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Faculty of Graduate Studies

Smart Home Healthcare Vehicle Routing Problem Considering Patient's Condition and Quality of Service

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Dedication

This thesis is dedicated to my amazing parents, beloved wife and my beautiful children for their endless support, encouragement and devoted partnership for success in my life.

Acknowledgment

﴿قَالُوا سُبْحَانَكَ لَا عِلْمَ لَنَا إِلَّا مَا عَلَّمْتَنَا ۖ إِنَّكَ أَنتَ الْعَلِيمُ الْحَكِيمُ﴾

First and foremost, I would like to express my sincere gratitude and thanks to ALLAH Almighty for the countless blessings, knowledge and patience to complete this thesis.

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الإقرار

أنا الموقع أدناه, مقدم الرسالة التي تحمل عنوان:

Smart Home Healthcare Vehicle Routing Problem Considering Patient's Condition and Quality of Service

أقر بأن ما اشتملت عليه هذه الأطروحة إنما هو نتاج جهدي الخاص ,باستثناء ما تمت الاشارة إليه حيثما ورد .وأن هذه الرسالة كاملة ,أو أي جزء منها لم يقدم من قبل لنيل أي درجة او لقب علمي أو بحثي لدى أي مؤسسة تعليمية أو بحثية أخرى.

Declaration

The work provided in this thesis, unless otherwise referenced, is the researchers own work, and has not been submitted elsewhere for any other degree or qualification.

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Date: **التاريخ: 2021/5/9**

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List of Abbreviations

HHC	Home Healthcare
GHHC	Green Home Healthcare
GHHCSC	Green Home Healthcare Supply Chain
VRP	Vehicle Routing Problem
HHCVRP	Home Healthcare Vehicle Routing Problem
SSHHCVRP	Smart-Sustainable Home Healthcare Vehicle Routing Problem
CVRP	Capacitated Vehicle Routing Problem
VRPTW	Vehicle Routing Problem with Time Windows
PS-VRPTW	Production Scheduling and Vehicle Routing with Time Windows
PVRP	Periodic Vehicle Routing Problem
DVRP	Dynamic Vehicle Routing Problem
RVRP	Rich Vehicle Routing Problem
AC-VRP-SPDVCFP	Asymmetric and Clustered Vehicle Routing Problem with Simultaneous Pickup and Deliveries, Variable Costs and Forbidden Paths
GVRP	Green Vehicle Routing Problem
OVRP	Open Vehicle Routing Problem
GOVRPTW	Green Open Vehicle Routing Problem with Time Windows
EV	Electric Vehicle
BSNs	Body Sensor Networks
WSNs	Wireless Sensor Networks
GHG	Greenhouse Gases
WHO	World Health Organization
ICT	information and communication technologies
TBL	Triple Bottom Line
IoT	Internet of Things
RFID	Radio Frequency Identification
4G	The Fourth Generation of broadband cellular network
GIS	Geographic Information system
MINLP	Mixed Integer Non Linear Programming
LP	Linear Programming
ILP	Integer Linear Programming
MILP	Mixed Integer Linear Programming
DFA	Discrete Firefly Algorithm

ACO	Ant Colony Optimization
NDS	Non-dominated Sorting
NS-ACO	Non-dominated Sorting Ant Colony Optimization
CMEM	Comprehensive Modal Emission Model
RPM	Revolutions Per Minute

Smart-Sustainable Home Healthcare Vehicle Routing Problem Model Considering Patient's condition and Quality of Service

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Abstract

The demand on home healthcare services has increased dramatically, due to the escalating expenses of the typical healthcare services and the frequent diagnosis of chronic diseases patients. This research aims at solving a home healthcare vehicle routing problem model that considers the three pillars of sustainability, to be executed in smart cities. More specifically, our approach intends on taking advantage of the technology available in smart cities, by placing body sensors on patients to keep updating their condition and prioritizing critical conditions in service. In addition to the dynamism and uncertainty caused by the variation in patient's condition, our approach extends the reality of the model by considering parameters and variables which enhance its practicability, such as assuming different patient's importance (priority) levels. Furthermore, to ensure a sustainable flow of business, the model considers electric vehicles which will result in saving fuel costs and preserving the environment from greenhouse gases. Also, the social aspect was tackled by maximizing patient's and employee's satisfaction through improving quality of service and managing workload respectively. The model was solved using a metaheuristic algorithm approach, via Ant Colony Optimization algorithm along with Non-

dominated Sorting technique due to the ability of such combination to work out with dynamic models with uncertainties and multi-objectives. Sensitivity analyses showed the benefits of using heart rate sensor in the developed model, especially in improving the quality of service. In addition to the arising in quality costs when increasing the importance levels of patients. The implementation of this model in the healthcare sector comes with a great advantage for service providers, due to the continuous monitoring of patient’s status, as well as, the classification of patient’s importance levels (based on medical status); thus, ensuring healthy satisfied patients.

Chapter One

Introduction

Chapter One
Introduction

1.1 General Background

Home healthcare (HHC) is a broad set of medical and non-medical services which are provided to patients at their own premises. Such medical services include diagnoses and treatment of diseases, medical injections, changing wound dressing, and monitoring vital signs. Whereas non-medical services may include helping the elderly with daily activities such as dressing, bathing, housekeeping and eating. The aforementioned services are provided by either medically-certified personnel such as doctors, registered nurses, certified nursing assistant and therapists, or skilled caregivers whom aren't medically-certified (World Health Organization, 2015).

According to the World Health Organization (WHO), by 2050 the rate of people living in their sixties and above will increase rapidly to reach two billions, which is due to the phenomena of population aging caused by the increase of life expectancy and infertility rates (World Health Organization, 2015). In addition, HHC is believed to be usually cheaper, more convenient and in many situations provides services as effective as traditional hospital healthcare (Alodhayani, 2017). Therefore, the demand for HHC services has evolved rapidly (OECD, 2013). According to Market Analysis Report (2020), about 7.9% compound annual growth rate of HHC market size is expected from 2020 to 2027 as presented in Figure 1.1, which shows the market size of HHC in the United States from 2016 to 2027. This growth in demand inspires HHC companies and researchers in the field to provide patients with comprehensive

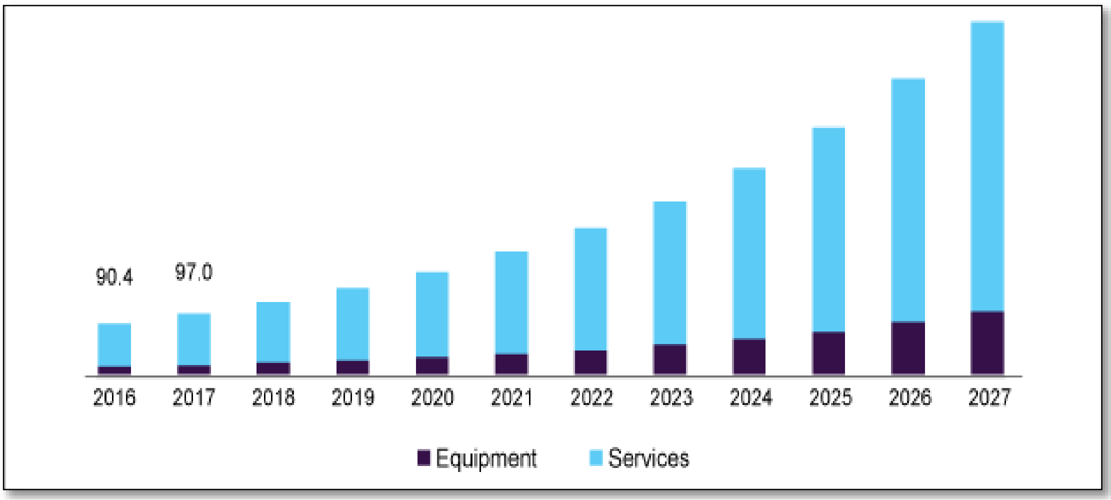

Figure 1.1: United States HHC Market size 2016-2027 in Billions of USD (Market Analysis Report, 2020)

wide range of services with a fleet of qualified personnel (Erdem & Koç, 2019; Fathollahi-Fard et al., 2018; Shi et al., 2017).

In HHC services, a nurse (or any certified HHC worker) leaves his/her location whether it's a pharmacy, HHC company or home to the patient's location to provide the necessary healthcare service, using transportation means such as cars or public transportation. According to Zhang et al. (2014), transportation possess the largest share in pollution of environment among other logistic and supply chain systems. In addition, the growing demand of HHC service will result in tens of millions of miles travelled by nurses and caregivers to provide requested services. In 2013, 7.88 billion miles were driven by HHC workers to meet the needs of 718 million patients (Erdem & Koç, 2019). Therefore, Vehicle Routing Problem (VRP) and scheduling should be considered in order to perform services in an effective and efficient manner, as well as, reducing the impact on environment. Various efforts were made in the field of HHC Vehicle Routing Problem (HHCVRP) with different objectives, some studies investigated the possibility of reducing costs by minimizing fuel consumption and other associated operational costs (Wang et al., 2008; Zhang et al., 2017), while other efforts considered the well-being of mother nature by minimizing the effect of HHC routing and practices on the environment, mainly by decreasing the emissions of Greenhouse Gases (GHG) caused mainly by the burn of fuel (Fathollahi-Fard et al., 2018; Kramer et al., 2015). GHG are gasses that are responsible for trapping heat in the atmosphere surrounding the earth, where transportation is one of the major sources of such gases (Asrawi et al., 2017). In addition, many articles in the literature presented more complex and realistic HHC vehicle routing models, which are multi-objective, considering different tradeoff between conflicting goals and solved by novel heuristics algorithms (Fathollahi-Fard et al., 2019; Shi et al., 2017).

