through (4.34) to (4.36), where (4.34) and (4.35) guarantee to visit each stop only once, and (4.36) ensures the flow conservation. The time constraints are given through (4.37) to (4.41), where the arrival time to a node, τ_i , is determined for each state of departing from and arriving to nodes, considering possible recharging at node $i \in N_s$. The amount of the energy loaded, q_i , and the service time at the preceding node, s_i , that is defined as a function of passenger

flows: $s_i = s \cdot (m_i + n_i)$, where s represents a constant corresponding to the time required to meet a single passenger's demand. The route duration is limited with T . The number of passengers to be accommodated in bus regarding its capacity is limited using the constraints given through (4.42) to (4.46). Constraints given through (4.47) to (4.51) are used to determine the remaining energy (remaining battery load) at each node $i \in N$, where a bus is assumed to start its route with full battery as ensured by (4.51). Decision on siting a recharging station is made processing the constraints (4.52) and (4.53) that ensure mounting a recharging station at any bus stop node, where recharging is needed while respecting the maximum number of recharging stations to be mounted. Constraints on decision variables are given by (4.54).

$$\sum_{j \in N \setminus N_d, j \neq i} x_{ij} = 1 \quad \forall i \in N_s \setminus N_a \quad (4.34)$$

$$\sum_{i \in N \setminus N_a, j \neq i} x_{ij} = 1 \quad \forall j \in N_s \setminus N_d \quad (4.35)$$

$$\sum_{j \in N \setminus N_a, j \neq i} x_{ji} - \sum_{j \in N \setminus N_d, j \neq i} x_{ij} = 1 \quad \forall i \in N \setminus N_a \cup N_d \quad (4.36)$$

$$\tau_j \geq \tau_i + (t_{ij,1} + s_i) \cdot x_{ij} + (o \cdot q_i) - T \cdot (1 - x_{ij}) \quad \forall i \in N_s, j \in N_s \setminus N_d, i \neq j \quad (4.37)$$

$$\tau_j \geq \tau_i + (t_{ij,2} + s_i) \cdot x_{ij} + (o \cdot q_i) - T \cdot (1 - x_{ij}) \quad \forall i \in N_s, \forall j \in N_i, i \neq j \quad (4.38)$$

$$\tau_j \geq \tau_i + (t_{ij,3} \cdot x_{ij}) - T \cdot (1 - x_{ij}) \quad \forall i \in N_i, j \in N_s \setminus N_d, i \neq j \quad (4.39)$$

$$\tau_j \geq \tau_i + (t_{ij,4} \cdot x_{ij}) - T \cdot (1 - x_{ij}) \quad \forall i \in N_i, \forall j \in N_i, i \neq j \quad (4.40)$$

$$\tau_{N_a} \leq T \quad (4.41)$$

$$p_j \geq p_1 + n_1 \cdot x_{1j} - K \cdot (1 - x_{1j}) \quad \forall j \in N \setminus N_d \cup N_a \quad (4.42)$$

$$p_j \geq p_i + (n_i - m_i) \cdot x_{ij} - K \cdot (1 - x_{ij}) \quad \forall i \in N_s, \forall j \in N \setminus N_d, i \neq j \quad (4.43)$$

$$p_j \geq p_i - K \cdot (1 - x_{ij}) \quad \forall i \in N_i, \forall j \in N \setminus N_d, i \neq j \quad (4.44)$$

$$p_1 = 0 \quad (4.45)$$

$$p_i \leq K \quad \forall i \in N \quad (4.46)$$

$$b_j \leq b_1 - E_{1j} \cdot x_{1j} + Q \cdot (1 - x_{1j}) \quad \forall j \in N \setminus N_d \cup N_a \quad (4.47)$$

$$b_j \leq b_i + q_i - E_{ij} \cdot x_{ij} + Q \cdot (1 - x_{ij}) \quad \forall i \in N_s \setminus N_d, \forall j \in N, i \neq j \quad (4.48)$$

$$b_j \leq b_i - E_{ij} \cdot x_{ij} + Q \cdot (1 - x_{ij}) \quad \forall i \in N_i, \forall j \in N, i \neq j \quad (4.49)$$

$$0 \leq q_i + b_i \leq Q \quad \forall i \in N_s \quad (4.50)$$

$$b_i = Q \quad (4.51)$$

$$q_i \leq Q \cdot y_i \quad \forall i \in N_s \setminus N_d \cup N_a \quad (4.52)$$

$$\sum_{i \in N_s} y_i \leq Y \quad \forall i \in N_s \quad (4.53)$$

$$x_{ij}, y_i \in \{0,1\}; \tau_i, q_i, b_i, p_i \geq 0 \quad (4.54)$$

4.1.5 Objective functions

Considering the possible optimal solutions each objective means a new look at the optimization problem the EVRP formulation presented in this study involves a number of various objective functions in order to propose a wider perspective for decision makers on fleet and route planning, and to reveal the importance of concentrating on the appropriate problem-specific objective. Objectives to be minimized that are considered in this study are given through equations (4.55) to (4.58) regarding respectively the total distance traveled, number of recharging stations mounted, total traveling time, total energy consumption, and the total cost. Objective (4.55) considers the 2-dimensional distance in calculating the total distance traveled. Total travel time (equation 4.56) is considered to be dependent on the arc traveling and recharging times that are determined using the vehicle speed, the amount of energy loaded, and the recharging speed, while some real-world parameters are neglected such as the effect of traffic congestion and the time spent at recharging stations other than recharging. Equation (4.57) aims to minimize the total energy consumption. Minimizing the total cost is sought by carried through equation (4.58), where the cost function is composed of the energy cost considering the energy losses during recharging, distance cost, vehicle purchasing cost, and the recharging station mounting cost. Considering that the costs of vehicle purchasing and recharging station mounting correspond to long-term investments, coefficient β is used to handle all parameters in the identical cost term.

$$\text{minimize } \sum_{i \in N, j \in N, i \neq j} d_{ij} \cdot x_{ij} \quad (4.55)$$

$$\begin{aligned} &\text{minimize } \sum_{i \in N_s, j \in N_s, i \neq j} (t_{ij,1} \cdot x_{ij}) + \sum_{i \in N_s, j \in N_i, i \neq j} (t_{ij,2} \cdot x_{ij}) + \\ &\sum_{i \in N_i, j \in N_s, i \neq j} (t_{ij,3} \cdot x_{ij}) + \sum_{i \in N_i, j \in N_i, i \neq j} (t_{ij,4} \cdot x_{ij}) + \sum_{i \in N_s} (q_i \cdot o \cdot y_i) \end{aligned} \quad (4.56)$$

$$\text{minimize } \sum_{i \in N, j \in N, i \neq j} E_{ij} \cdot x_{ij} \quad (4.57)$$

$$\text{minimize} \\ \sum_{i \in N, j \in N, i \neq j} c_e \cdot E_{ij} \cdot n_g \cdot x_{ij} + \sum_{i \in N, j \in N, i \neq j} c_d \cdot d_{ij} \cdot x_{ij} + \beta \cdot \sum_{j \in N} c_v \cdot x_{1,j} + \beta \cdot \sum_{i \in N_s} c_s \cdot y_i \quad (4.58)$$

4.1.6 Linearization of proposed formulation

The formulation proposed for the ELRP-IN is partially nonlinear because of the constraints (4.47), (4.48) and (4.49) and the objective functions (4.57) and (4.58), where the product of two decision variables, E_{ij} and x_{ij} , creates nonlinearity. In order to improve the computational efficiency by linearizing the formulation, a new parameter that represents the product $E_{ij} \cdot x_{ij}$ is introduced as given by Equation (4.59).

$$E_{ij} \cdot x_{ij} = E'_{ij} = \begin{cases} E_{ij} & \text{if } x_{ij} = 1 \\ 0 & \text{if } x_{ij} = 0 \end{cases} \quad (4.59)$$

4.2 Input Data Processing

A number of numerical experiments are performed to evaluate the features of the formulation presented in sub-section 4.1 using: (i) widely employed test instances; (ii) a medium-scale real case instance; and, (iii) a large-scale real case instance. Frequently tested instances in problems involving network design, i.e., Sioux-Falls and Nguyen Dupuis, are handled for the former set of test instances, where the optimal locations for recharging stations are sought through the optimal routing plan for busses by considering the network demands and respecting to a number of assumptions defined in sub-sections 4.2.1 and 4.2.2 The problem for the real case considered has been formulated to help to improve in an environment-friendly fashion the entire operation of a shuttle fleet that serves the main campus of the Technical University of Istanbul (ITU) with the objective of finding the optimal routing plan as well as the optimal locations of possible recharging stations by taking into account the energy consumption characteristics of EVs accurately. Since the network of the real case is relatively smaller in terms of distances when the EVs' driving ranges due to the advances in EV battery technology is considered, solution to the formulation proposed is sought for a larger scale real life instance, in terms of graph-size and hence the total distance covered, as well.

4.2.1 Nguyen-Dupuis network test instance

As a sample hypothetical network, the Nguyen-Dupuis network that is introduced by Nguyen and Dupuis (1984) is used in this study as test network to test the proposed formulation. Differing from the original network, the traffic is considered to flow in both directions, as the ELRP-IN is defined on an undirected graph. The Nguyen-Dupuis graph is composed of 38 arcs and 13 nodes as shown in Figure 4.5. $\{1\}$ and $\{3\}$ are specified respectively to be the departure and arrival depots, where each of the stop nodes in the set $\{2, 4, 6, 8, 9\}$ is indicated with a red circle in Figure 4.5. The driving speed that is assumed to be constant and the desired speed that is targeted to be decelerated to at intersection nodes are considered respectively as 54 km/h (Long et al., 2013) and 27 km/h.

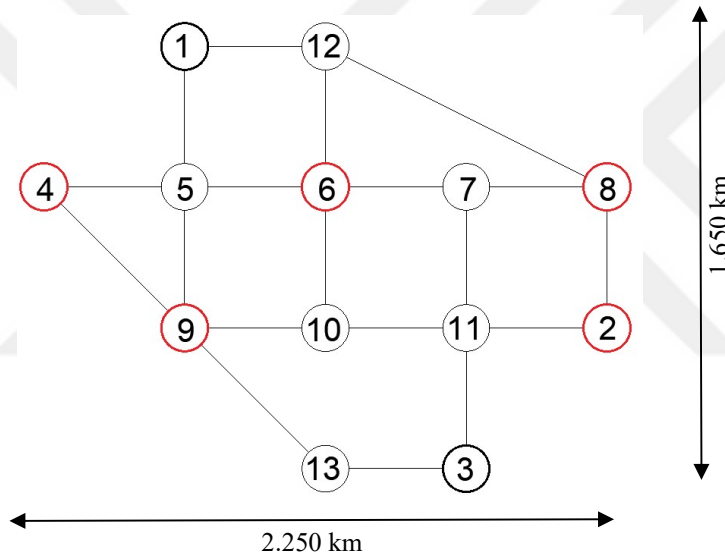


Figure 4.5 : Nguyen-Dupuis network.

The frequency distribution of the arc lengths of Nguyen-Dupuis graph is given in Figure 4.6, where the total length of the arcs on the network is 21.3 km. Taking into account the OD demand profile provided for Nguyen-Dupuis network (Long et al. 2013), passengers' getting on and off demands are specified (Figure 4.7) considering that each vehicle set in the OD demand consists of 4 passengers that corresponds to 120 passengers in overall network. The distance matrix of nodes (Long et al., 2013) and the number of getting off and on passengers at bus stops are given in Url-4, where the nodes' elevations, and hence arcs' grades are neglected as the network is hypothetical. Capacity of a vehicle capacity, K , is assumed to be 50 passengers, approximately the 0.4 times of passengers' total demand, where the maximum number

of vehicles and the recharging stations are set respectively to 3 and 2, and the time limit is set to 1200 seconds that corresponds approximately to three times the traveling time with the average speed through the average path length between nodes {1} and {3}. In order to evaluate the recharging station siting decision, battery capacity is considered as twice the amount of battery charge required for longest distance between an intermediate node and a stop (Schneider et al. 2014), equivalent of which is 1.5 kWh considering the characteristics of the Nguyen-Dupuis network. The time to completely recharge the battery is assumed to be approximately three times the average service time (Schneider et al. 2014), which yields to 80 seconds per kWh of the recharging rate. Vehicle acceleration and deceleration rates are determined respectively as 0.7 m/s^2 and 1.0 m/s^2 (Hinse, 2010; Vaz, 2015). The rest of the parameters that are common among all the instances tested in this study are given in sub-section 4.2.4 in Table 4.14.

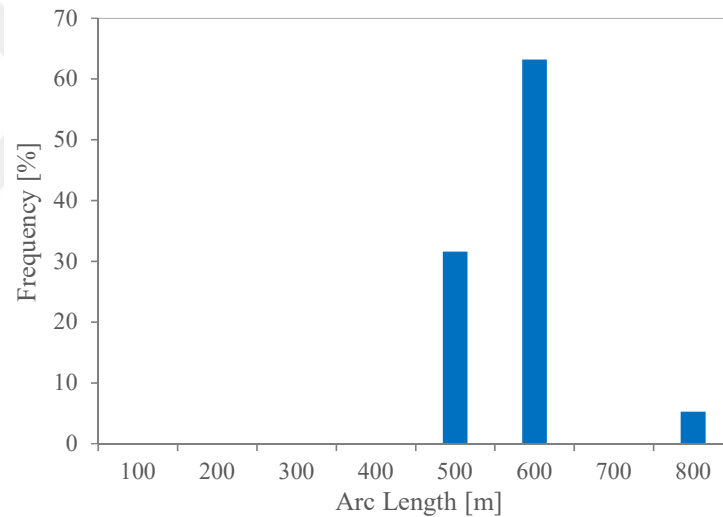


Figure 4.6 : Arc length frequency distribution at Nguyen-Dupuis graph.

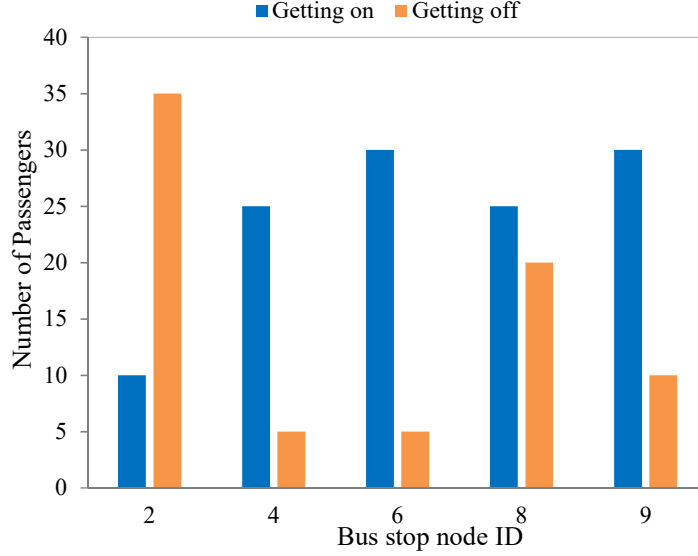


Figure 4.7 : Bus stop passenger demands for Nguyen-Dupuis network.