Quality management is a well-known and important form of practices that is essential for business and market success. In the last century, many efforts were presented to improve quality in different sectors. Due to its significance, quality improvement actions are sought in operational, tactical and strategic levels of decision making. In the literature of VRP, many contributions were made to improve the quality of service (Bulhoes et al., 2018; Expósito et al., 2019), most of these efforts discussed time windows for service time and patients’ preferences as a measure of quality. However, such measures are intuitive and don’t use any quality models or tools to measure and improve quality of service. Therefore, using such tools will significantly improve VRP models and promote the issue of quality management in vehicle routing to the next level.

According to Streitz (2015), the United Nations estimates a growth of population to reach 9.5 billion by 2050, of which 6.5 billion will be located in cities. Indeed, such facts and numbers raised many concerns. Challenges and issues will exist and will be associated with the increase of citizens in urban cities. Challenges in transportation, delivery of services, healthcare, education, pollution and waste management must be expected. An effective way to face such challenges is to adapt the concept of smart cities. Ismagilova et al. (2019) presented different definitions by various authors for smart cities. However, all of them agreed that smart cities must be enabled by technology to be smart. Therefore, smart cities are cities which promote the use of information and communication technologies (ICT) as well as artificial intelligence in its various sectors to improve the quality of life and the well-being of its stakeholders and the environment.

This research aims at formulating a novel and smart HHC vehicle routing and scheduling model. This model considers the concept of smart mobility which is one of the eight pillars of smart cities introduced by Singh (2015), smart cities facilitate the use of various types of technologies to gain operational efficiency and citizens well-being. In addition, the issue of sustainability of the HHC system is considered and measured using the Triple Bottom Line (TBL) concept. While economic and environmental aspects of TBL are frequently addressed in research, the social aspect is usually ignored (Vega-Mejía et al., 2019). Therefore, one of our goals in this study is to tackle this aspect. Moreover, this work analyzes and measures the level of the provided services. Thus, including the three pillars of sustainability in a comprehensive well-defined approach integrated with smart mobility concept, as well as, analyzing the risk of poor service quality will lead to a positive remark and contribution to HHCVRP.

1.2 Research Problem

The request for HHC services evolved dramatically in recent years, mainly because of the global phenomena of aging societies, the presence of chronic diseases, the high costs of traditional healthcare system in hospitals and lately due to social distancing policies to stop the spread of Covid-19 pandemic. In addition, patients noted that it would be more convenient and easier in terms of money and effort wise to receive medical care in their homes rather than hospitals and medical centers. In a traditional HHC system, nurses travel from a single or multi depot to serve one or more patients using different types of transportation in predefined time windows. As the demand for HHC service increases, a great necessity for adequate planning and scheduling for nurses' activities arise, such plans embrace matching the right nurses to right patients based of the demanded services and qualifications, allocating different patients and nurses and route planning, in addition to several operational, tactical and strategic levels of planning. The importance of route planning lies on the fact that as demand increases the fleet size for both nurses and vehicles increases, therefore, planning vehicle routing possess a significant importance in HHC companies from money and time perspectives, where enhancing profitability and level of service could be achieved through cutting travel costs and meeting customer demands in a professional and timely fashion. Moreover, in addition to profitability, HHC companies have social and environmental responsibilities to be addressed in vehicle route planning, since the increase in operational activities may lead to harmful violations to the environment and staff. Furthermore, to present a realistic HHCVRP model, research goals must be matched with real world needs, problems and trends. Trends such as shifting toward technology-based life style, which makes use of technology to assist the execution (and the process of problem solving) of nearly all activities, must be addressed by HHCVRP researchers. Similarly, to develop a realistic model, the issue of rivalry among different service providers and the matter of customer’s satisfaction should be considered, to ensure success and financial prosperity. Therein lays the importance of measuring quality of service, to guarantee a pioneer service execution and gain customers satisfaction. In this context, this study aims at creating and solving a smart-sustainable HHCVRP (SSHHCVRP) with service quality optimization which is feasible for implementation in real life applications. To the best of our knowledge, the variants in the proposed model are either considered alone or not considered at all (the case of smart HHCVRP and measuring the quality of service) in the reviewed literature of HHCVRP services. Therefore, developing a realistic and comprehensive model considering the three pillars of sustainability, as well as, different constraints that make it applicable for the emerging concept of smart cities is a worthy contribution to the literature of HHCVRP.

1.3 Research Significance

From what has been discussed earlier, a model solving the HHCVRP with service quality concerns which support sustainability concept to be employed in smart cities is expected to improve the current models in the literature. Since logistical activities are one of the most important and developing industries in the world; vehicle routing and planning process becomes more complex and forked. Therefore, considering different variants and constraints of VRP with the aim of developing a realistic scenario that ensures a smooth flow of the process, is the first contribution of the model. In addition, the concept of sustainability has been addressed, in terms of shifting to a green environment, while considering profitability and corporate social responsibility of the firm. Moreover, the integration of rich-sustainable VRP with smart logistics and smart healthcare systems that uses different types of technology plays a significant role in the continuous efforts of enhancing and optimizing smart cities. Finally, the analysis of service quality will mitigate the possibility of failures and thereby a better experience for the patient and higher profitability of HHC companies. Therefore, the aforesaid contributions justify the significance of this study, since using ICT and Internet of Things (IoT) technologies in HHCVRP is a novel notion, as well as, the innovative approach of measuring customer’s satisfaction on quality of service for the first time in VRP, by measuring the gap between expected and perceived service, which wasn't considered before by researchers in VRP as debated in literature review chapter.

1.4 Summary of the Solution Methodology

The methodology used to conduct this research is as follows: first, a deep review in the literature of HHCVRP was done to analyze and understand previous contributions, for the reason of defining research gaps and thereby defining the research problem. After that, a mathematical model was developed to translate the problem into mathematical equations and related constraints; the model was presented as a Mixed Integer Nonlinear Programming (MINLP) model. Then, data was generated hypothetically and from some related existing studies. MATLAB 2014a software was used to solve the mathematical model and make it ready for validation and providing solutions. Since VRP is considered as an NP-hard problem, and addressing real world problems is associated with a lot of complexities in variables, parameters and constraints, using exact methods to solve the optimization problem is nearly impossible. Thus, approximate methods were used for the optimization problem; namely a combination of Ant-Colony algorithm and Non-dominated Sorting are used to provide solutions for the proposed problem. At this point, computational results are generated to provide solutions and test whether results are logical and applicable. Finally, sensitivity analysis is conducted to understand how the variation of independent input variables would impact the dependent output ones which is referred to as model robustness. Figure 1.2 summarizes the HHCVRP at hand and shows the flow of the process, which was adopted from the thesis of Reyes-Rubiano (2019), and modified to address the structure and contributions of the developed model. The aim of this thesis is to develop a HHCVRP model that considers the use of technology in performing services, as well as, taking in to account the three pillars of sustainability and the gap between expected and perceived quality of service.

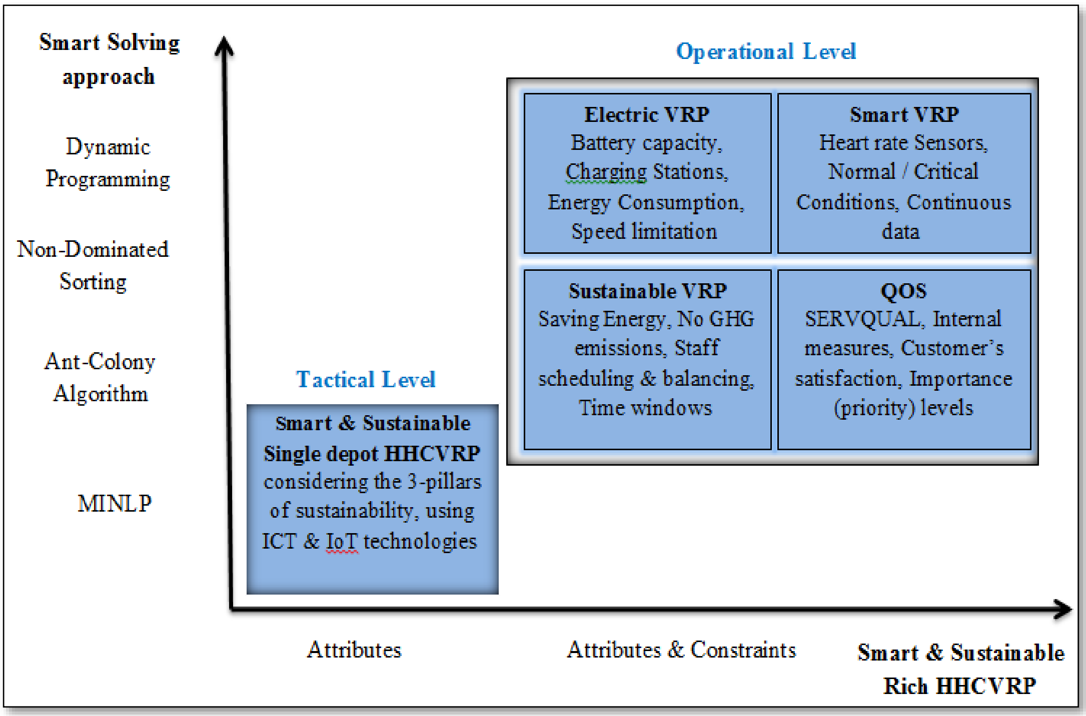

Figure 1.2: Structure and contributions of the proposed HHCVRP model (Reyes-Rubiano, 2019).

1.5 Thesis Organization

The rest of this thesis is organized as follows: chapter two is the literature review which includes a presentation of previous contributions in classical VRP, HHCVRP, Smart VRP, Sustainable VRP and measuring quality of service in VRP. In this chapter, a better understanding of the relationship between various aspects of the proposed SSHHCVRP model is achieved; moreover, research gaps are given. In chapter three, the developed mathematical model is discussed; the MINLP model that includes indices, definitions, parameters, decision variables and constraints is presented and explained in details. Chapter four discusses the research methodology. In chapter five, the obtained results are discussed and explained, where the results for the targeted objective functions are presented. Chapter six presents the sensitivity analyses on the model. Specifically, different values of parameters are applied to verify that each value will present acceptable and reliable solutions. Finally, chapter seven provides conclusions, recommendations and future work.

Chapter Two

Literature Review

Chapter Two
Literature Review

2.1 Chapter Overview

In this chapter, a detailed review on the literature of optimizing Smart and Sustainable Home Healthcare Vehicle Routing Problem (SSHHCVRP) is presented. The aim of this literature review is to build a strong foundation of knowledge on the research problem, as well as, identifying previous contributions related to the aforementioned aspects by summarizing their objectives, solution methodologies and results. This review is expected to reveal gaps in the literature for the aim of developing a realistic model which is applicable for implementation in real life practices. This chapter includes five sections which are selected based on their relevance to the research problem. These sections are organized as follows:

- Classical Vehicle Routing.
- Sustainable Vehicle Routing.
- Home Healthcare Vehicle Routing.
- Quality of Service in Vehicle Routing.
- Smart Vehicle Routing.

2.2 Classical Vehicle Routing Problem

VRP is the process of finding the optimal route which yields minimum operational costs (by using less vehicles and shorter routes) to visit geographically-distributed customers while satisfying some constraints

(Yeun et al., 2008). Earlier, in classical VRP, the route starts and ends at an initial depot, and in between different nodes with different demands should be visited ones using one vehicle (Belfiore et al., 2009). However, different variants were introduced by time. VRP was introduced for the first time by Dantzig and Ramser (1959), the authors introduced a fleet of gasoline delivery trucks which delivers gasoline to different service stations. The objective was to satisfy all customers' demands while minimizing the mileage traveled by the trucks using linear programming formulation. Clarke and Wright (1964) modified the work of Dantzig and Ramser (1959) by considering a fleet of trucks with varying capacities to serve geographically-scattered customers from a central depot to create the optimal network of routes while considering the covered distance. However, when dealing with real life applications, a great deal of complexities will appear which wasn't considered in earlier models, while on the contrary, the current VRP models aim at integrating such complexities (Braekers et al., 2016a). Those complexities such as traffic congestions, customer demands and time windows, offer a more realistic approach to model and solve VRP.

Eksioglu et al. (2009) contributed to the literature of VRP by introducing a taxonomy methodology for VRP researches which examines 1021 articles between 1959 and 2008. Their work was motivated by the difficulty of tracking the development in VRP research; they argue that the literature was disjoint and disparate. Inspired by the work of Eksioglu et al. (2009), Braekers et al. (2016a) introduced a comprehensive taxonomy framework which classifies 277 VRP articles between 2008 and mid-2015 based on the method used, individual characteristics, combination of characteristics and specific problems of real life aspects. The result of their work showed that researchers tend to pay more attention to real life aspects; such approach will promote their work to be more realistic and applicable for practical implementation.

To gain a better and wider perspective on the literature, different variants and modifications of VRP should be observed. Capacitated VRP (CVRP) is an extension VRP which considers the capacity of vehicles while planning to deliver the demand of customers (Toro et al., 2015), it considers a fixed fleet of vehicles with even capacities. Baldacci et al. (2004) added a new integer programming formulation based on two commodity flow approach to solve CVRP. On the other hand, Baldacci et al. (2010) and Lysgaard et al. (2004) examined the use of exact algorithms and branch-and-cut algorithm respectively to solve the problem with large instances.

Another popular variant which often arises in the literature of VRP is Vehicle Routing Problem with Time Windows (VRPTW). It is used for efficient utilization of vehicles to serve various geographically-distributed customers within pre-defined time window considering vehicle capacity, with the aim of travel cost minimization (Desrochers et al., 1988). Therefore, VRPTW is a generalization of VRP with service time and capacity constraints (Ellabib et al., 2002). The combination of routing and scheduling made VRPTW feasible to solve many real life applications (Yeun et al., 2008). Kim et al. (2006) studied the waste management VRPTW, considering multiple disposal depots, commercial waste, single start depot and lunch breaks. This article contributed to the literature by adding two objective functions which are route compactness maximization and balancing tasks among vehicles. In addition, a Production Scheduling and Vehicle Routing with Time Windows (PS-VRPTW) was addressed by Chen et al. (2009), their work introduced a model in which the supplier decides the quantity of perishable food to be produced, starting time of producing and the optimal route to pick. Additionally, Periodic VRP (PVRP) was defined as the process of planning the service pattern of clients in a pre-defined time horizon (say in a two day time horizon, client A should be visited twice while client B should be visited once) (Campbell & Wilson, 2014; Gulczynski et al., 2011). Then each client is assigned to a vehicle route. Recently, Rodríguez-Martín et al. (2019) introduced a model of PVRP with driver consistency where each customer is served by the same vehicle (driver) with one or more visits in a planning period based on demand. This work was motivated by different real-life applications such as logistics, distribution companies, trading and elderly healthcare services in which a driver develops knowledge about the customer, which allows him/her to forecast demand or special needs (in case of elderly healthcare).

Referring to the problem of information ambiguity regarding instances, where some data arises during service execution such as customer new requests or change order in demand and service time, a Dynamic VRP (DVRP) was introduced for the first time by Psaraftis (1988). In regard to this problem the author suggested that the dispatching of vehicles will follow a dynamic trend similar to real life instances. A detailed review on the problem was proposed by Pillac et al. (2013), different applications such as maintenance, transportation and emergency services, as well as, solving methods ranging from linear programming to meta-heuristics were discussed. Figure 2.1 presents an example of DVRP, figure t_0 shows a predefined set of customers to be served, whereas, figures t_1 and t_f shows two new customers to be served that must be included in the vehicle routing plan. Moreover, López-Santana et al. (2016) studied DVRP in HHC sector; the authors discussed the issue of receiving new service requests while providing the pre-defined services. To solve the problem a multi-agent approach was used to manage new requests as well as, a mathematical model to create routing plan.

Most of the studies presented in this section considered single constraint or variant in VRP, however, nowadays the tendency is to imitate the real-life complexities so that proposed models can be generalized and applicable for realistic implementation in various industries and services as suggested by Braekers et al. (2016a).

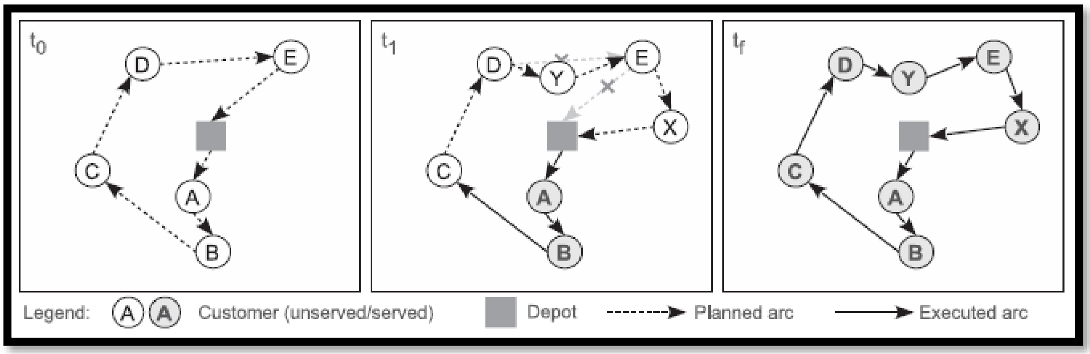

Figure 2.1: Example of DVRP (Pillac et al., 2013)

Due to this tendency another extension of VRP known as Rich VRP (RVRP) arises. RVRP deals with real life complexities such as uncertainty, dynamic operations, multiple constraints, environmental issues, smart operations and citizens' welfare (Caceres-cruz et al., 2015). In addition, the authors presented a classification of solving optimization problems which is applicable for VRP as shown in Figure 2.2. Since real life issues are considered routing problems having large instances to be analyzed, which can't be solved in a reasonable amount of time using exact optimization algorithms therefore, heuristic and meta-heuristic algorithms were used (Pellegrini et al., 2007). The authors argued that thanks to technological advancement and powerful computing powers the proposed algorithms can be solved more efficiently. Osaba et al. (2017) addressed the problem of newspaper distribution and recycling, an Asymmetric and Clustered VRP with Simultaneous Pickup and Deliveries, Variable Costs and Forbidden Paths (AC-VRP-SPDVCFP) model was proposed to handle the complex nature of the problem. It's noteworthy that the complexity is due to the following restrictions with the aim of delivering as realistic conditions as possible: (i) traveling from node A to node B and vice versa have asymmetric travel costs, (ii) Clients are clustered in different geographical areas, (iii) two types of nodes exist in the problem, one for newspaper delivery and the other of newspaper pick up for recycling, (iv) variable travel time due to rush hours and weather conditions for example, (v) forbidden paths such one way routes. Additionally, a Discrete Firefly Algorithm (DFA) was used to solve the problem.