4.2.2 Sioux-Falls network test instance

Sioux-Falls, is a city in South Dakota, USA, whose network characteristics of edges and nodes have been considered within a set of test instance that is widely-used in researches on problems involving the design, modeling, and optimization of transportation networks (Url-5). The test instance corresponds to the road network of Sioux-Falls city with the length of 314 km in total and having 24 nodes and 76 arcs as shown in Figure 4.8, where, in this study, a tour is assumed to start at node {1} and end at node {20} by visiting the bus stops nodes {5, 8, 11, 15, 18, 24} (see the red circles in Figure 4.8(a)). The driving speed that is assumed to be constant and the desired speed that is targeted to be decelerated to at intersection nodes are considered respectively as 88 km/h (Url-6) and 44 km/h.

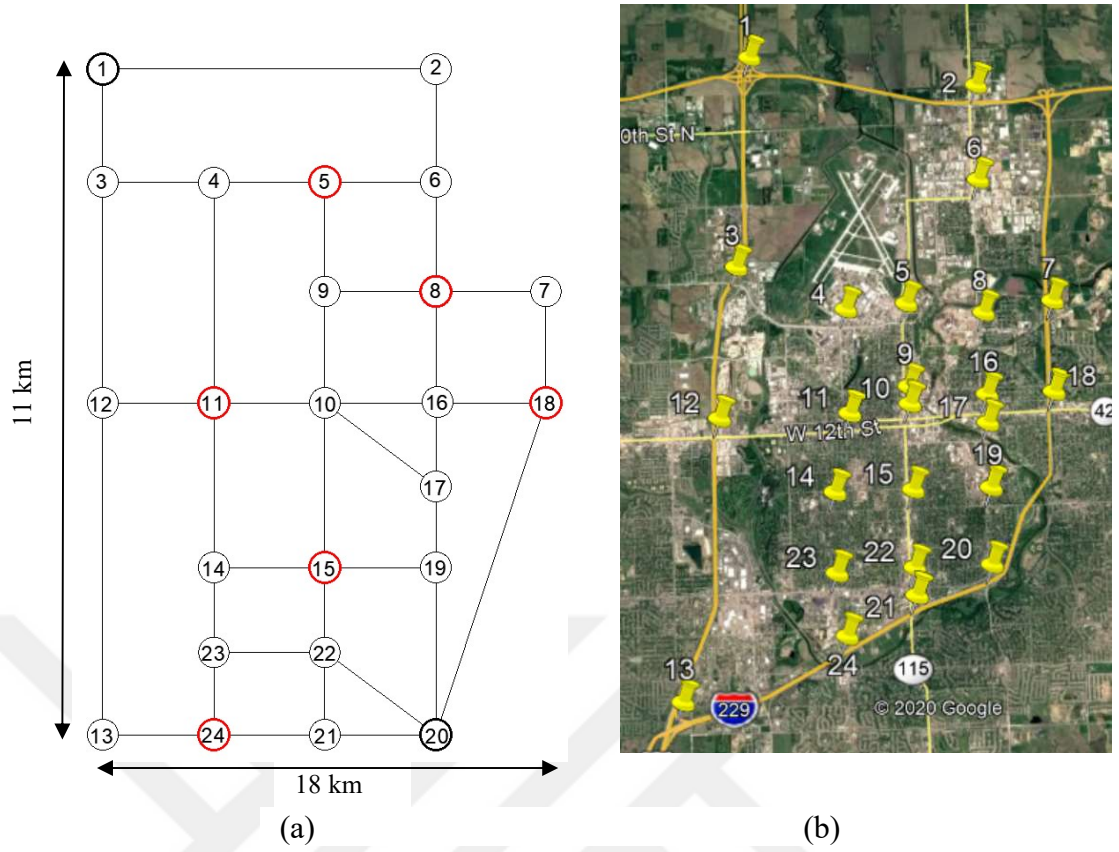


Figure 4.8 : Sioux-Falls network (a) Illustration, and (b) Actual locations of network nodes (Google Earth, 2020a).

The frequency distribution of the arc lengths of Sioux-Falls network that are extracted using the information from (Url-5) is given in Figure 4.9. The demand scenario for passengers' getting on and off (Figure 4.10) are setup properly proportional to the OD flows given in Cen et al. (2018). As the coordinates are determined, the elevations of the nodes (see in Figure 4.11), and hence the road grades are determined accordingly. The distance matrix of nodes, the elevations, and the numbers of getting off and getting on passengers at bus stops are given in Url-4. Considering the fluctuations in passenger demand that is 330 in total vehicle passenger capacity is assumed as 80, where maximum number of recharging stations and number of vehicles assigned are set respectively to 4 and 3. Assuming that the time limit equals the three times of the travelling time, that is obtained by multiplying the average path length between node {1} and {20} with the constant speed, V , the parameter T is determined as 7200 seconds. Following Schneider et al. 2014, the parameter related to the battery capacity is set considering (i) the 60% of the average route length between the depots, and (ii) twice the amount of battery charge required for longest distance between an intermediate node and a stop node. However, in contrast to Schneider et al. 2014, the

battery capacity is set to the minimum of the values determined by (i) and (ii) in order to reflect the limitations in EVs. In this context, the battery capacity for tests over the Sioux-Falls network is assumed to be 20 kWh, where the recharging rate is assumed as 17 seconds/kWh considering that the complete recharge requires three times of the average service times (Schneider et al. 2014). Vehicle acceleration and deceleration rates are determined respectively as 0.7 m/s² and 1.0 m/s² (Hinse, 2010; Vaz, 2015). The rest of the parameters that are common among all the instances tested in this study are given in sub-section 4.2.4 in Table 4.14.

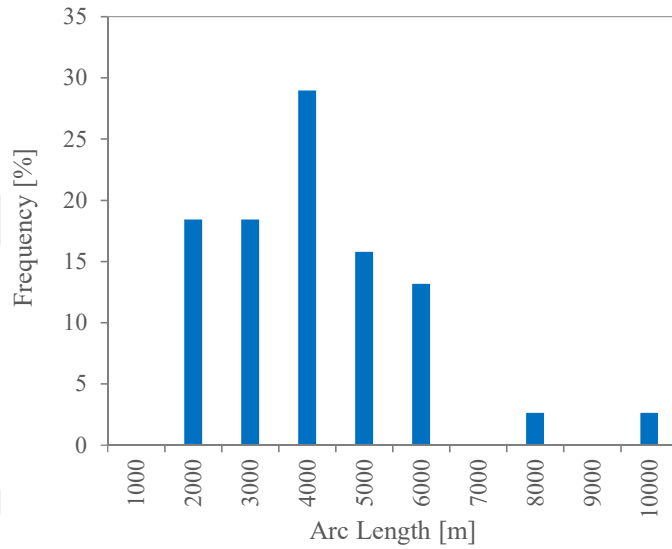


Figure 4.9 : Arc length frequency distribution at Sioux-Falls graph.

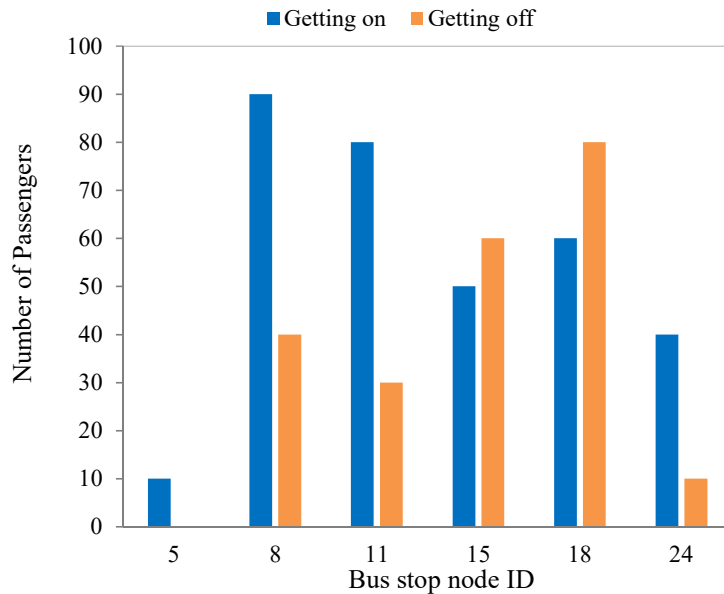


Figure 4.10 : Bus stop passenger demands for Sioux-Falls network.

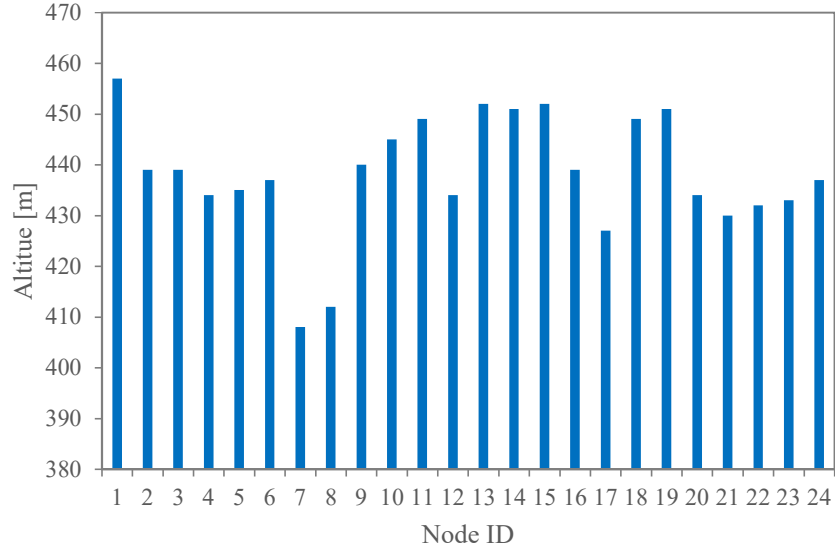


Figure 4.11 : Elevations of Nodes at Sioux Falls network.

4.2.3 Formulation extension for medium-scale real case: ITU Ayazaga Campus road network

The ELRP-IN formulation proposed is used to obtain environment friendly optimization in order to aid the decision making in updating the routing plan for the existing shuttle fleet that is operated in the Ayazaga Campus of ITU, which is located on the European side of the city of Istanbul and directly accessible with road and rail transport. The campus, whose housing and infrastructure is being improved with a green campus project vision (Url-7), is bounded in the North-West by the Buyukdere Arterial (Figure 4.12) that accommodates intercontinental heavy traffic from/to Asian side of the city especially in peak hours. Reducing emissions throughout the campus area, where its Green Campus vision approved by the GreenMetric with the rank of 67 in world (Url-7), is a great challenge when the consequent congestion of attracting/generating pedestrian and vehicular traffic because of being settled in a business district with several skyscrapers is considered.

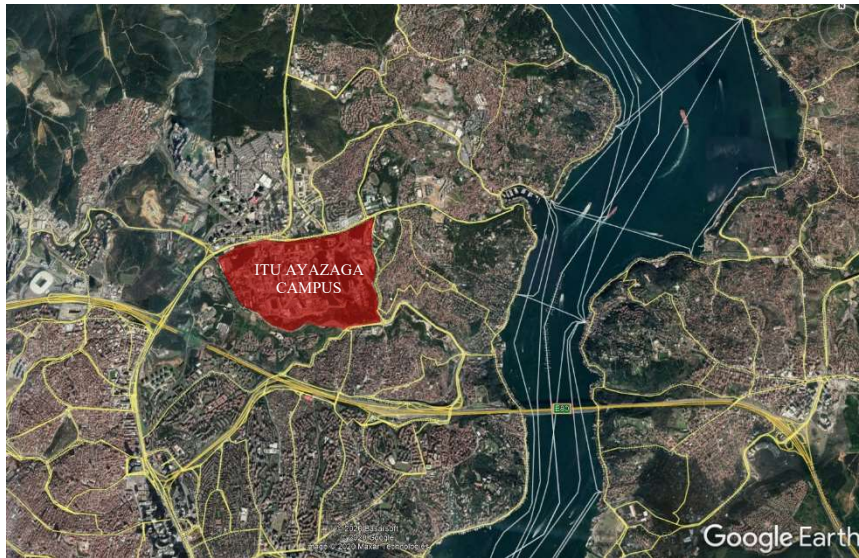


Figure 4.12 : Overview to ITU Ayazaga Campus (Google Earth, 2020b).

Ayazağa Campus accommodates 13 faculties and institutes, 10 research centers, a library, cultural and sports centers, public housing buildings, and dormitories that are spread over an area of 247 hectares as shown in Figure 4.13.

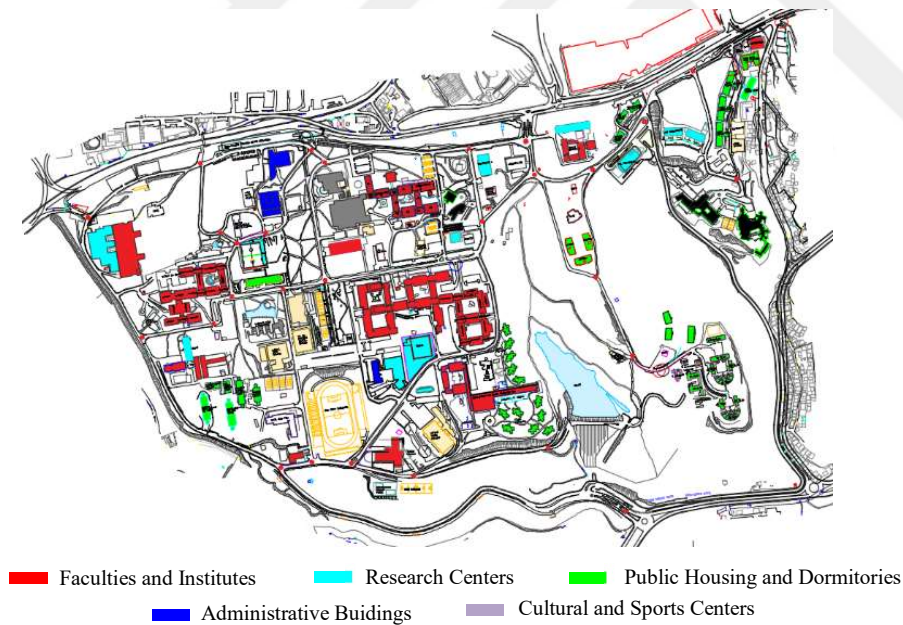


Figure 4.13 : Settlement plan of Ayazaga Campus.