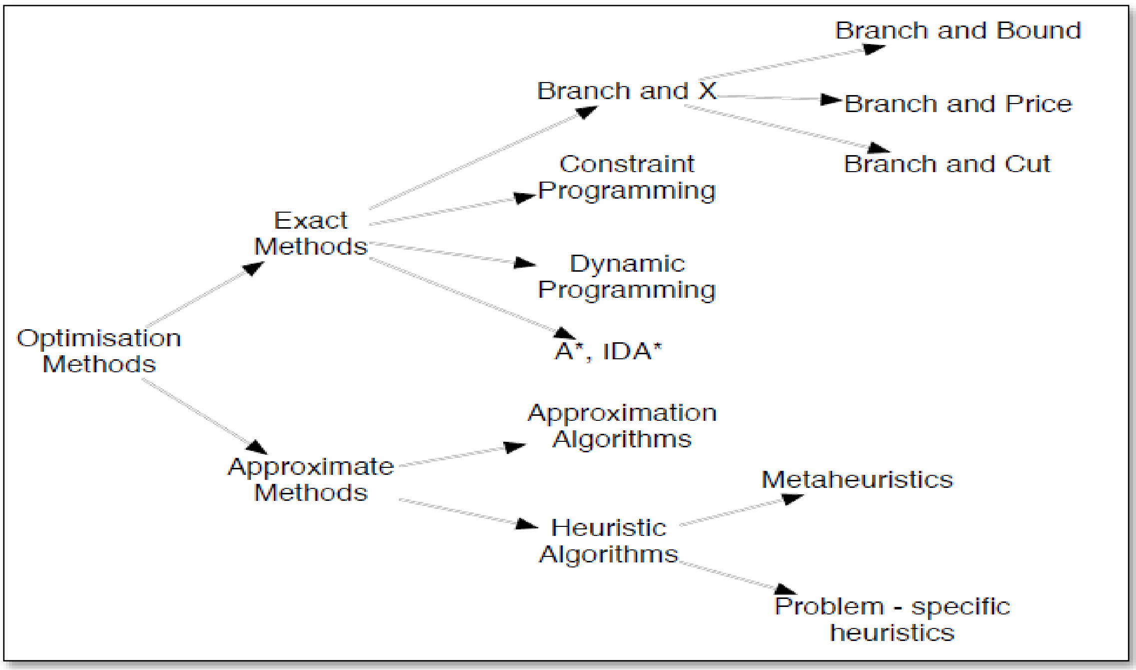

Figure 2.2: Classical methods of solving optimization problems (Caceres-cruz et al., 2015)

2.3 Sustainable Vehicle Routing

In general, sustainability is defined as the set of practices where current generations can achieve their needs without compromising the ability of other generations to develop and meet their necessities (WCED, 1987). Such practices should sustain resources (economical & environmental) and human well-being rather than dwindling and relying on them. Similarly, in routing (logistics) a broad concept which takes into account the Triple Button Line (TBL) aspects, where economic, environmental and social implication on practices is considered in various models (Macharis et al., 2014). The literature of vehicle routing considering the 3 pillars of sustainability are discussed separately in the following sections.

2.3.1 Economic Dimension

The economic dimension of sustainability in vehicle routing mainly focuses on maximization of profit and minimization of cost considering different constraints. Zhang et al. (2017) considered vehicle loading and time windows constraints in their work with an objective function of minimizing traveling distance which in return will reduce fuel consumption and minimizes cost. However, other constraints such as traveling time affects profit indirectly, Kramer et al. (2015) studied pollution routing problem, which is a variant VRP that considers pollution of environment. The authors argued that higher vehicle speed can be achieved in shorter travel time and therefore lower fuel consumption. Their objectives aim at minimizing operational costs such as salaries and fuel, and greenhouse gases emission costs. Additionally Wang et al. (2008) studied the effect of loading capacity on vehicle routing costs, by solving a Container Loading Problem. The authors suggested that by optimizing the container space usage, the number of needed trips to deliver all goods is minimized and thereby, minimizing fuel consumption and cost. Since most of VRP models seek to minimize costs, vehicles fuel consumption is the first aspect to be examined. In their research, Demir et al. (2014) introduced a summary of factors affecting fuel consumption as shown in Figure 2.3. It is worth mentioning that the three pillars of sustainability are interrelated, mainly the environmental and social dimensions impacts can be translated into economic costs indirectly as shown in the results of Vega-Mejía et al. (2019). For instance, minimizing CO_2 emissions is a result of fuel consumption reduction and workload balancing among driver will result in higher loyalty and productivity of workers.

2.3.2 Environmental Dimension

This dimension deals with the issues in vehicle routing that affect the environment and the prosperity of nature. In vehicle routing, such practices are referred to as Green VRP (GVRP). It is defined as the branch of green logistics where different techniques and practices are considered in route planning in a way that green gases emission, travel time, vehicle speed, fuel consumption and vehicle capacity are utilized to have minimum impact on the environment (Lin et al., 2014; Vega-Mejía et al., 2019)

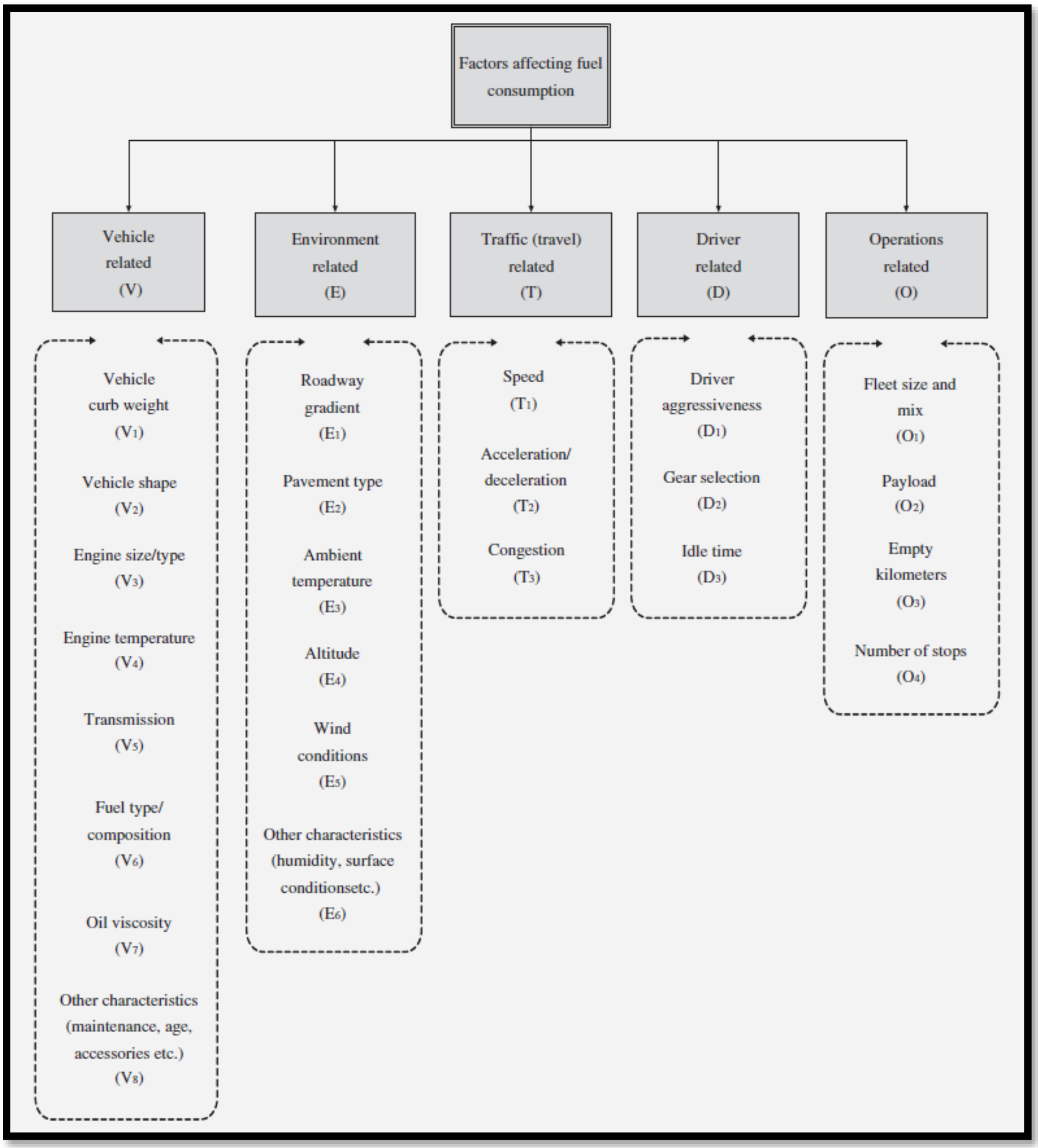

Figure 2.3: Factors affecting fuel consumption (Demir et al., 2014)

Lin et al. (2014) presented an extensive review and classification of GVRP. Their methodology consists of comprehensive review on classical VRP, literature from 2006 to 2014 on GVRP and the interaction between GVRP and various VRP variants. On the other hand, Demir et al. (2014) studied the impact of transportation on the environment and introduced various factors affecting fuel consumption and CO_2 emissions. In addition, different fuel consumption estimation models were discussed, which aided the researchers to develop the following conclusions: (i) the literature focused on limited factors affecting the environment such as speed and load of vehicles, (ii) light duty vehicles are preferred than medium and heavy duty ones, (iii) road gradient should be considered while route planning, (iv) fuel consumption models and other traffic externalities (rather than CO_2 emissions) should be studied. Recently, Niu et al. (2018) discussed the possibility of outsourcing logistic services to a third party, for the purpose of reducing costs. An Open VRP (OVRP) approach was used since outsourced vehicles aren't requested to return to initial depot. Therefore, a rich vehicle routing tactic was followed by combining three variants to develop a Green Open VRPTW (GOVRPTW) model. Also, a Comprehensive Modal Emission Model (CMEM) was used to estimate fuel emissions cost. Finally, results showed that open routing methodology leads to 20% reduction in the total cost.

2.3.3 Social Dimension

This dimension focuses on the human's well-being. It's usually debated that social impacts are a result of economic and environmental attributes, for example air pollution caused by transportation and other industries results in a risk on health conditions. Despite the importance of social impact since it deals with the most important resource (human being), it's usually ignored and given less focus in the researches of sustainability and supply chain context (Bhinge et al., 2015; Seuring, 2013). Regardless the difficulty in measuring the social aspects, several attempts were found in the literature.

Yang et al. (2015a) studied VRP by introducing a multi-objective model which considers maximizing customer satisfaction levels as a social dimension. Moreover, Wang et al. (2015) investigated the impact of speed variations (among other factors) on travel safety, therefore, minimizing the risk of accidents or maximizing travel safety could be considered as a measure of social aspect in sustainability. Workload equity in VRP where workload (in terms of time and travel distance) are distributed among drivers was presented by Matl et al. (2018). On the other hand, Habibnejad-Ledaria et al. (2019) developed a multi objective model with the aim of minimizing operational costs, maximizing customer's satisfaction and reducing the number of staff in each service. In their model the social dimension was triggered twice, first, from customer's perspective by including constraints such as staff preferences where the assignment of caregivers is based on the patient preferences regarding service, secondly, from the employee's perspective by considering maximum working hours and cross training.

2.4 Home Healthcare Vehicle Routing

As mentioned earlier, HHC services are emerging rapidly. Moreover, it was noticed that due to the importance of logistics many of HHC models connects HHC with vehicle routing, in fact Bahadori-Chinibelagh et al. (2019) argued that HHC is a variant of VRP given the fact that each caregiver needs to travel through nodes to service patients. Therefore, it is reasonable to address the HHCVRP for proper optimization in terms of planning, scheduling and allocation of vehicle routing scheme and the caregivers carrying out the service. To a certain extent the first work on HHCVRP was first introduced by Fernandez et al. (1974) with a model considering working days of community nurses to identify the ideal location of service providing nurses. The authors studied the effect of travel and visit times on the level of service quality. Recently, various articles have addressed this problem with different VRP variants. Furthermore, Fikar and Hirsch (2017) suggested that in contrast to classical VRP (which focuses in minimizing travel distance), HHCVRP models paid more attention to minimizing travel cost and travel time, as shown in the work of Yuan et al. (2015) that minimizes travel cost and penalty costs, and the work of Rest and Hirsch (2016) that minimizes travel and waiting times.

Braekers et al. (2016b) presented a novel model that studies the tradeoff between the well-known conflicting objectives cost and service quality. This model considers tight and loose time windows, nurse qualification and overtime costs. The objectives of the model were minimizing total costs (including travel and overtimes) and patients' inconvenience. Similarly, Ait Haddadene et al. (2019) developed a HHCVRP model with a bi-criteria nature to minimize travel costs and maximize patients' preferences of service. The authors considered that each patient will ask for a specific service type with time constraints for the duration, start and end of service time. Shi et al. (2019) developed a robust optimization model that considers uncertainty in travel and service times. The authors suggested that there is a considerable degree of uncertainty in the field of HHCVRP mainly with respect to caregiver travelling time to reach patients in addition to the service providing time; therefore, treating the problem in a non-deterministic approach is more realistic. The single depot model had an objective function of minimizing total travel costs. Likewise, Doulabi et al. (2020) addressed the issue of uncertainty by studying the HHCVRP with stochastic travel and service times, along with synchronized visits and scheduling. The model was solved using two-stage integer programming approach that minimizes various costs such as travel, overtime and waiting costs. Figure 2.4 shows an example of the problem.

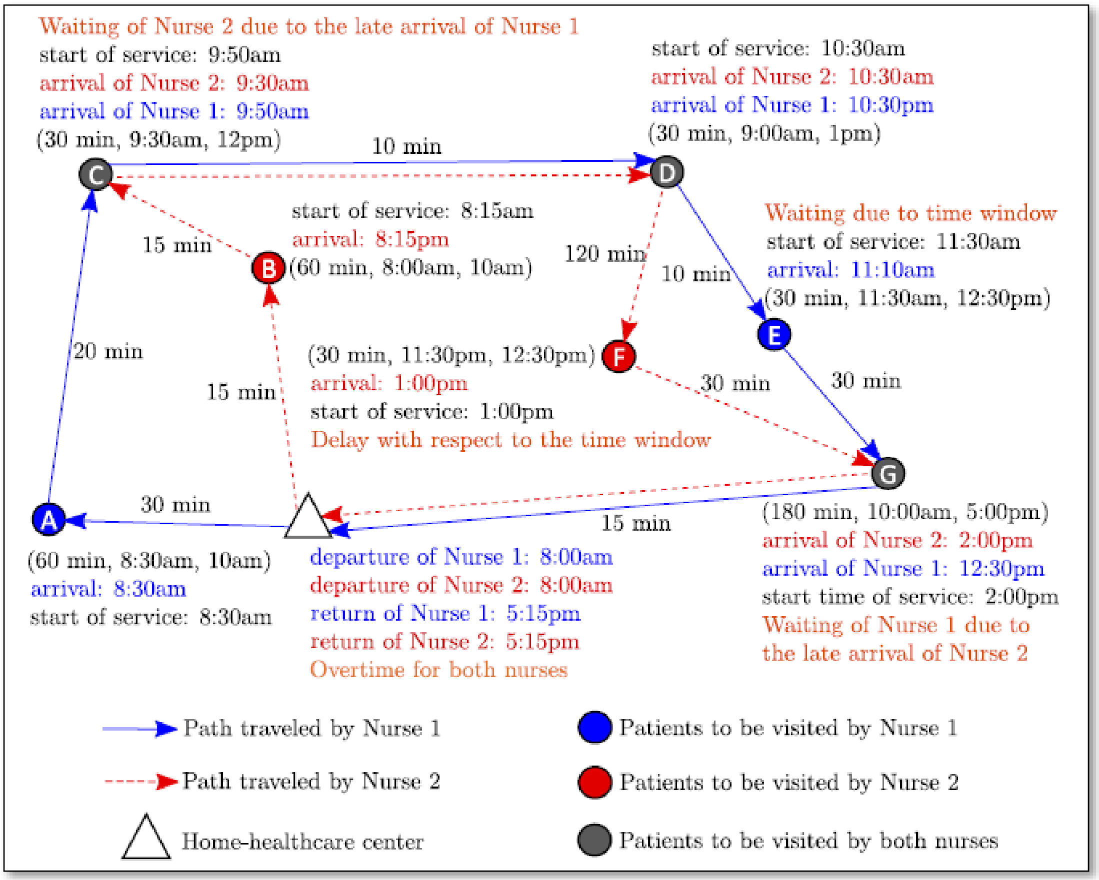

Figure 2.4: HHCVRP with two nurses and synchronized jobs (Doulabi et al., 2020).

In order to address real life challenges, several researches were conducted in HHCVRP to provide models which is applicable in real life applications. To achieve such models, a multi-objective approach was used to include as many objectives and constraints as needed. Hiermann et al. (2013) presented a multi objective model that considers customer and staff satisfaction. The authors included 13 objective functions which are divided into hard constraints violations (such as violation of nurse availability), soft constraints violations (such as the deviation from the start time window) and additional aspects such as travel and work times that impact the solution quality. The model results prove its ability to solve real life instances, however, due to the complexity of the model, significant computational time is needed to solve each instance. On the other hand, Decerle et al. (2019) argued that a tradeoff between conflicting objectives is essential for the applicability of HHCVRP models. The authors proposed a multi-objective model which considered workload balancing between nurses and auxiliary nurses to fulfill three objectives, namely minimizing total working time, patient waiting time and maximal working difference between nurses. The model was solved using a memetic algorithm.

Green HHC (GHHC) services were discussed by many authors in the literature to reduce the impact of those services on the environment toward creating sustainable cities. Fathollahi-Fard et al. (2018) presented a green model with the aim of minimizing transportation costs and green emissions to reduce environmental pollution. Additionally, this model considered a penalty for exceeding predetermined maximum travel distance. The authors argue that this is the first model to consider the issue of greenhouse gas emissions and environmental pollution in solving HHCVRP models.

Furthermore, Fathollahi-Fard et al. (2019) suggested that HHC could be treated as a supply chain where HHC companies provide service to clients (patients) using a certain process (routing and scheduling), thus a Green HHC supply Chain (GHHCSC) model was developed. The aforementioned model uses a location-allocation-routing strategy so that location of patients, pharmacies and laboratories are set, then each patient is allocated to one pharmacy (nurse) and finally route planning decisions took place.