An overview to the case area with the road network of around 16.2 km with 34 nodes including 7 gates is presented by Figure 4.14, where the gates for entry/exit are shown with blue and red respectively for pedestrians and vehicles.

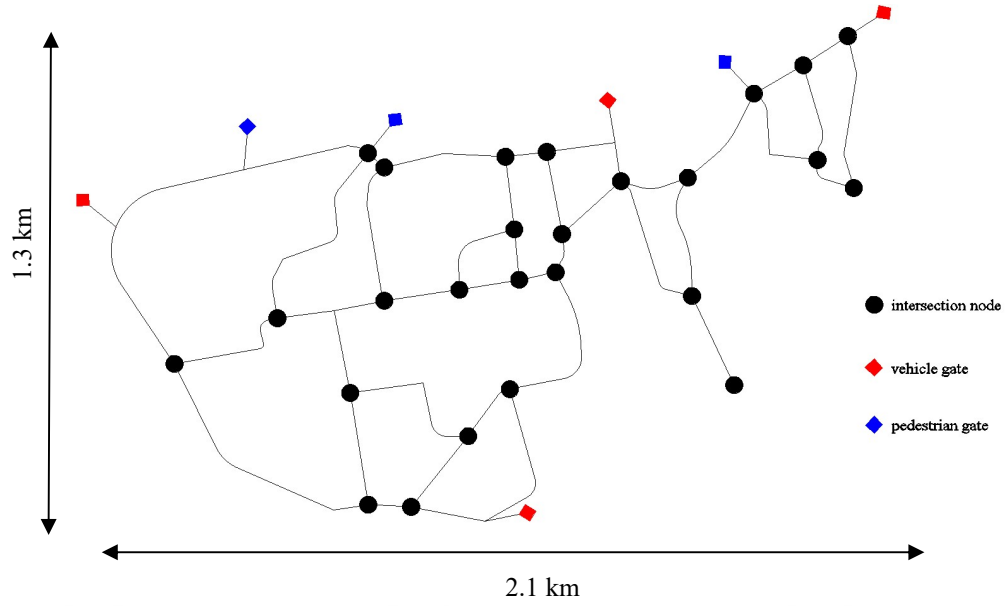


Figure 4.14 : Considered road network serving case area.

The network shown in Figure 4.14 is simplified to form the graph that the ELRP-IN model formulation is specialized for, involving intermediate nodes, bus stops and depot nodes. An illustration of the simplified network graph with all its arcs and nodes is provided by Figure 4.15, by representing nodes according to their node degree values that shows the number of incident edges to a node (Kaveh et al., 2019). The graph shown by Figure 4.15 is composed of 74 arcs and 26 nodes.

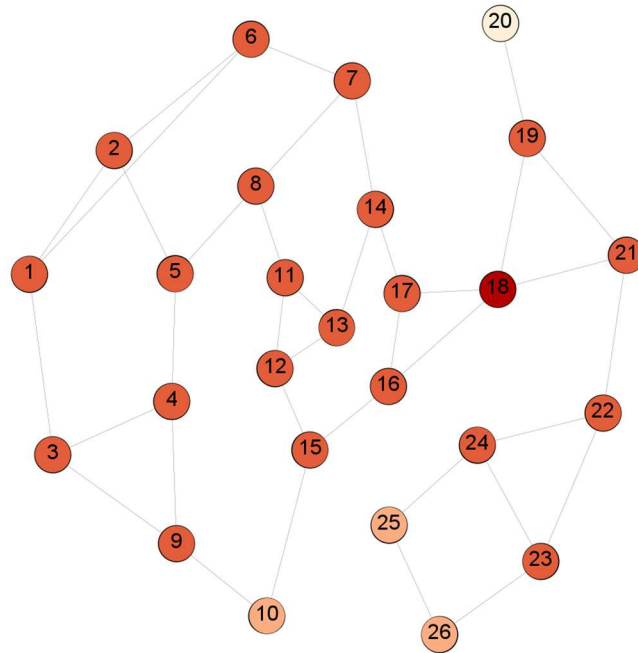


Figure 4.15 : Graph considered to represent road network of real-case area, where node degree increases as color gets darker.

Given the 3-dimensional spatial data and the existing routes over the road network of the Ayazaga Campus, where the nodes' demands for getting on and getting off, and elevations are given in Url-4. Passenger demands are extracted from real time field observations and measurements on get ons and get offs, and GPS trajectories performed in December 2018 (Atasayar et al., 2020). The frequency distributions specific to arc (i,j) grades and arc lengths over the undirected graph are presented in Figure 4.16.

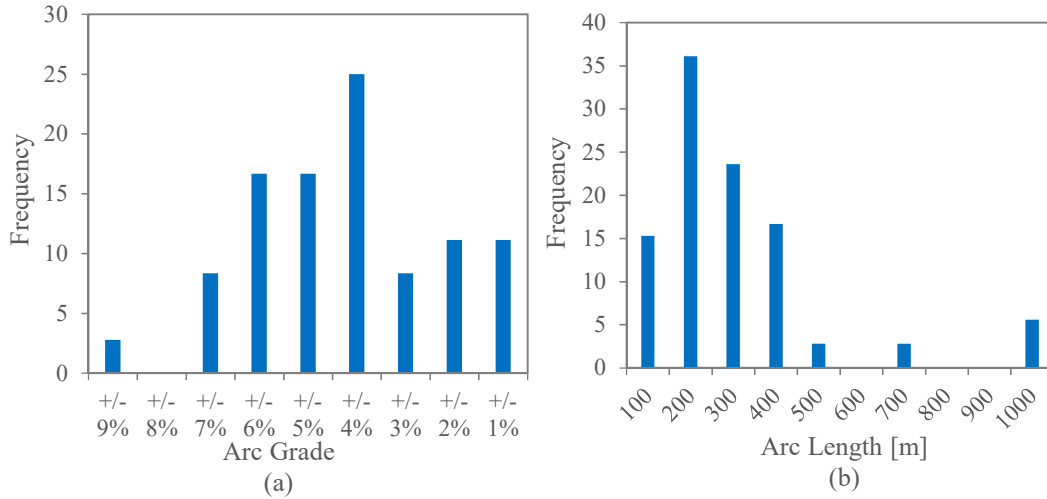


Figure 4.16 : Frequency distribution specific to: a) grades of arcs, and b) lengths of arcs.

There are two shuttle lines operated over the campus network in order to serve to academic staff to and from housing area, and students around the campus area. The housing shuttle line (Shuttle 1) serve 463 households by visiting 6 stops that are shown with red circles in Figure 4.17, where the 18 intersection nodes connecting the bus stop nodes are indicated with grey color. Shuttle 1 starts its route at node {20} and ends at node {10} traversing through the stop nodes {2, 6, 8, 15, 18, 19}, and completes a cycle by returning to node {20} visiting the identical stop nodes. Starting at 07:45, Shuttle 1 completes its daily 33 cycles at approximately 20:00, where each route corresponds approximately to 2.4 km. Considering the passenger demands at bus stop nodes for Shuttle-1 given in Figure 4.18, the vehicle capacity and the time limit are set respectively to 35 passengers and 15000 seconds.

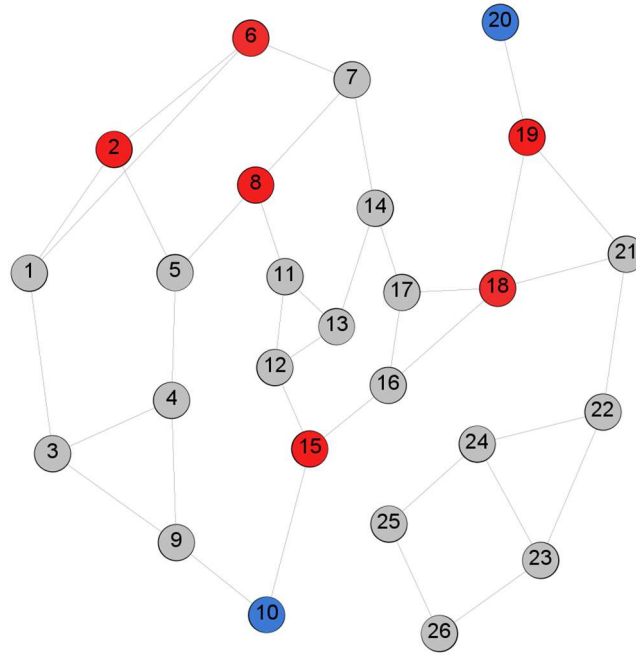


Figure 4.17 : Node type based colored graph for Shuttle-1, where blue, red, and gray colors represent respectively depot, bus stop, and intermediate nodes.

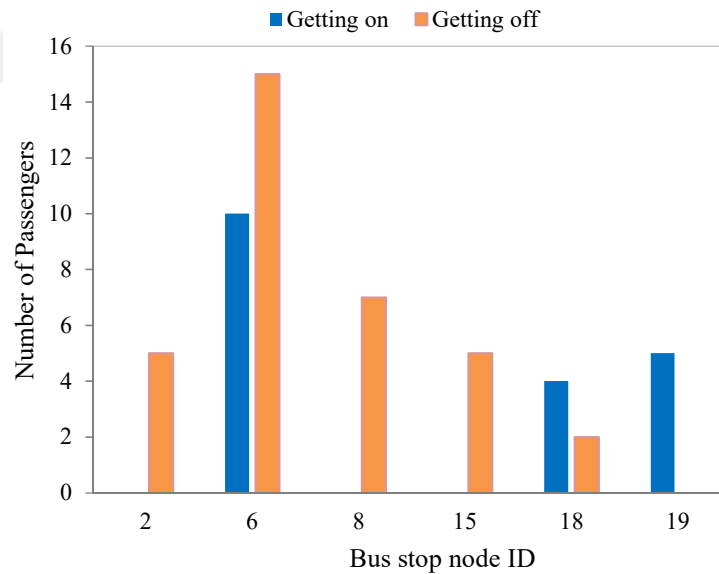


Figure 4.18 : Passenger demands for Shuttle-1 at bus stop nodes.

Among 5 campuses of ITU, Ayazaga is the main one, and hence a large portion of 39330 students of ITU trip to and from the Ayazaga Campus for attending lectures or/and some cultural/sports/administrative activities, while 4819 of the students accommodate in Ayazaga Campus (Url-8). The large and dynamic population of Ayazaga Campus necessitates higher frequencies and longer schedules of shuttle service operations. In this context, a student shuttle service (Shuttle 2) starts touring,

for approximately 4 km, at 07:30 and completes its daily 43 cycles at approximately 23:45, where there is a second shuttle serving to the students in the opposite direction. Figure 4.19 provides an overview to the graph for Shuttle 2 that starts at node {26} and ends at node {10} depots visiting the 7 bus stops {2, 3, 6, 8, 15, 18, 22}. Given the passenger getting on and getting off demands in Figure 4.20, the vehicle capacity for Shuttle 2 is assumed to be 50.

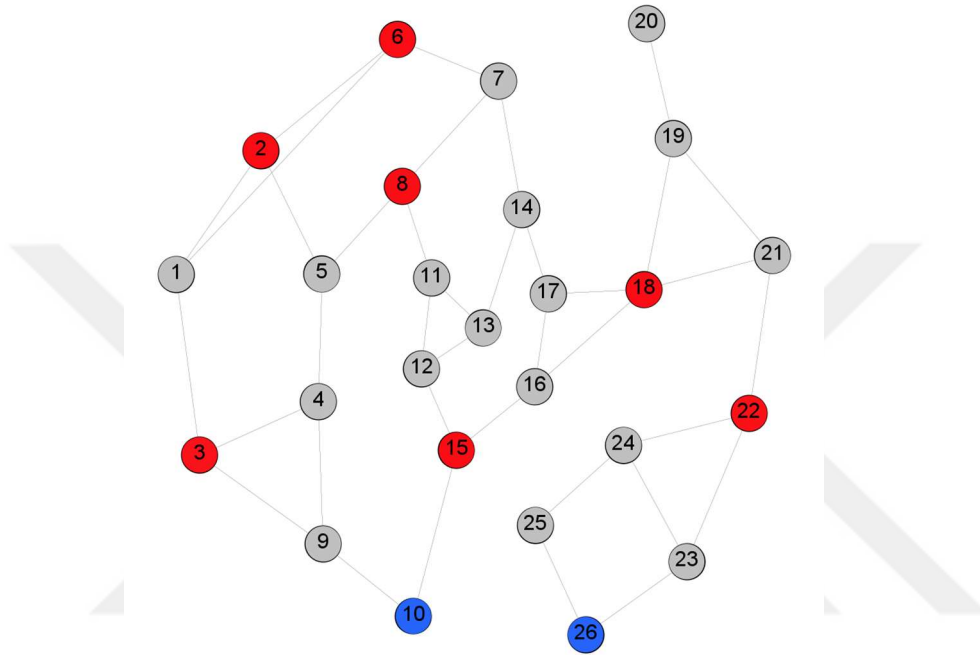


Figure 4.19 : Node type based colored graph for Shuttle-2, where blue, red, and gray colors represent respectively depot, bus stop, and intermediate nodes.

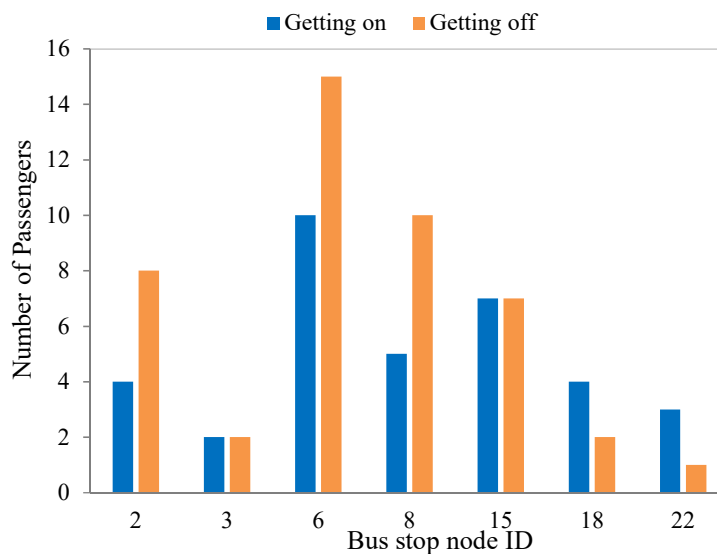


Figure 4.20 : Passenger demands for Shuttle-2 at bus stop nodes.

Considering the network topology, the input parameters including the vehicle capacity, recharging rate, and the time limit are set to identical values for both the two shuttles. In this context, the battery capacity is set to 2 kWh (Schneider et al. 2014), where the time limit is specified as 1700 seconds. Due to the fact that the real case implies the maximum number of vehicles to be assigned is 1, the maximum number of recharging stations to be located is set to 3 and, the recharging rate is set to 15 seconds per kWh. Note that the recharging rate parameter is derived in the same way as done for the previous instances. For the sake of simplicity, the time required to meet a single passenger's demand is set to 1 seconds in all instances. Vehicle acceleration and deceleration rates are determined respectively as 0.7 m/s^2 and 1.0 m/s^2 (Hinse, 2010; Vaz, 2015). The rest of the parameters that are common among all the instances tested in this study are given in sub-section 4.2.4 in Table 4.14.

4.2.4 Formulation extension for large-scale real case: Buyukada road network

In order to discuss on the effects of introducing intersections as intermediate nodes in the road network graph, Buyukada, as the large-scale real case, is handled. Buyukada is a member of the Prince Islands archipelago, that is located in the Sea of Marmara Figure 4.21, in which the transportation throughout the island is mainly based on barouches and bicycles due to the limitation of uses on internal combustion engine vehicles. Both the daily long-trip of islanders, asif to serve like taxis, and touristic tours of visitors, asif to serve like tour buses, are met by barouches that are operated as private travel mode according to individual travelers' demands.

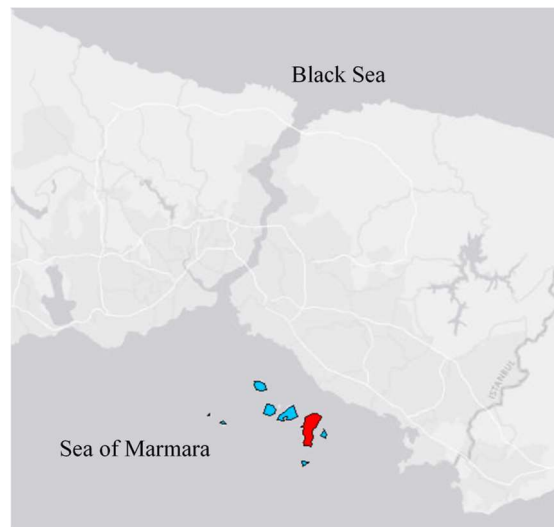


Figure 4.21 : Map view of Prince Islands: the archipelago in blue color, the case area in red color.

The parameters related to the road network of the island including arc distances, node elevations, and arc grades, are extracted by using OSMnx library (Url-9) in Python, where the road network is simplified as each node has 2 degrees at least. The simplified road network has 226 nodes and 700 arcs, where the elevation of nodes are varied between 1.48 m to 130.13 m, that results to have a rugged surface, which is an actual difficulty for both daily life and touristic visits, but create an opportunity to gain advantage from regenerative braking of EVs. The length of each arc is determined to be at least 25 meters to fit with the speed profile defined. Figure 4.22 shows the change in node elevations and arcs absolute grades on the network piece considered that spread on 10.8 km².

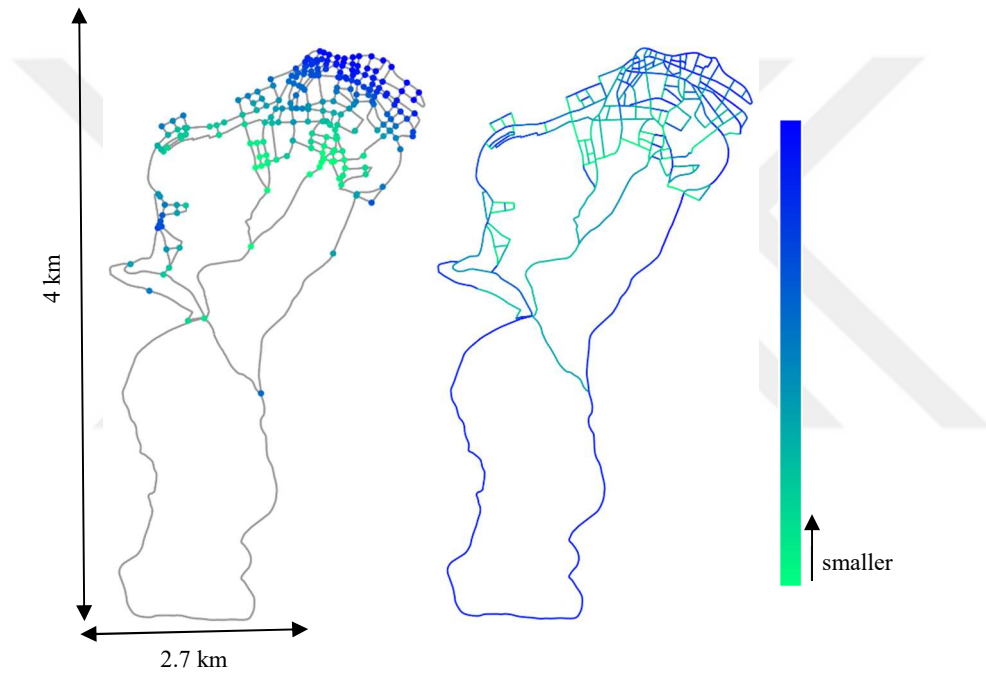


Figure 4.22 : Change in node elevations and absolute grades.

Buyukada is handled for 10 and 30 bus stops setups to provide a short and long tour throughout the island. Since the island is vehicle-restricted, it is assumed that the buses have always enough passenger capacity, considering the data inadequacy. Vehicle battery capacity is set to 6 kWh and 10 kWh, the time limit is set to 4000 seconds respectively for instances with 10 and 30 stops. The distribution of bus stops is illustrated in Figure 4.23 with the starting and ending depots. Vehicle acceleration and deceleration rates are determined respectively as 2.0 m/sn² and 3.0 m/sn² (Makridis, 2019), where the parameters that are common among all the instances tested in this study are given in Table 4.4.

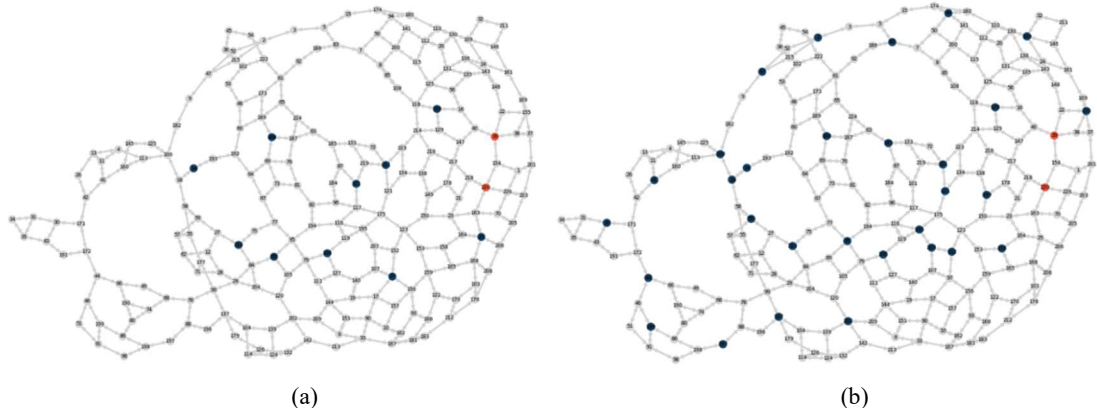


Figure 4.23 : Illustration of Buyukada network where bus stops and depots are colored respectively blue and red for instance with (a) 10 bus stops (b) 30 bus stops.

Table 4.4 : Input parameters common to all instances.

Parameter	Value
m	6740 kg (Warren Santiago Vaz, 2015)
g	9.81 m/sn ²
μ_r	0.01 (Goeke and Schneider, 2015)
ρ	1.2256 kg/m ³ (Fiori and Marzano, 2018)
μ_a	0.6 (Warren Santiago Vaz, 2015)
A	6.1 m ² (Warren Santiago Vaz, 2015)
ξ	1.05 (Warren Santiago Vaz, 2015)
η_e^{-1}	1.064 (Fiori and Marzano, 2018)
η_{rg}	0.6 (Zhang and Yao, 2015)
η_g	1.25 (Zhang et al., 2018)
φ	80 kg
c_s	2.68 [\$/station-day] (Shiffer et al. 2016)
c_v	57.80 [\$/vehicle-day] (Shiffer et al. 2016)
c_e	0.11 \$/kWh (Goeke and Schneider, 2015)



5. RESULTS AND DISCUSSION

Solutions involving the four different objectives defined in Section 4.1 are sought separately for all instances and, the effects of objectives to the decision variables as well as to the parameters are discussed. In this context, for setups of instances described in Section 4.2, model based exact solution on routing plan(s) that offer the minimum: (i) energy consumption; (ii) distance traveled; (iii) cost that includes costs of vehicle rent, recharging station rent, and energy; and, (iv) travel time are obtained through the commercial solver IBM ILOG CPLEX 12.9.0 using an Intel(R) Core (TM) central processing unit with i3-8130U processor running at 2.20 Ghz, and 16 GB of random access memory.

5.1 Results from and Discussions on Solution Obtained for Instances

Instance specific results are discussed in detail in sub-sections of 5.1 in terms of routing plans, recharging station locations, energy consumption and recovery characteristics, in addition to the effects of objective functions to the solutions obtained.

5.1.1 Results for test instances: Nguyen-Dupuis and Sioux Falls Network

The lack of grade and elevation values in Nguyen-Dupuis network have resulted in the energy consumption being dependent on rolling and air resistances, and thus on the distance traveled. In this context, optimal routing plan for each objective have returned identical solutions, where two vehicles are assigned and, two recharging stations are located to meet the requirements on passengers and vehicle battery, respectively, as illustrated in Figure 5.1. Total distance traveled and time spent on the Nguyen-Dupuis network by the two vehicles are found respectively to be 6.6 km and 750.27 seconds.

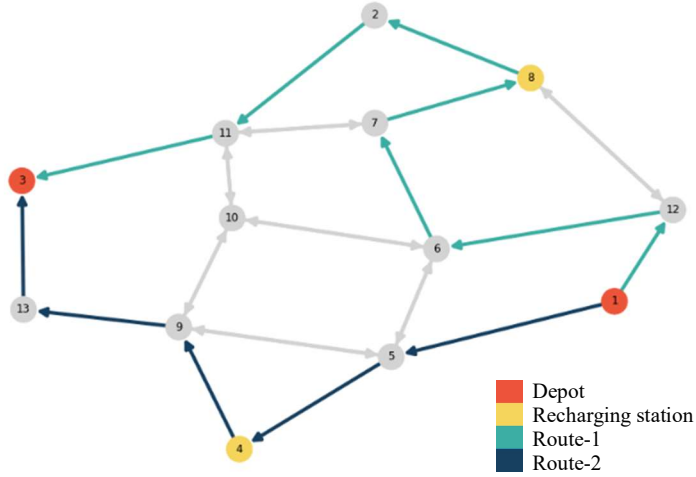


Figure 5.1 : Illustration of optimum routes for Nguyen-Dupuis network subject to all objectives.

Optimal routes obtained for Sioux-Falls network are given in Figure 5.2. Considering the passenger demand and limitation on vehicle passenger capacity, it is seen that at least two vehicles need to be assigned in order to meet the demand given, regardless of the objective sought, where the recharging station siting decision is varied among the objectives. Within the context of optimal routing solutions, the objectives of minimum energy consumption and minimum cost have returned identical routing plans since the total cost includes the energy cost as well. According to the solution presented in Figure 5.2(a), two vehicles are assigned to serve passengers, where one needs to visit a recharging station. The routing plan that ensures minimum distance traveled as well as the minimum travel time spent that is shown in Figure 5.2(b) requires two recharging stations to be sited in order to prevent running out of battery. In this context, results reveal that even if the grades along a route are very low, which there is no energy recovery, the shortest distance and path with the least energy consumption can be different.

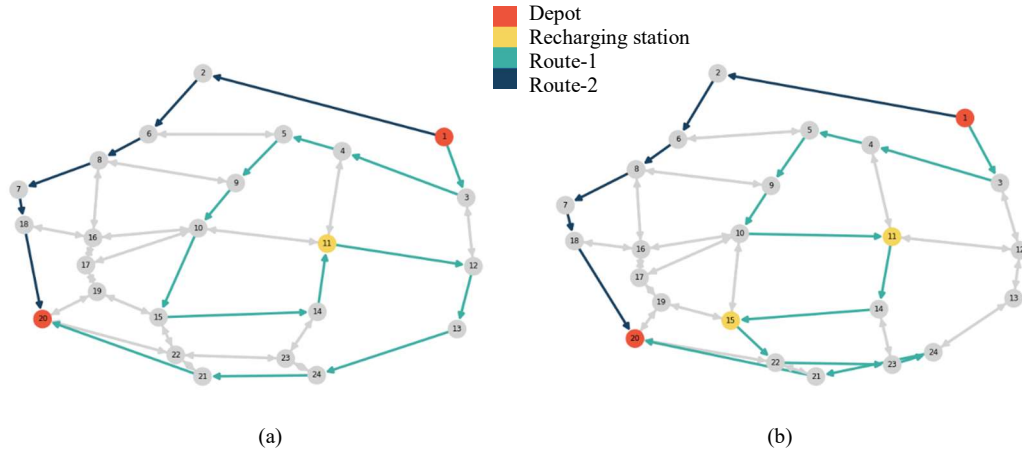


Figure 5.2 : Illustration of optimum routes for Sioux Falls network subject to different objective functions: a) minimum energy consumption/cost; and, b) minimum distance/time.

In order to figure out the effects of objectives on the parameters for Sioux-Falls network instance, the differences in energy consumption, traveled distance, and the travel time of the minimum energy consumption/cost routing solution with respect to the minimum distance/time solution is shown in Figure 5.3. According to the results, energy consumption is reduced by 2.86% with an increase in the minimum travel distance and time, that corresponds 72 km and 3313.29 seconds in total, respectively by 6.94% and 6.29%. By decreasing the number of recharging stations required from two to one for the minimum energy consumption/cost routing plan, the total cost is decreased 2.25% when compared to the minimum distance/time routing plan.