In the context of smart mobility and the use of technology in vehicle routing, Erdem and Koç (2019) proposed a novel approach which uses electric vehicle (EV) in HHCVRP. The multi-objective problem consists of multi depots where each nurse starts from one depot to serve one or several patients with a possibility of visiting charging stations. The model includes constraints about the vehicle battery capacity, charging status and synchronized jobs where one than one nurse is required to serve a patient. The use of electric vehicles reduces the impact of green emissions caused by fuel combustion and thereby preserves the environment; besides using the technology to produce electrical engines rather than fuel combustion ones promote the implementation of smart mobility and transportation sector in the promising smart cities.

After reviewing the literature of HHCVRP, we concluded that researches had covered many aspects that promote their models to be applicable in real life applications by including different type of costs, time constraints, green practices, location and allocation of resources, workload balancing and many other objectives in their models. Despite that inclusion, to the best of our knowledge, none of the previous approaches linked HHCVRP to the concept of smart sustainable cities in terms of developing models that take into account the use of ICT, IoT and other forms of technology in the process of planning and solving the routing problem.

2.5 Quality of Service in Vehicle Routing

There is no argument about the importance of quality management in any organization. Indeed, measuring and planning quality in manufacturing and production industries is easier than service industries, since measuring the quality of tangible products with physical characteristics is easier than measuring the quality of intangible services. Nevertheless, actions and efforts must be taken to improve quality for the purposes of reducing costs, satisfying customers, reducing waste, meeting standards and building reputations.

Despite the importance of quality, there is a lack of models considering quality in the literature of vehicle routing. However, the work of Paquette et al. (2009) provides different definitions of quality in service sector by including different dimensions of quality and quality related constraints. The authors reviewed previous studies that take into account improving quality in vehicle routing by including time windows, waiting times and other constraints that define quality of service. Most of the mentioned models tend to define and measure quality of service by the difference between expected and actual time of service, a strict time interval with start and end of service periods is used as a reference. It is believed that by complying with the planned time of service customers will be satisfied and therefore adequate level of quality of service is met. Expósito et al. (2019) tackled the issue of quality by improving customer's satisfaction which is done by minimizing response time of service. The model contains time dependent constraints in form time windows with start and end times. In addition to minimizing the response time, this model includes another classical objective of minimizing travel cost. Results showed promising and effective solutions for improving quality and satisfaction in vehicle routing. Bullo et al. (2011) studied the dynamic VRP, and suggested two criterions for measuring quality of service; firstly is the waiting time for service delivery, and secondly the fraction of demands delivered successfully. Moreover, Yang et al. (2015b) discussed dynamic VRP with time windows and multiple priorities. The authors included uncertainty of demand and classified customers based on their priority level. Quality of service was measured by the difference between the arrival time and the upper bound of service interval which the planned time to start the service. The objectives of the model were minimizing travel distance as well as the penalty associated with service time delay. Without a doubt, by optimizing the service levels customers' expectations and satisfaction will be gained. Bulhoes et al. (2018) solved a vehicle routing model with service level constraints, their model aimed at minimizing the transportation costs and lost profits. Meeting the requirements of different customers in various locations to achieve the desired service level will encounter some deal of complexity to the problem. Therefore, the authors achieved solutions by using mathematical modeling, branch and price algorithm and hybrid genetic algorithm. Similarly, Orlis et al. (2020) measured quality by studying the service level requirements; customers will set minimum acceptable level of service which is if not meet by service provider penalties will be incurred. The model is a variant of VRP which is capacitated vehicle routing with profit and service level requirement, with the objective of maximizing total profit which is the difference between revenues from provided service and transportation costs with penalties if failure in service delivery happens.

Khorshidi and Hejazi (2011) measured the quality of service using the well-known SERVQUAL model. The authors argued that obtaining data for SERVQUAL model that includes expected and perceived level of service is not always applicable and doesn't provide continuous data, therefore internal measures specified by experts were used along with SERVQUAL model to measure quality and maximize customer's satisfaction. This effort will create a continuous measure of quality of service without using questionnaires. Finally, Ghannadpour and Zarrabi (2019) published a research which aimed at maximizing customer's satisfaction by measuring any deviation from the desired time of service. In their VRP model, a triangular membership function was used to measure the above-mentioned deviation with the presence of earliest and latest time windows for different customers. In addition, different customers with different importance levels (casual and important customers) and priority of service are considered, where high importance customers are serviced with a hard time windows to ensure precision in service, whereas, less importance ones are served with soft more flexible time windows. As a result, a product of customer's priority level and the deviation from the desired time of service was calculated for different importance level customers, which present the customer satisfaction level on the quality of provided service.

After reviewing the literature of measuring quality of service in vehicle routing, it was noticed, to the best of our knowledge, that there is vagueness and no precision in measuring quality. Indeed, including time related constraints such as time of service, waiting time, time intervals to perform service and service duration, in addition to service level requirements constraints will eventually standardize the service and therefore improving quality. However, many scenarios may happen where service providers perform what they believe is sufficient without investigating the opinion of customers, especially in sensitive services such as in healthcare services. Given what had been discussed, our research aims at fulfilling this gap by studying and measuring quality of service to evaluate the actual and expected performance and apply suitable actions, combining quality measuring methods and quality related constraints such as time of service is believed to produce promising results.

2.6 Smart Vehicle Routing

The emergence of smart city concept was noticed lately; many initiatives called for the implementation of those cities. As they believe it can handle the challenges of growing urbanization and environmental exhaustion, as well as, to enhancing the quality of life for citizens and create a green sustainable environment. Such cities foster the use of Information and Communication Technologies (ICT) mainly the innovative solution of Internet of Things (IoT), so that citizens can engage and be connected with every aspect of the smart city using technologies such as wireless communication and clouding. Similarly, smart mobility is one of the components of smart cities which use technology and ICT to improve traffic, transportation and all types of logistics for the purpose of preservation of environment, secure and safe transport system and making life easier and smarter for citizens (Albino et al., 2015). Waste management is one important field in the transportation network. Proper waste collection routing and scheduling planning will result in saving labor, operational and various other costs. The work of Mamun et al. (2016), Hannan et al. (2018), and Ramos et al. (2018) studies the combination of ICT along with the decision-making process of planning routes and scheduling waste bin visits. Mamun et al. (2016) introduced a novel model and a sensing algorithm that provides continuous real time data regarding the status of waste bins. The authors argued that using such network of sensors that instantly provides data will significantly contribute in reducing cost and harmful emissions. Also, Hannan et al. (2018) studies the capacitated VRP in solid waste collection. The authors introduced a model that selects the optimal path to follow, as well as, selecting which waste bin to visit and which one is not depending on the waste threshold level. The decision-making process is supported by real time data obtained from ultrasonic sensors and load sensors to measure waste bin level and waste weight respectively. Moreover, Ramos et al. (2018)

presented a smart waste collection model which considers uncertainty in terms of waste bins fill levels. The authors suggested the use of volume sensors to provide real time data about full levels to decide bins to be visited and plan vehicle routing. Likewise, in the field of waste collection, Hrabec et al. (2019) proposed a novel approach by developing a quantity predictive model which takes into account the current status of waste bin levels and predicting that level for the upcoming days and thereby planning the future routes. The authors believe that such a model can be both deterministic and stochastic by providing real time reading from the bin as well as including and solving the randomness of future waste bin levels. The authors assumed that waste bins are equipped with sensors and wireless technology devices.

On the other hand, Liu et al. (2019) employed Radio Frequency Identification (RFID), the fourth generation of broadband cellular network (4G) and Geographic Information system (GIS) technologies to develop a smart logistics model, so real time data are transmitted and analyzed. Finally, route planning and optimization take place with an objective of minimizing total delivery and delay penalty costs. Furthermore, in logistics sector, Ding et al. (2020) introduced a review on smart logistics by exploring the employment of IoT technologies in logistics. Different modes of transportation were reviewed including road, railway and water way transportation. In addition, the review showed various IoT technologies used in logistics, including RFID, WSNs, 4G, barcodes and ZigBee. However, despite the comprehensiveness of the provided review, a lack of smart VRP in logistics was found in the above mentioned review.

Given what had been discussed earlier in this section, it was noticed that the employment of ICT and IoT solutions in VRP was explicit to the logistics distribution and waste management sectors at least to the extent of our knowledge. Moreover, dynamic routing (in a sense that the path of the vehicle changes while routing and serving customers or patients) due to provided real-time data from IoT technology wasn’t considered. Therefore, a gap was found in the literature of smart vehicle routing which is not including such smart practices in other sectors mainly healthcare sector. Thus, in this research we are attempting to use ICT and IoT solutions in solving a HHC vehicle routing model and exploring the benefits associated with it to business owners, patients and society, in addition to integrating such a model in smart cities concept.

2.7 Body Sensor Networks

To carry on this research, a review on the sensors used in healthcare including types and functionality is essential. According to Lai et al. (2013), Body Sensor Networks (BSNs) is a division of Wireless Sensor Networks (WSNs), which through the rapid development of technology, is employed in many sectors such as healthcare, sports and social welfare. BSNs can be classified into two categories based on the signal type to: (1) sensors that measure continuous signal that supports real-time data acquisition, such as Electrocardiography (ECG) and Electromyography (EMG) sensors. (2) Sensors measuring discrete time signals with low sampling frequency, such as temperature, blood oxygen and glucose sensors (Lai et al., 2013).