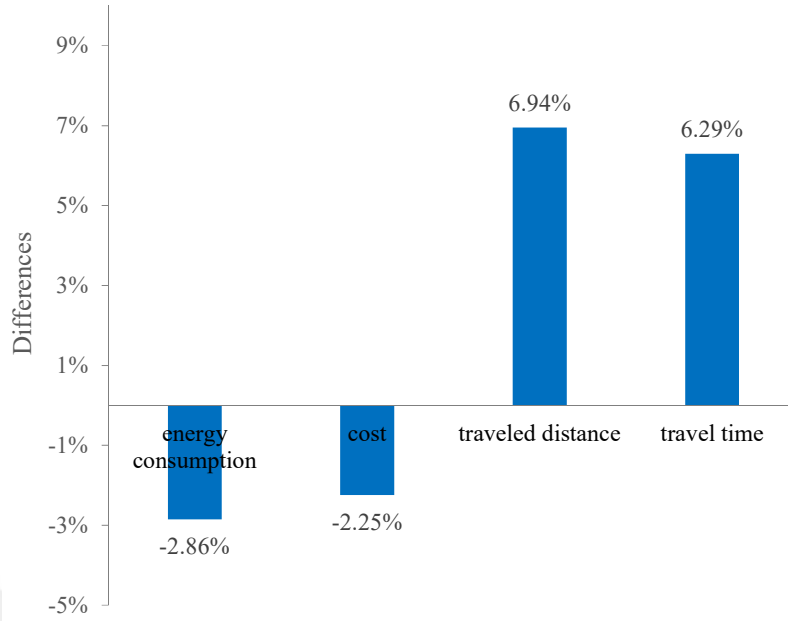


Figure 5.3 : Differences in energy consumption, cost, distance traveled, and travel time of minimum energy consumption/cost routing solution with respect to the minimum distance/time routing solution.

5.1.2 Results for medium-scale real case instance: ITU Ayazaga Campus

Results for the shuttle serving the housing area through ITU network, Shuttle-1, are presented in Figure 5.4, 5.5, 5.6, and 5.7. Similar to the results obtained for Sioux-Falls instance, two optimal route options are obtained as shown in Figure 5.4a, where the former have resulted with minimum energy consumption and cost (Figure 5.4(a)), while the latter have ensured that the vehicle completes its tour by traveling the minimum distance and at minimum time (Figure 5.4(b)). Thanks to the topographic characteristics of the road network, energy have been recovered by regenerative braking, so the tour could be completed without visiting any recharging station. The arcs on routes, where energy is recovered, are shown by Figure 5.5(a) and (b) respectively for the minimum energy/cost and the minimum distance/time, where the 20.79% and 20.16% of the energy consumption is recovered respectively.

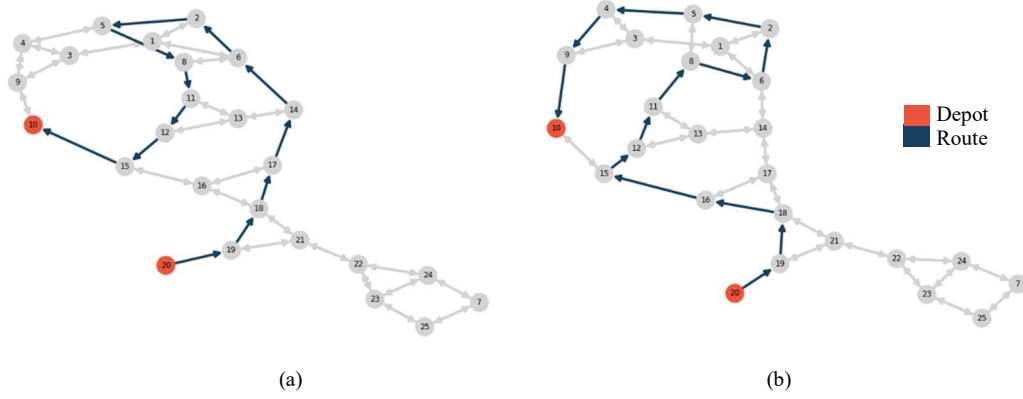


Figure 5.4 : Illustration of optimum routes for Shuttle-1 subject to different objective functions: a) minimum energy consumption/cost; and, b) minimum distance/time.

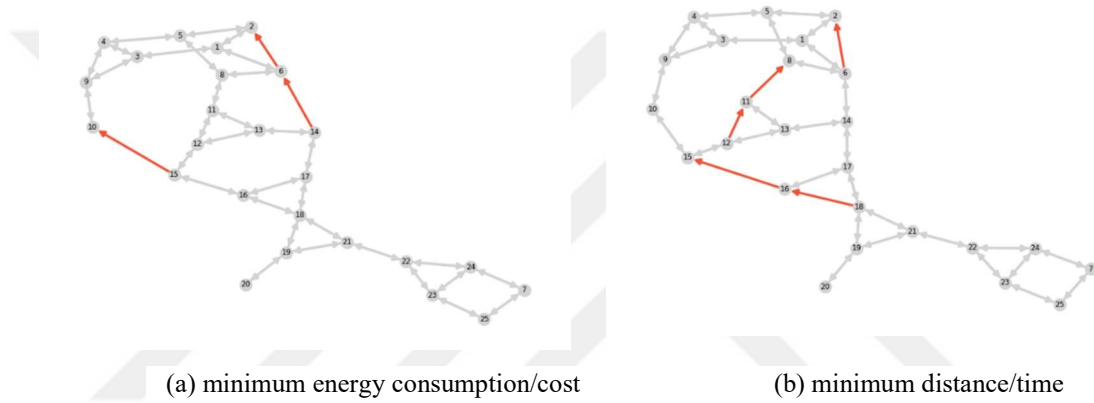


Figure 5.5 : Illustration of arcs, where energy is recovered (see red colored arcs), through optimal routes for Shuttle-1.

According to Figure 5.6 that shows the elevation profile of optimal routes as well as the cumulative net energy consumed/recuperated by traveled distance, it is seen that a difference in the elevation directly affects the energy consumption, where an instantaneous increase in elevation leads to high energy consumption. Here, it is important to note that the “cumulative net energy” corresponds to the cumulative load of the battery that is calculated as the total of the energy consumption by traction and the energy recuperation by regenerative braking. In addition, Figure 5.6 shows that braking is not required in all the sections that elevation decreases, that is, it does not mean that the sections where the grade is negative are necessarily the energy recovery sections.

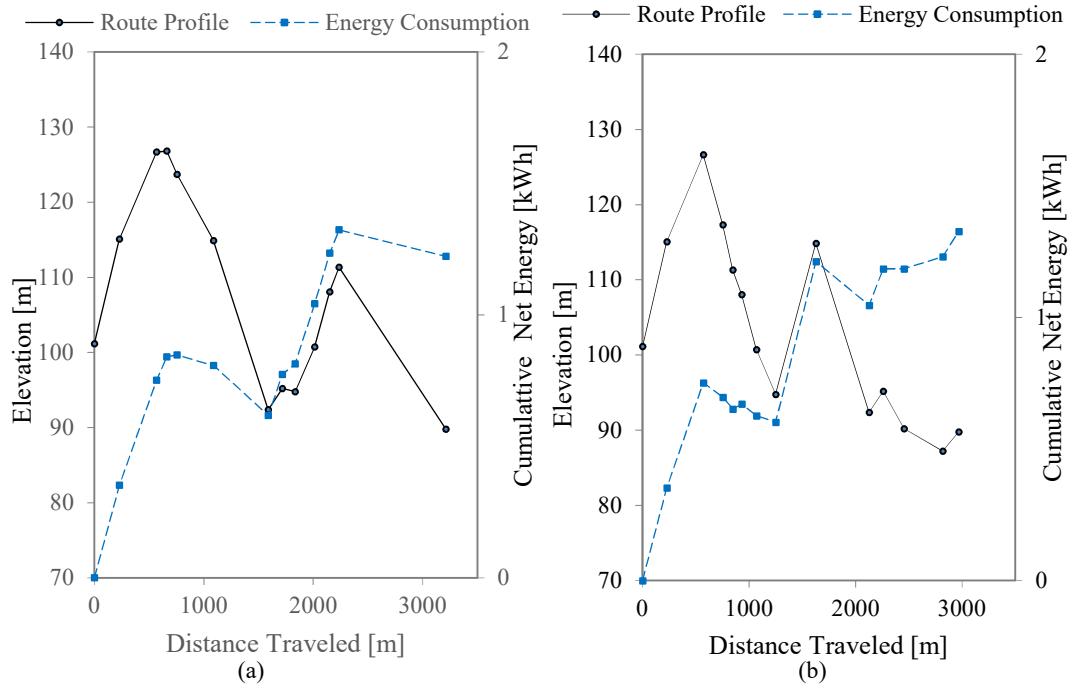


Figure 5.6 : Elevation and cumulative net energy changes corresponding to distance traveled for routes of Shuttle-1 with: (a) minimum energy/cost; and, (b) minimum distance/time.

The trade-off between the energy consumption and the distance traveled is revealed clearly in Figure 5.7, in which energy consumption is decreased by 8.27%, while the travel distance and travel time have increased respectively by 8.18% and 5.98% by driving on energy/cost optimal rather than distance/time optimal route, where the route that ensures to travel in minimum distance and time is 2.969 km and takes 444.49 seconds. Although the cost of energy is determined considering the daily cyclic operation of the shuttles and the recharging efficiency, the cost gain is limited with 0.78% by choosing the least cost routing solution since the energy cost is relatively too low when compared to the daily equivalent of vehicles and recharging station costs.

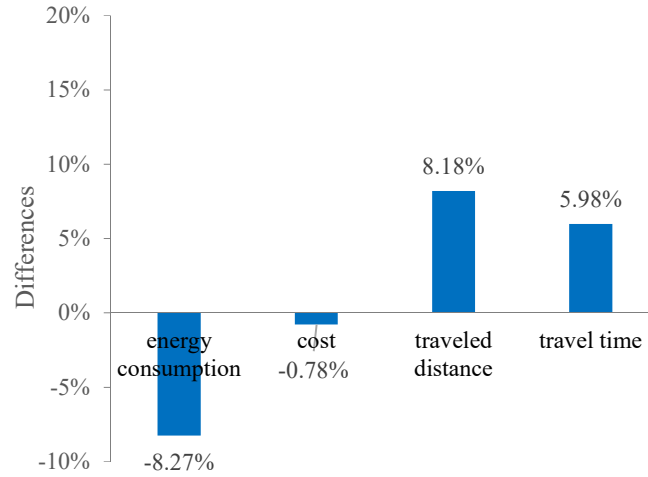


Figure 5.7 : Differences in energy consumption, cost, distance traveled, and travel time of minimum energy consumption/cost routing solution to with respect the minimum distance/time routing solution for Shuttle-1.

Optimum routing plans obtained for Shuttle 2 are given in Figure 5.8, in which there is higher passenger demand, as well as the higher number of bus stop nodes than Shuttle 1. By driving on the routing plan that ensures minimum energy consumption and cost, Shuttle-2 completes its tour without any need to visit a recharging station, where 20.03% of the energy consumption is recovered. Although 24.65% of energy consumption is recovered on the minimum distance/time route, Shuttle-2 needs to recharge to complete its tour as shown in Figure 5.8(b). Arcs on the routes of Shuttle-2, where energy is recovered, are shown in Figure 5.9 in details.

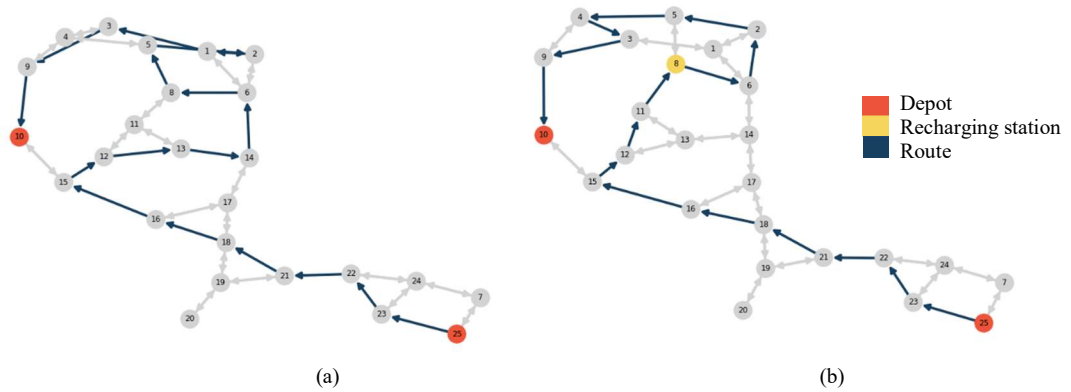
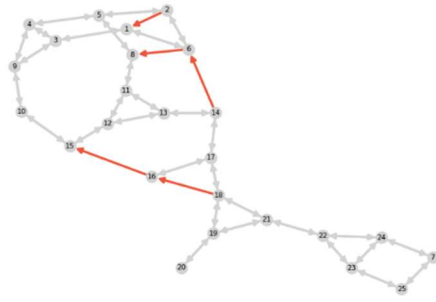
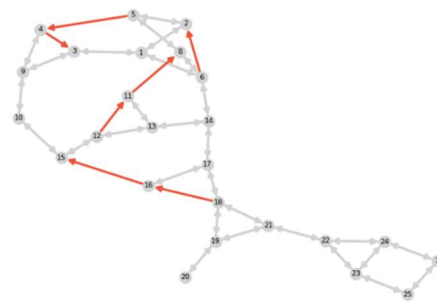


Figure 5.8 : Illustration of optimal routes for Shuttle-2 subject to the different objective functions: a) minimum energy consumption/cost; and, b) minimum distance/time.



(a) minimum energy consumption/cost



(b) minimum distance/time

Figure 5.9 : Arcs, where energy is recovered (see red colored arcs), on routes of Shuttle-2.

Although the total energy consumption on minimum energy consumption/cost and minimum distance/time routes are nearly the same, the reason behind the recharging requirement on minimum distance/time route can be interpreted using Figure 5.10 that shows the elevation change and the cumulative net energy by traveled distance. The instantaneous and greater changes in elevation, between 1455 and 1835 meters, through the minimum distance/time route results in a need to more energy that exceeds the remaining battery load, where the recharging station requirement is marked in Figure 5.10 (b).

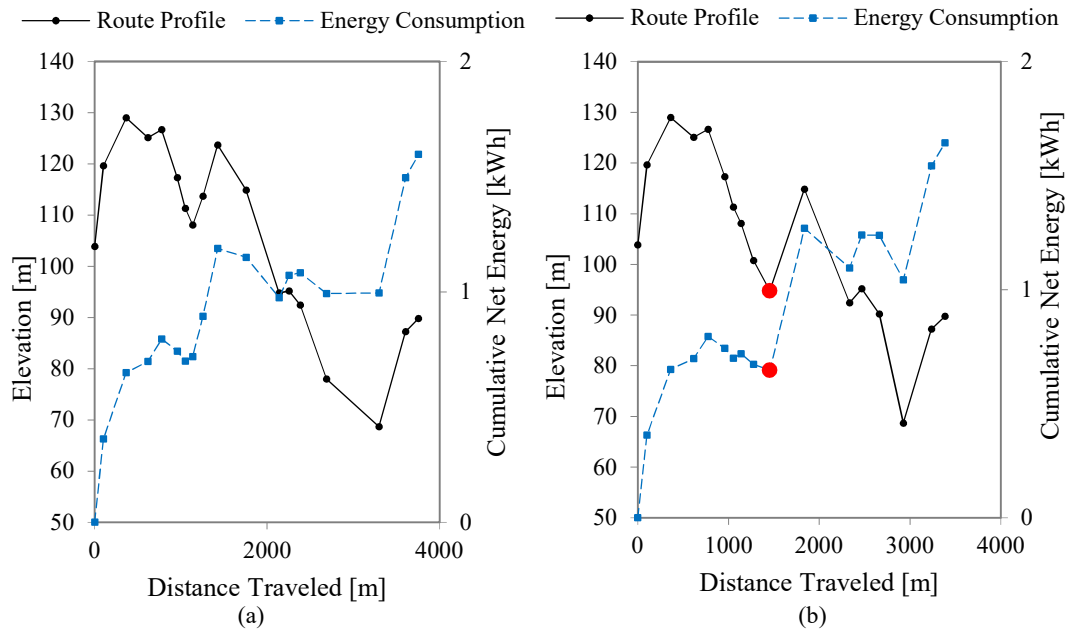


Figure 5.10 : Elevation and cumulative net energy changes corresponding to distance traveled for routes of Shuttle-2 with: (a) minimum energy/cost; and, (b) minimum distance/time (see recharging station location marked with red dot).

In order to minimize the energy consumption and the cost as well, the traveled distance and the travel time need to be increased under the circumstances given for Shuttle-2. On one hand, the traveled distance and the travel time can be reduced respectively by 10.99% and 6.20% by driving on the minimum distance/time route that corresponds 3.384 km and takes 524.98 seconds, on the other hand, the total cost and the energy consumption can be reduced respectively by 4.21% and 2.86% using the least energy consumption/cost routing plan of Shuttle-2, as shown in Figure 5.11.

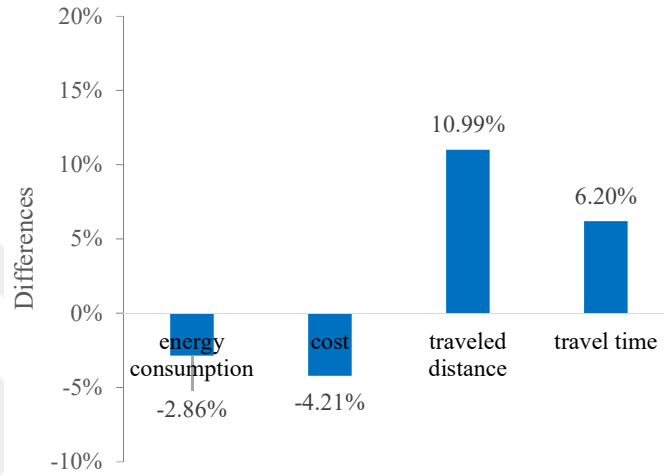


Figure 5.11 : Differences in energy consumption, cost, distance traveled, and travel time of minimum energy consumption/cost routing solution with respect to the minimum distance/time routing solution.

5.1.3 Results for large-scale real case instance: Buyukada

Optimal solutions for different setups of Buyukada network are sought considering the instances designed, in which bus stop locations sprawl around the network as the bus stop number increases from 10 to 30 and, the battery capacity differs from 2.5 kWh to 6 kWh and from 6 kWh to 10 kWh respectively for the instances with 10 bus and 30 bus stops. Figure 5.12 shows the optimal route to serve the instance with 10 bus stops, where the minimum travel distance and minimum energy consumption objectives are achieved. The arcs, that energy recuperation has taken place, are shown in Figure 5.12 as well, where 25% of the total energy consumption is recovered in total. Results show that, by traveling 3.52 km, the shuttle serves 10 bus stops by passing through 29 intersections with an average energy consumption ratio of 0.73 kWh/m. In the setup by decreasing the battery capacity to 2.5 kWh from 6 kWh, a recharging station is required to be located at the bus stop node 14, as shown in Figure 5.12. Although the optimal routes obtained are identical for the instances with 2.5kWh and 6 kWh battery

capacities, the total cost and the travel time are increased respectively by 4% and 16% due to the recharging visit.

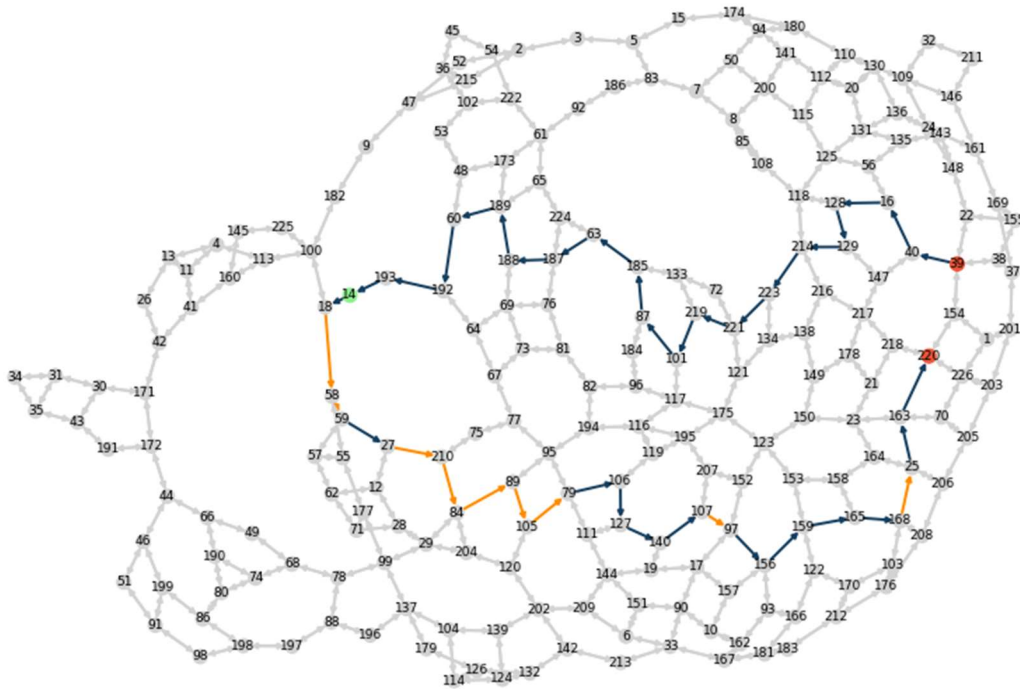


Figure 5.12 : Illustration of optimal route for Buyukada instance with 10 bus stops (see energy recovered arcs colored orange).

From the graph that shows both the elevation change and the energy consumption along the route (Figure 5.13), the effect of regenerative braking on energy consumption can be figured out. Although the route profile possesses symmetry considering the distance traveled the energy consumption profile is not symmetrical given that all the energy cannot be recovered. Due to the fact that the energy is recovered as much as the regenerative braking efficiency, it is not possible to recover the energy that compensates the energy consumption resulting from the increase in grades, unless the regenerative braking efficiency is 1.

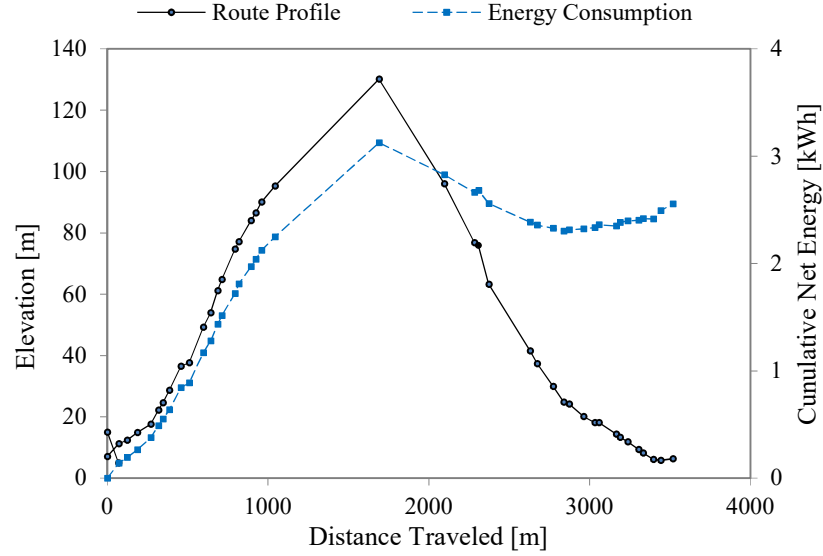


Figure 5.13 : Elevation and cumulative net energy consumption changes by distance traveled.

Optimal routes serving to 30 bus stops differ by the objectives of minimum energy consumption and traveled distance. Figure 5.14 shows that the possible shortest path ensures to visit each bus stops in 8.70 km by consuming 7.70 kWh in total, where 2.57 kWh of energy is recovered on the arcs marked in orange. In order to deal with the driving range limitation by reducing the battery capacity from 10 kWh to 6 kWh, a recharging station is located at the bus stop node 207 (see in Figure 5.14). When compared to the solution obtained for the battery capacity of 10 kWh, the total cost and travel time are increased respectively by 4% and 10% at solutions for 6 kWh battery capacity.

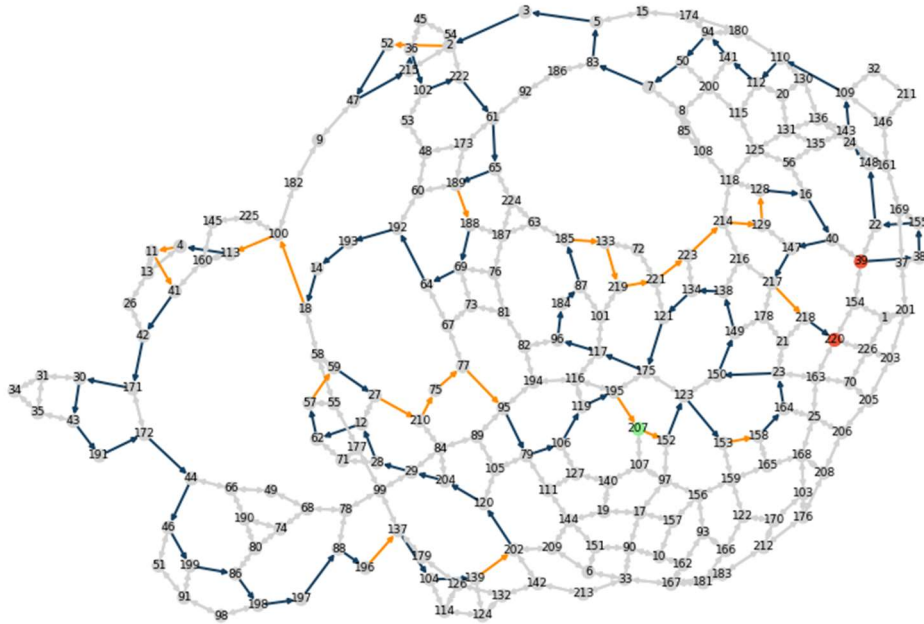


Figure 5.14 : Illustration of distance-optimal route for Buyukada instance with 30 bus stops (see energy recovered arcs colored orange).

Increasing the total distance traveled by 17%, the energy consumption is reduced to 5.96 kWh with the energy-optimal route that is illustrated in Figure 5.15. Although covering the path illustrated in Figure 5.15 requires less energy than the distance optimal route does, the energy recovery ratio is limited with 16%, which is 7% less than that of the distance optimal route.

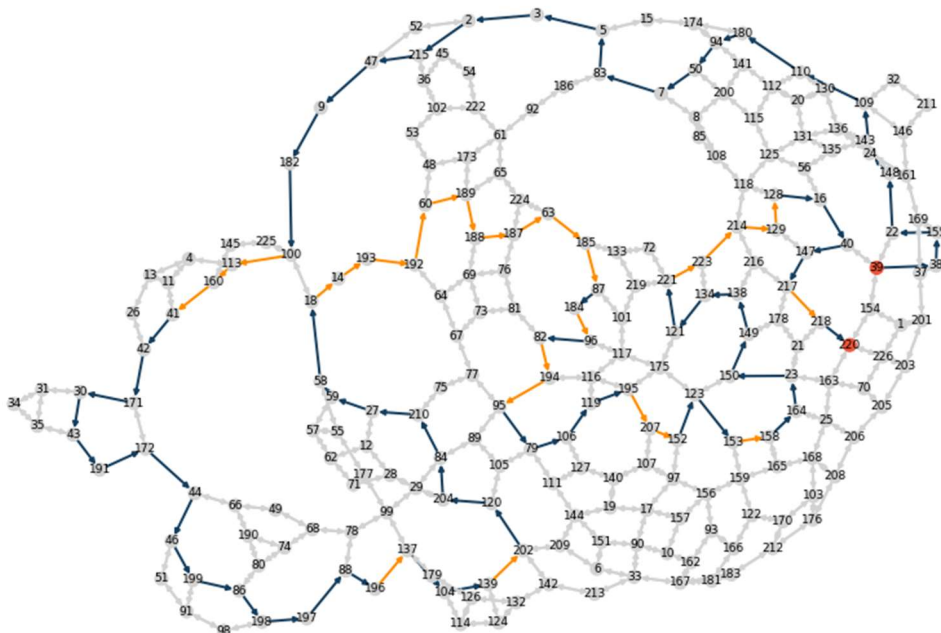


Figure 5.15 : Illustration of energy-optimal route for Buyukada instance with 30 bus stops (see energy recovered arcs colored orange).

From Figure 5.16 that reveals a comparison on profile of the routes that differ from each other according to the minimization point of view as the distance traveled (Figure 5.16 (a)) and the energy consumption (Figure 5.16 (b)), it is seen that in terms of the elevation profile almost completely different routes are obtained following the objective sought. According to the results, it is seen that, by avoiding roads over high hills, the energy consumption has been reduced by 23%, where the distance covered has increased around 26%.