Moreover, Hao and Foster (2008) provided a comprehensive review on BSNs and its application in the healthcare sector. Their work aimed at reviewing the development of wireless sensors technology in monitoring physiological responses of patients such as ECG and EMG. In addition, the authors suggested that wireless sensors improve the effectiveness and efficiency of the healthcare system by: (1) Alerting the patient if there is a potential emergency in vital signs. (2) Alerting the medical emergency system if any up normal readings arises. (3) Providing real-time continuous bio-data. Finally, the monitoring of health status using sensors was classified as critical monitoring such monitoring patients with heart diseases, and non-critical monitoring such as monitoring physical condition of athletes while exercising. Other researches were conducted in the employment of BSNs in healthcare sector, they suggest that the integration between BSNs and various healthcare applications creates patients and physician's convenience through improving the effectiveness and efficiency of service (Gope & Hwang, 2015; Ying et al., 2019). A general architecture of BSNs is shown in Figure 2.5. As shown in the figure, different types of body sensors with different functions and purposes are employed on patient's body, then the data will be collected and processed to be ready for transmission to a base station. Finally, the gathered data are shared over the internet to a predefined address. Note that different transmission methods could be used to deliver data from patients to physicians or service providers.

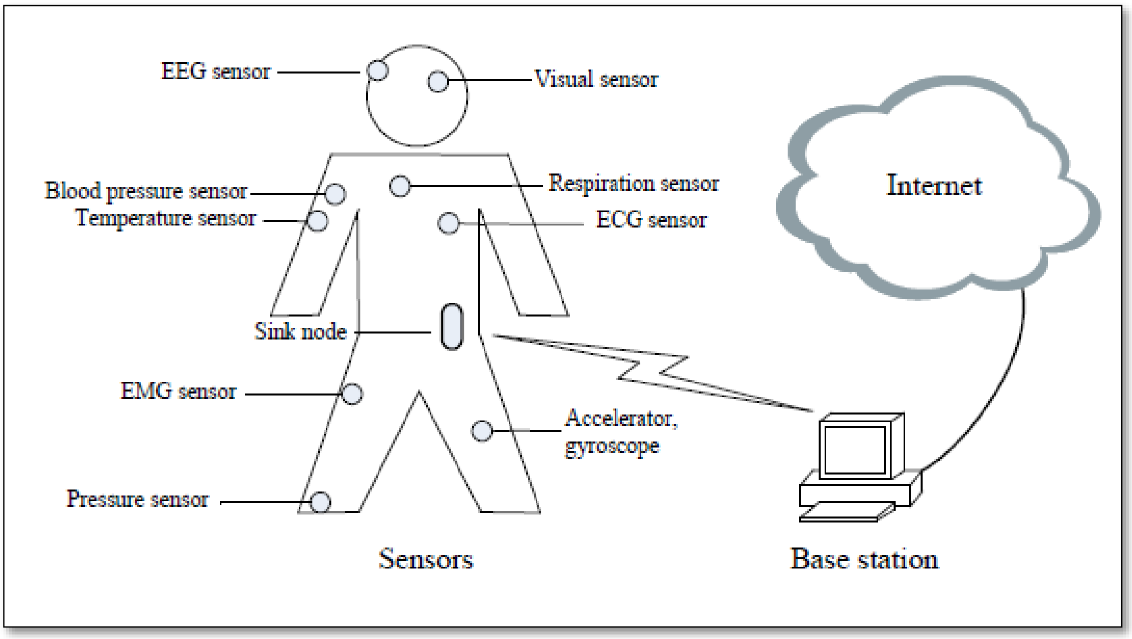

Figure 2.5: General BSNs architecture (Lai et al., 2013).

To the extent of our knowledge, the employment of BSNs was not considered before in the literature of VRP in general or the literature of HHCVRP in particular. Therefore, one of our objectives in this research is the successful employment of BSNs on patients to establish a continuous monitoring data of patients while they are at home. Mainly, heart rate sensor was considered in this research to monitor patients with heart related conditions. Note that according to Anaya et al. (2018), ethical issues arises when using wearable technology, such as privacy and security concerns. However, in this research, all ethical obligations are assumed to be met, since the aim of using sensors is only measuring patients' heart rate.

Chapter Three

Model Formulation

Chapter Three
Model Formulation

3.1 Chapter Overview

This chapter takes the research to the next level by converting the generated ideas, defined gaps in the literature and assumptions on the research problem to a mathematically-presented model. This model translates all aspects of the problem to mathematical equations, which on the other hand were solved to generate results. In addition, the proposed model was formulated as an MINLP model. The structure of this chapter is as follows: Section (3.2) presents a review on Mixed Integer Non-Linear Programming to gain a broad knowledge of linear programming, integer programming, MILP and MINLP. Next, section (3.3) is model description which includes a detailed description on the problem presentation, problem assumptions (to define necessary assumptions to carry out the model), model sets and parameter, defining equation (to illustrate how certain parameters were calculated), decision variables, objective functions and finally model constraints.

3.2 Mixed Integer Non Linear Programming (MINLP)

Since the proposed model was developed as MINLP model, it's essential to understand and define MINLP models. To do so, some terms must be defined. Linear Programming (LP) is an optimization method to minimize or maximize a function, however, to apply this optimization technique the objective function, as well as, the constraints in the model must satisfy linearity conditions. LP may produce solutions that include fractional numbers, which are sometimes unacceptable and not realistic in real life applications, due to the fact that rounding numbers up or down might produce infeasible or suboptimal solutions (Sam et al., 2018). Therefore, Integer Linear Programming (ILP) was introduced to deal with this issue. ILP generates integer results to the unknown variables, while demanding the same linearity conditions such as in LP. However, the complexity of problems has increased due to the efforts by researchers to solve real life problems and include multi objectives to the developed models. Therefore, some solutions must produce integer results while others must present continuous fractional results, in this case Mixed Integer Linear Programming (MILP) optimization technique should be used. In order to apply MILP, three conditions must be met. First, objective functions must be characterized as linear function. Second, constraints should be linear, and finally linear functions must have either minimizing or maximizing objective. Due to the growing demands to solve real life problems, researches tend to place huge efforts to address these problems. As a result, the developed models may include nonlinear objective function or constraint or both. Therefore, to address this issue Mixed Integer Non-Linear Programming (MINLP) approach is used to solve optimization models. Thus, MINLP is an optimization technique that uses mathematical programming to minimize or maximize a desired nonlinear objective function subject to nonlinear constraints, in addition, MINLP support the inclusion of integer (discrete) and fractional (continuous) variables. MINLP is used in many applications including logistics, transportation, supply chain management, waste collection and manufacturing, since it supports the addition of many real conditions and decision variables. In the proposed SSHHCVRP model, a great deal of complexity is presented due to the efforts of addressing a real-life problem, such efforts lead to a more realistic model. On the other hand, the model includes many decision variables with different values. For instance, variables such as heart rate sensor reading are binary variables, whereas, battery sate of electric vehicle is fractional. Variables such as level of customer satisfaction are real numbers ($\in [0,1]$). Thus, the use of MINLP for optimization is more reasonable and yields more realistic results.

3.3 Model Description

In this section, a detailed presentation of the research problem and the developed model are introduced. In addition, model assumptions are stated; finally, the developed model is presented including a detailed description of each parameter, variable, constraint and objective function.

3.3.1 Problem Presentation

The demand on HHC services witnessed a great leap recently. Possibly due to the high expenses of the healthcare system in hospitals and clinics compared to HHC services. And most recently, the presence covid-19 pandemic that demanded preventive measures including social distancing .There is no doubt that HHC services can’t replace the services provided in hospitals. However, in many cases patients might need low to medium medical service skills in repetitive periods of time. Such patients include the elderly, chronic diseases patients and patients recovering from injuries or surgeries. In recent years, researchers studied the HHCVRP and inserted different variants and objectives of VRP in their models, such as minimizing costs, GHG emissions, travel times and patients preferences consideration. Also, authors assume different scenarios including single depot, multi depots, multi vehicles / caregivers and uncertainty in travel times and services. By time, HHCVRP becomes more and more complex to meet the persistent necessities to address real life problems. However, none of these previous efforts considered the use of technology for the benefits of HHC service providers and patients, compared to other industries such as waste collection where technology were employed to ensure more efficient actions (Ramos et al., 2018). In addition, there is no evidence from the reviewed literature of VRP that there is a clear and direct measurement of service quality and the level of customer's satisfaction. Therefore, in this research our aim is to spotlight on the integration of technology and quality of service measurement with HHCVRP. Regarding technology use, this model presents a novel approach that uses heart rate sensors to identify patients with normal or critical conditions. Given so, the developed model presents a multi-objective SSHHCVRP which aims at achieving the following goals: (1) minimizing travel time from one node (patient) to another while considering patient's condition (normal or critical) and the type of route, (2) maximizing the velocity of the vehicle travelling between nodes while considering patient's condition and route type, (3) minimizing costs related to the deviation from the average workload of a caregiver, (4) minimizing the penalty costs due to poor quality of service, by measuring the difference (gap) between the expected and perceived quality of service. To the best of our knowledge, this model presents a novel approach by adding two innovative (not considered before) elements to HHCVRP which are the use of technology (sensors) and measuring the quality of service by measuring and minimizing the gap between expectation and perception. Also, this research supports its intends to present a more comprehensive and realistic model by considering the three pillars of sustainability together, in terms of minimizing travel time (which eventually minimizes fuel consumption), the use of electric vehicles and considering the minimization of deviating from the average workload which yields a better working condition. The proposed model can be described as follows. In a network of single depot, multiple vehicles (caregivers) and a predefined number of nodes (patients), a caregiver travels in a vehicle to service a predefined set of geographically distributed patients. These patients could have two conditions, either normal condition or critical condition. The status of the patient is judged to be normal or critical using a heart rate sensor which provides continuous reading of the patient and transmits the data to the HHC service provider. The technology of data transmission is not considered in the model, so we assume that transmission is done by other third party. In addition, patients are assumed to have chronic cardiovascular conditions or recovering from any heart surgeries. In this model, one type of vehicles is assumed which is the electric vehicle. Such vehicles are operated by electrical energy rather than fuel, thus, there is no fuel combustion and no emissions of GHG. The model considers battery charging status, charging duration and charging stations for the electric vehicles as shown in the work of (Erdem & Koç, 2019). The battery level of this vehicle is represented by a percentage. Battery levels before and after visiting the charging station as well as, when arriving and leaving patient nodes must be monitored. Additionally, if the battery level reaches 10%, the driver (caregiver) should visit a charging station. Using such vehicles presents an environment friendly HHCVRP (Erdem & Koç, 2019). Figures 3.1 and 3.2 illustrate an example of the proposed problem that considers electric vehicles and heart rate sensors. Figure 3.1 shows an example of HHCVRP with a single depot, two EV, two charging stations and five patients under normal conditions to be servied, the problem includes duration of service with a predefined time windows to conduct the service. Also, energy levels of the electric vehicle at each patient node is considered. On the other hand, Figure 3.2 demonstrations the situation where one patient shows critical heart rate readings and thus, a higher priority of service was given to him. Moreover, it's assumed that there is more than one available route between each two nodes; specifically there are four types of routes, each route corresponds to different speed range, energy consumption and different terrain nature (such as rural areas, urban areas and highways) (Hosseini-Nasab & Lotfalian, 2017). Furthermore, each caregiver is assigned with a defined number of jobs each day, the model considers the normalized time duration for each service and the deviation from this normalized time to calculate any deviations from the predefined workload for each caregiver complying with labor laws and regulations. If any deviation from these workloads exists, costs will be incurred in form of overtimes paid to caregivers and penalties for breaking regulations. In addition, with regard to caregivers, this model considers their satisfaction by minimizing the workload deviation from its average working hours.