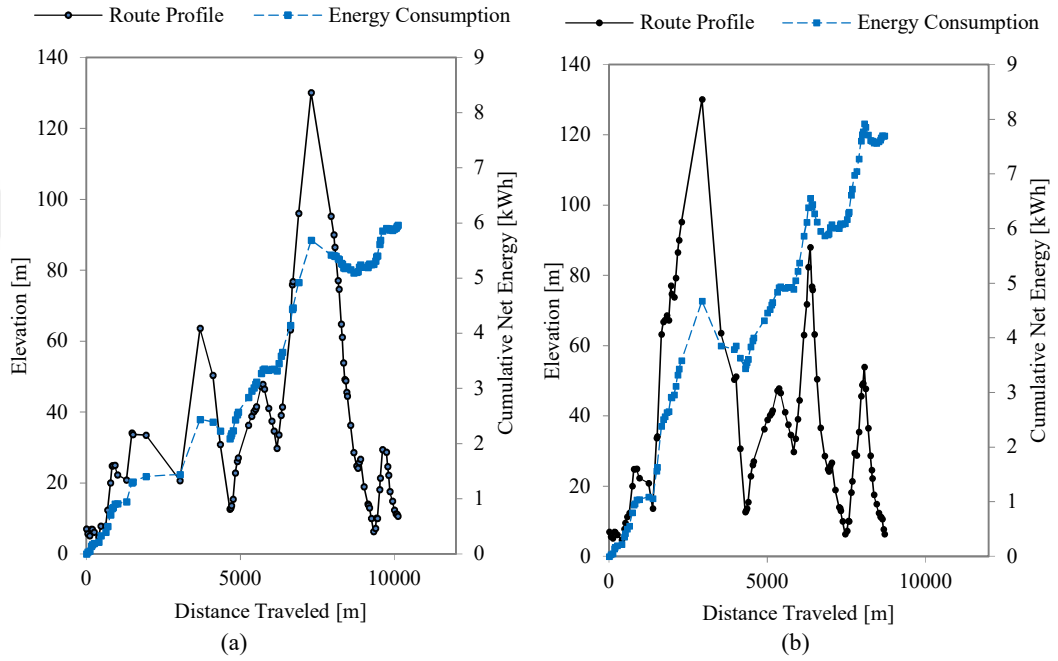


Figure 5.16 : Elevation and cumulative net energy changes by distance traveled obtained for routes with objective of: (a) minimum energy consumption; and, (b) minimum distance.

5.2 Overall Discussion

Results for all the instances tested are summarized in Table 5.1, focusing mainly on the objective sought, number of vehicles assigned, number of recharging stations, amount of energy required and energy recovered, total cost, distance traveled, travel time, energy consumption, and energy recovering ratios. In order to perform a fair analysis and provide a fair comparison, instance sets are entitled according to: i- the network handled, where ND, SF, ITU, and BA represent respectively the networks of Nguyen-Dupuis, Sioux-Falls, Istanbul Technical University, and Buyukada; ii- the number of nodes at the network, such as n13 to represent 13 nodes; iii- the number of arcs at the network, such as a38 to represent 38 arcs; iv- the number of bus stops

considered, such as b5 to represent 5 bus stop nodes; and, v- the battery capacity, such as q1.5 to represent a 1.5 capacity battery.



Table 5.1 : Results obtained specific to instance sets.

Instance Set	Objective	Number of Vehicles Assigned	Number of Recharging Stations	Energy Consumed [kWh]	Energy Recovered [kWh]	Total Cost [USD]	Distance Traveled [m]	Travel Time [sec]	Energy Consumption Ratio [kWh/km]	Energy Recovering Ratio [kWh/km]
ND_n13_a38_b5_q1.5	E, C, D, T	2	2	4.13	-	121.53	6.60	750.27	0.63	-
SF_n24_a76_b6_q20	E, C	2	1	46.64	0.00	124.69	77.00	3521.62	0.61	0.00
SF_n24_a76_b6_q20	D, T	2	2	48.01	0.00	127.56	72.00	3313.28	0.67	0.00
ITU1_n25_a72_b6_q1.6	E, C	1	0	1.22	0.32	63.34	3.21	471.06	0.38	0.10
ITU1_n25_a72_b6_q1.6	D, T	1	0	1.33	0.34	63.83	2.97	444.49	0.45	0.11
ITU2_n25_a72_b7_q1.6	E, C	1	0	1.60	0.40	67.24	3.76	557.50	0.43	0.11
ITU2_n25_a72_b7_q1.6	D, T	1	1	1.64	0.54	70.20	3.38	524.98	0.49	0.16
BA_n226_a700_b10_q2.5	D	1	1	2.10	0.85	63.51	3.52	586.62	0.73	0.24
BA_n226_a700_b10_q6	E, D	1	0	2.10	0.85	60.83	3.52	506.62	0.73	0.24
BA_n226_a700_b30_q10	E	1	0	5.96	1.13	61.30	10.19	1439.223	0.58	0.11
BA_n226_a700_b30_q6	D	1	1	7.70	2.57	64.22	8.71	1389.803	0.89	0.30
BA_n226_a700_b30_q10	D	1	0	7.70	2.57	61.54	8.71	1266.451	0.89	0.30

5.2.1 Effects of introducing intersection nodes

In order to evaluate the effects of having introduced the actual intersections to the road network graph in terms of the total time spent on a network, vehicle trajectory data are analyzed, where the speed reduction is either considered or neglected. In this context, distance optimal routing plan for BA network with 30 bus stops is handled, where there are 74 intersections along the route. According to the vehicle trajectories given in Figure 5.17, it is seen that when the speed reduction, in terms of deceleration, while approaching towards the intersection is neglected, the total time spent is 10% lower than the solution of the problem adopting a realistic speed profile with deceleration and acceleration phases. Results indicate that even for the relatively low traveling speeds, which is set to 30 km/h for this specific instance, a probable speed reduction at intersections affects the arc traveling time by increasing up by 54%, and the total traveling time by increasing up by 10%. The significance of having introduced the actual intersection nodes in a network to the problem formulation through a graph is underlined by the findings, in which intersections can be handled as the points where the traffic conditions change.

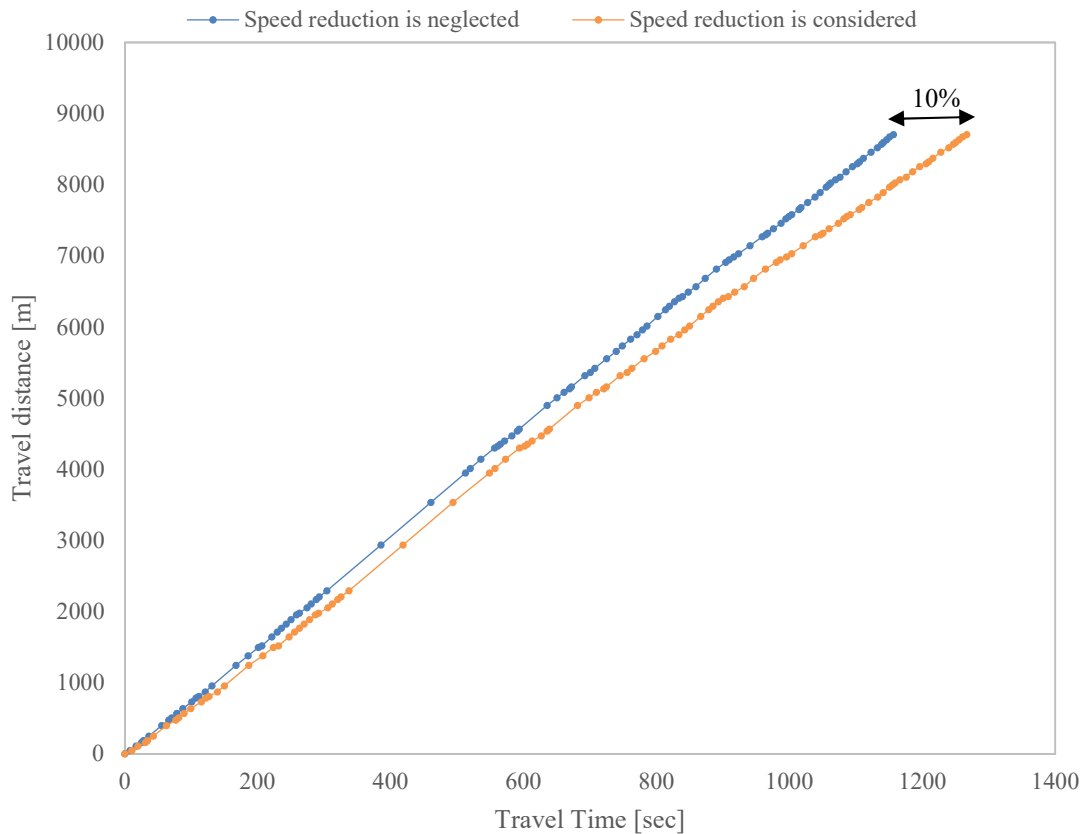


Figure 5.17 : Vehicle trajectories with and without speed reduction at intersections.

In addition to the time-related issues, intersection nodes have a significant role in order to ensure the consistency between bus stop nodes. By ignoring intersections, the connectivity between the bus stops is neglected as well that may result in unrealistic or impracticable solutions in real-world. In order to reveal the importance of having introduced intersection nodes to the formulation to ensure a reasonable routing plan for a vehicle, Buyukada network is handled, where the intersection nodes are neglected by determining the shortest distances between all bus stops. According to the results of the network graph that consists of 30 nodes and 870 arcs, examples of inconsistency with the real-world applications are given in Figure 5.18. For instance, within the path provided by the solution without intersection nodes, vehicle is driven from bus stop node 47 to 14. According to the network topology, the shortest path between nodes 47 and 14 involves the nodes 47-9-182-18-14 to be traversed, in which the nodes 182 and 18 are bus stops as well (as shown in blue in Figure 5.18). Although the vehicle visits two other bus stops (182 and 18) to travel between 47 to 14, it visits those bus stop nodes again for the second time after visiting bus stop nodes 188, 185, 95, 210, and 59 since the intersections, and hence the connectivity between nodes, have not been defined. The same issue arises when traveling between the bus stop nodes 158 and 121. According to what the solution implies, in order to travel from bus stop node 158 to 121, the vehicle either turns back to the opposite direction, or drives on the path composed of the nodes 158-164-23-150-149-138-134-121, in which the node 149 is a bus stop.

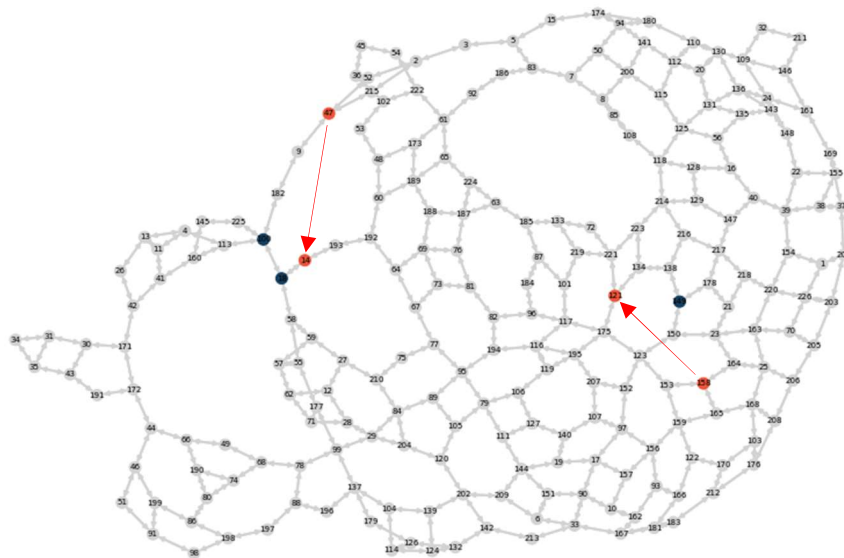


Figure 5.18 : Examples of paths with bus stops when intersection nodes are neglected.

The influence of introducing the intermediate nodes to network graph is examined considering the bus stop nodes and accessibilities among them. In this context, two versions of ITU Ayazaga Campus network graph with student shuttle bus stops is considered (Figure 5.19): Graph 1, with intermediate nodes; and, Graph 2, without intermediate nodes as frequently considered in VRP literature. The graphs considered are compared the graphs in terms of their eigenvector centrality values that depend on not only the nodes ‘connections, but also the neighboring nodes’ connections (Grassi et al., 2017), in which both the degree of a node and the degree of its neighbors are taken into account.

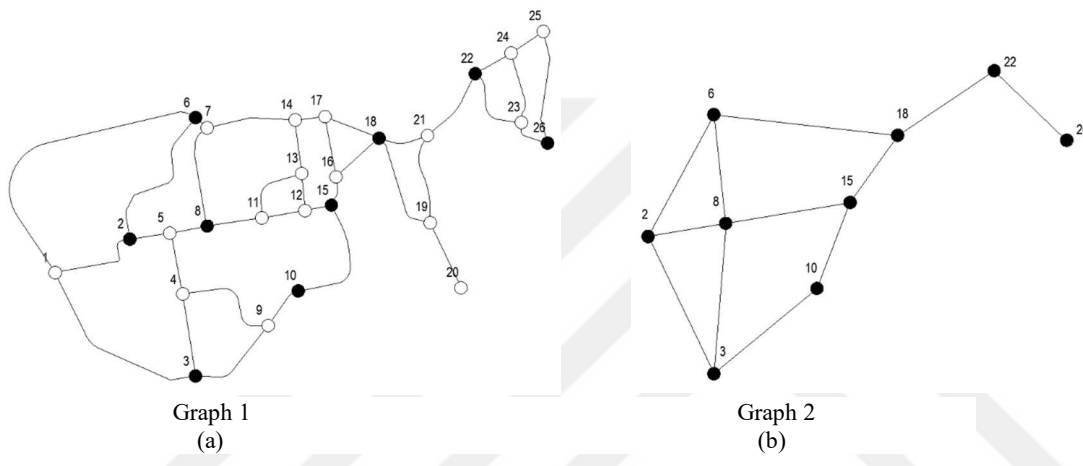


Figure 5.19 : ITU Ayazaga Campus network graph with student shuttle bus stops, with (a) and without (b) intermediate nodes.

Eigenvector centrality values of nodes that are shown on graphs as given by Figure 5.19, are revealed in Figure 5.20, where the graph without intermediate nodes has only 7 nodes to represent the bus stops and, the graph with intermediate nodes involves additional nodes in order to represent intermediate nodes. From the eigenvector centralities obtained, it is clear that the influence of any node can be misread by simplifying the road network by neglecting the intermediate nodes. For example: node 8 is a centrally high node for Graph 2, while it has an average centrality value when intermediate nodes are considered in Graph 1; or, the centrality of node 18 is undervalued in Graph 2 when compared to Graph 1. It can be concluded that by neglecting the intermediate nodes, the importance of a node on the network graph in terms of centrality can be over or underestimated since the actual connectivity between the nodes, which accommodates the characteristics of network flows, is not considered.

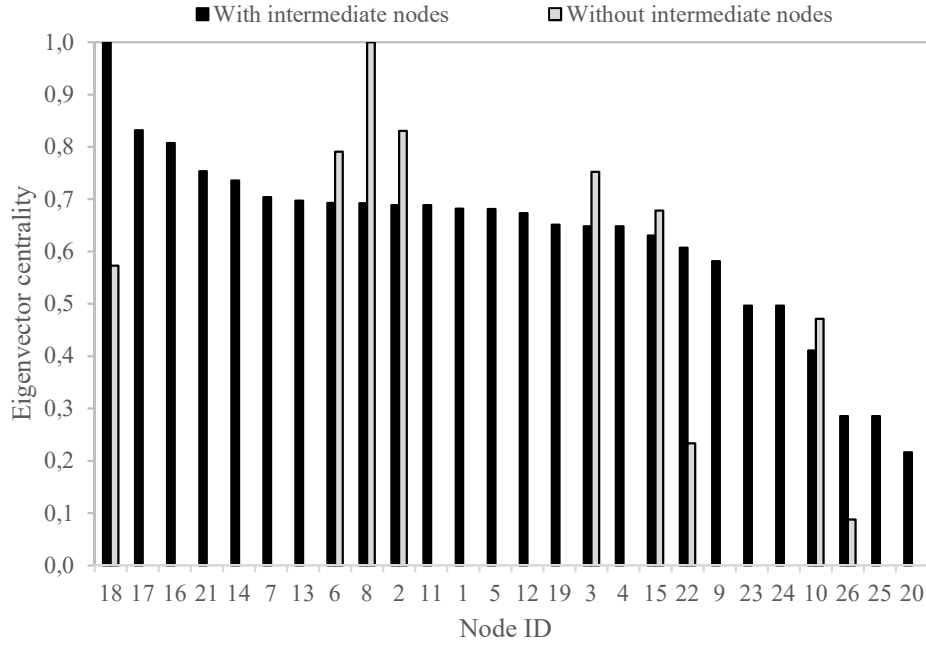


Figure 5.20 : Eigenvector centrality for different versions of graph as with and without intermediate nodes.

5.2.2 Effects of passengers' demand

In order to evaluate the influence of passengers' demands on the EV energy consumption, two variations of medium-scale real case instance are analyzed: (i) with demand; and, (ii) without demand. Unlike to the cases, in which the passenger demand is handled solely for getting on or getting off demands where the difference between the energy consumption for with and without demand setups are respectively increased or decreased along the route, for the cases involving both the getting on and getting off demands, the energy consumption difference fluctuates. In this context, as Figure 5.21 implies, the energy consumption of Shuttle-1 and Shuttle-2 are increased respectively by 9% and 10% in total, where the aforementioned difference is increased up by 11% for Shuttle-1 and by 34% for Shuttle-2.

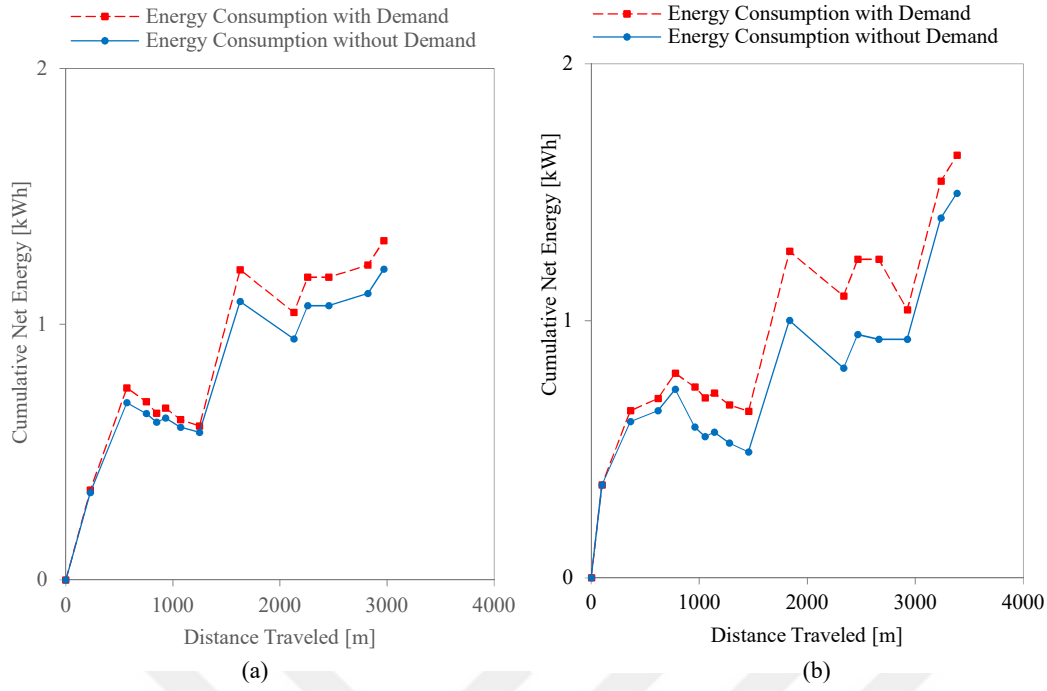


Figure 5.21 : Energy consumption differences with and without considering passengers' getting on and getting off demands at ITU network for: (a) Shuttle-1; and, (b) Shuttle-2.

The influence of passengers' demands on the energy consumption is analyzed for BA_n226_a700_b10_q2.5 instance with the ratio of the number of intersection nodes to all the nodes along the route is 70%, where this ratio is 38% and 44% for the routes of Shuttle-1 and Shuttle-2, respectively. In this context, considering the attraction points of the island, hypothetical getting on and getting off demands are derived respecting to the vehicle passenger capacity, 50. According to the results that are given in Figure 5.6, energy consumption is increased up by 27% considering the passengers' getting on and getting off demands, where the location of recharging station as well as the required recharging amount changes as well. The vehicle needs to be recharged at recharging stations with the amounts of 1.605 kWh and 1 kWh, respectively in cases of with demand and without demand at the recharging stations that are marked in Figure 5.22.

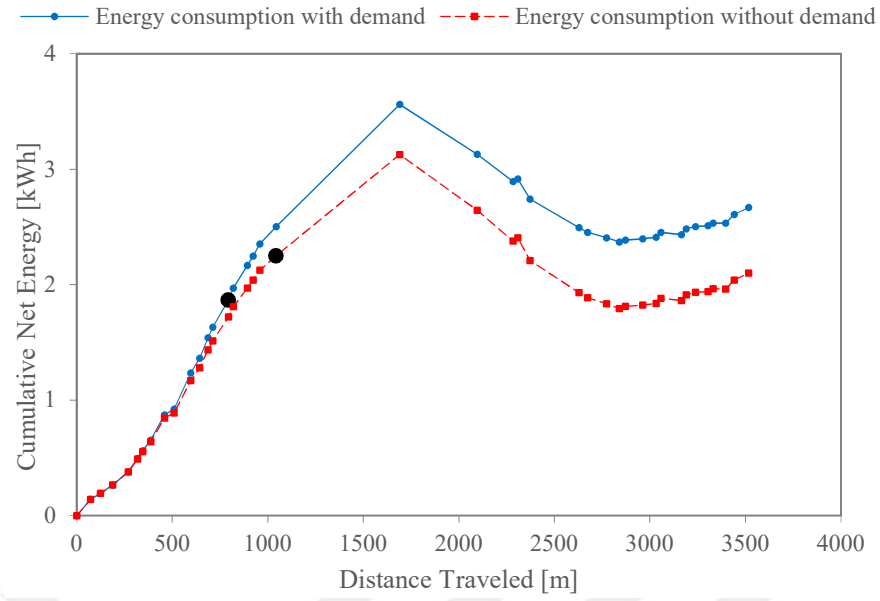


Figure 5.22 : Energy consumption differences obtained with and without considering passengers' getting on and getting off demands at BA_n226_a700_b10_q2.5 instance.



6. CONCLUSIONS

Regarding the battery constraints of EVs, the ELRP-IN proposed in this study focuses on finding the optimal paths together with the recharging station locations according to various objectives, where the energy discharging is determined realistically and, the nodes existing on a real road network including the points where traffic conditions change, i.e., intersections of roads, are considered to increase topological consistency of the actual road network. Considering the fact that the optimal location for a recharging station to serve EVs depends on the energy requirement, and hence the battery discharging of EVs along the route driven, a realistic battery discharging model is embedded to the proposed ELRP-IN formulation, in which both the energy consumption and the energy recovery potentials are explicitly taken into account. In addition to the attributes of 3-dimensional road geometry, the vehicle and battery characteristics related with the vehicle motion dynamics are incorporated to modeling while train-like speed profiles are adopted in order to take into account the acceleration and deceleration behavior of vehicles when approaching to/departing from the bus stops or intersections. The need to the tractive effort and the braking is determined with the net change in the kinetic and potential energy that is calculated as a function of mainly the driving resistances, the change in elevation, and the speed profiles. Since the total load of a vehicle directly affects the tractive effort, and hence the energy required, the cumulative passenger load is considered as a function of the get on and get off demands at bus stops together with the capacity of the vehicle, unlike to the VRP formulations for only collecting or distributing passengers/loads. In order to provide a discussion on the impacts of the objective function to the routing plans and to the parameters including energy consumption, cost, traveled distance and travel time, the objective functions adopted are alternated within the proposed ELRP-IN formulation.

Model based exact solutions are extracted by performing a number of numerical experiments including two widely employed test instances, a medium-scale real case instance, and a large-scale real case instance in order to evaluate the features of the ELRP-IN formulation as summarized briefly in section 6.1.

6.1 Findings

In order to evaluate the formulation and the solution of the ELRP-IN from varying perspectives, a brief summary of main findings from the numerical experiments are listed in following:

- Considering different objective functions, two routing plans are obtained for each of the instances except the Nguyen-Dupuis test instance, where the former routing plan corresponds to the energy and cost optimal solution, and the latter minimizes the distance traveled and total travel time. The importance of concentrating on the appropriate problem-specific objective is revealed by comparing the two optimal routing plans, where the energy consumption, cost, traveled distance and travel time may vary up respectively to 24%, 5%, 26%, and 10% according to the objective sought. Results remark the existence of the trade-off among the energy consumption and the total distance traveled, where the energy consumption is minimized by increasing the distance traveled, in which the need to recharging stations, and consequently the location of the recharging stations, are changed accordingly.
- The direct effect of the elevation on the energy consumption is revealed, where the importance of defining the braking sections is remarked by the finding that energy is not recovered in all the sections with negative grade. Results highlight as well that the location of a recharging station is affected by the instantaneous increase in the elevation and the consequent energy requirement.
- The effect of passengers' demands is discussed in terms of the routing plans, the decision on the recharging station location, and the energy consumption. Regarding the passengers' demands extracted using the O-D demands, solutions for Nguyen-Dupuis and Sioux-Falls test instances have required two vehicles in order to meet passengers' getting on and getting off demands in accordance with the passenger capacity of vehicles. Results from medium and large-scale real world instances with and without considering passengers' demands reveal that the total energy consumption is under estimated by 10% in total, and by up to 34% for specific arcs when the passenger demand is neglected, in addition to the decision on the recharging station location and the recharging amount.

- The limitation of energy recovery related to the braking efficiency is highlighted by revealing that all the energy can not be recovered even for the symmetrical route elevation profile. In addition, results show that the route where the minimum energy will be consumed does not necessarily correspond to the route where the maximum energy will be recovered: for some instances, the recovered energy is increased where the energy consumption increased but the traveled distance is minimized by not avoiding to drive over high hills.
- The influence on introducing the intersection nodes to the road network graph is evaluated with respect to the total time spent, network consistency and centrality measure in order to both quantify and qualify the nodes of the network. Results show that by neglecting the intersection nodes, and hence the consequent speed reduction in terms of deceleration, while approaching towards the intersections, the total time spent is shorter by 10% than that of obtained by the solution of the proposed ELRP-IN formulation, which adopts realistic speed profiles with deceleration and acceleration phases. Results have also revealed the significance of having introduced to the formulation the intersection nodes in providing reasonable routing plans in contrast to the common graph representation in the existing VRP literature, where the actual connectivity between nodes is simplified by neglecting the intersections. Eigenvector centrality values for the graphs with and without intermediate nodes show that a node on the network graph can be over or under estimated considering that the actual network topology is corrupted by focusing only on the bus stop nodes.

6.2 Further Research Directions

The present study contributes to the EVRP literature by handling a road network with intermediate nodes, i.e., intersection nodes, considering simultaneously the get on and get off demands at stop nodes, determining accurately the energy requirement of EVs considering the regenerative braking and driving resistances by adopting specific speed profiles while providing a decision on the location of recharging stations.

Modeling the actual intersection nodes in routing problems further opens up a space to analyze the traffic congestion, and to manage traffic flow with intelligent control. In this context, further research directions focus on the dynamic routing considering

especially the effects of changes in traffic conditions at intermediate nodes with or without control.

Further extensions of the proposed model will probably require the employment of heuristic approaches for solution as the computational load to obtain exact solutions goes far beyond reasonable figures, especially in cases with the increased complexity in the problem. However, it is important to note that such approximate solutions have been documented in the literature to be the results of making compromises on exact solutions.



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CURRICULUM VITAE



Name Surname : Selin Hülügü
Place and Date of Birth : İzmir/30.09.1992
E-mail : hulaguselin@itu.edu.tr

EDUCATION:

- **B.Sc.:** 2015, Ege University, Engineering Faculty, Civil Engineering Department
- **M.Sc. :** 2017, Ege University, Graduate School of Natural and Applied Science, Civil Engineering Department

PROFESSIONAL EXPERIENCE:

- 2017- Research Assistant at Technical University of Istanbul, Faculty of Civil Engineering

PUBLICATIONS ON THE THESIS:

- **Hulagu S., Celikoglu H.B.** (2018). An Integer Linear Programming Formulation for Routing Problem of University Bus Service. In: Daniele P., Scrimali L. (eds) *New Trends in Emerging Complex Real Life Problems*. AIRO Springer Series, vol 1. Springer, Cham. https://doi.org/10.1007/978-3-030-00473-6_33.
- **Hulagu S., Celikoglu H.B.** (2018). Karayolu Ulaştırmasının Çevresel Etkilerinin Azaltılmasında Elektrikli Araçlar ve Türkiye'deki Yeri, *4. Ulusal Karayolu Kongresi ve Sergisi*, Ankara, Türkiye.
- **Hulagu, S., & Celikoglu, H. B.** (2019). A Multiple Objective Formulation of An Electric Vehicle Routing Problem For Shuttle Bus Fleet at A University Campus. *2019 6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*. Cracow, Poland: IEEE. <https://doi.org/10.1109/mtits.2019.8883344>.

- **Hulagu, S., Atasayar, G., & Celikoglu, H. B.** (2019). Green Routing Plan for University Shuttle Services Using Mixed Integer Linear Programming. *2019 IEEE 5th International forum on Research and Technology for Society and Industry (RTSI)*. Florence, Italy: IEEE. <https://doi.org/10.1109/rtsi.2019.8895571>.
- **Hulagu S., Celikoglu H.B.** (2020). A Mixed Integer Linear Programming Formulation for Green Vehicle Routing Problem: Case for Shuttle Services. In: Moreno-Díaz R., Pichler F., Quesada-Arencia A. (eds) *Computer Aided Systems Theory – EUROCAST 2019*. EUROCAST 2019. Lecture Notes in Computer Science, vol 12014. Springer, Cham. https://doi.org/10.1007/978-3-030-45096-0_19.