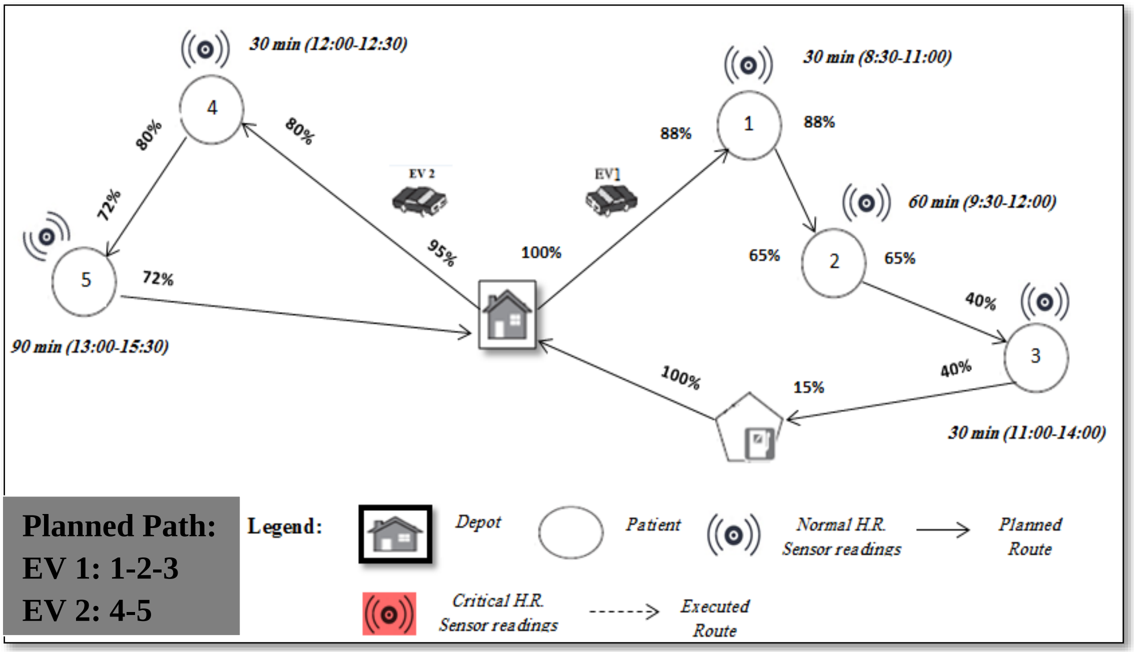

Figure 3.1: An example of the proposed HHCVRP with normal condition patients

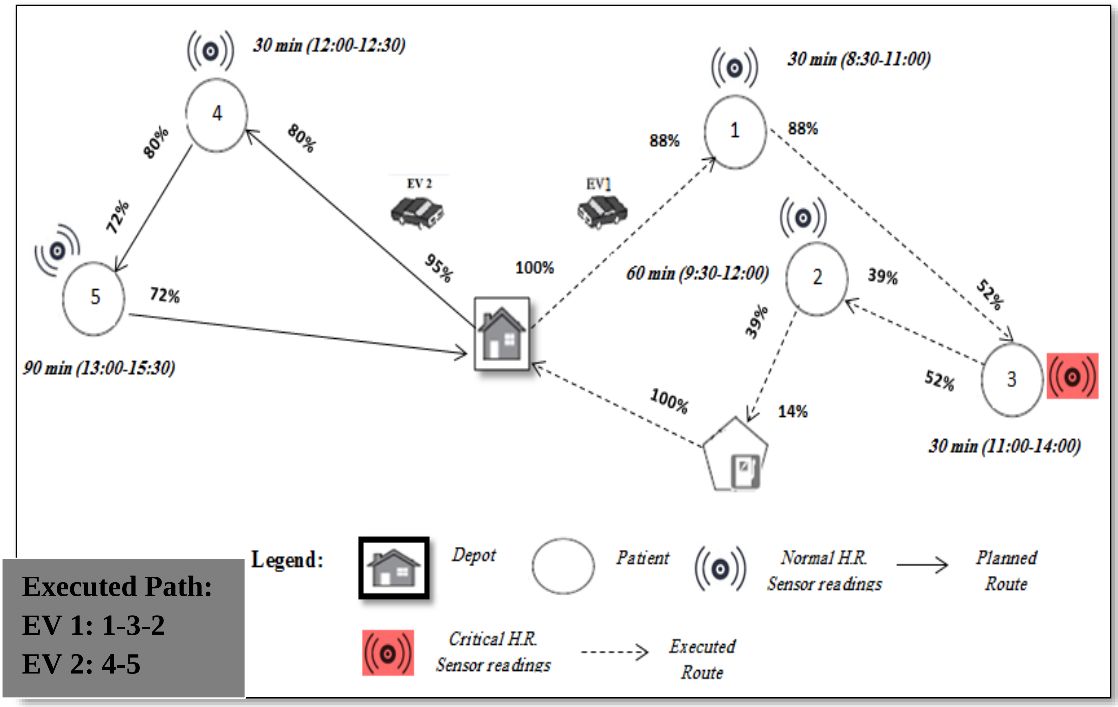

Figure 3.2: An example of the proposed HHCVRP with on critical condition patient

In order to develop a more comprehensive and realistic model, this research offers a novel approach in VRP by measuring the quality of service using quality-related models. The work of Khorshidi and Hejazi (2011) was adopted to measure the quality of the provided HHC service, as well as, internal measures set by experts in the field of HHC, where patient's needs and expectations are measured using internal measures. The normalized relationship between quality-related dimensions and the internal measure will be calculated and used along with the degree of fulfillment of the defined internal measure, to calculate the expected quality of service. Moreover, the work of Ghannadpour and Zarrabi (2019) was adopted to measure patient's perceived satisfaction. The patients in our model are classified in to two categories, casual and urgent to assign different levels of priority in service based on medical necessities. Casual patients are given a priority of service ranging from 1 to 3 (from a 5 scale) depending of their medical status. Whereas, urgent patients are given a priority level either 4 or 5. Note that among different quality dimensions, reliability and responsiveness dimensions are considered in this model in form of meeting the patient's desired time of service with a predefined acceptable time windows of service (reliability), as well as, being able to serve critical condition patients quickly using the data from the employed sensors (responsiveness). The difference between expectations and perceptions is multiplied with a penalty which is the cost of poor quality of service, with the aim of minimizing such costs.

3.3.2 Model Assumptions

1. Single depot (staring point) and multi destination points (patients to be served).
2. All vehicles are assumed to be identical in terms of energy consumption and battery capacity.
3. The patients to be served are assumed to have cardiovascular conditions, such as patients recovering from heart diseases or patients with chronic heart conditions.
4. All patients must be visited by a caregiver and their demand must be met.
5. Two types of patients were assumed: patients under normal and critical medical conditions.
6. Normal patients are assumed to have heart rate between 60 and 100 beats per minute (BPM), whereas, heart beats below 60 BPM and above 100 BPM classifies a patient as under critical conditions (Avram et al., 2019).

7. Two types of services are assumed: normal service and critical service, where each type involves different skills and training requirements.
8. The technology used for transmitting data from patients using heart rate sensor are assumed to be transmitted by a third party, in other words this model doesn't consider how the data is transmitted (technical wise). Such technologies may include Cellular technologies (3G, 4G and 5G in some regions), Fiber Optics and internet clouding.
9. There are four types of routes with different terrains and velocities, which was adopted from the work of Hosseini-Nasab and Lotfalian (2017).
    I. Route one (1-30 Km/hr.): such as in cities and urban areas, this speed limits leads to high fuel consumption.
    II. Route two (31-55 Km/hr.): such speed limits drops fuel consumption, as seen in routes in rural and sub-urban areas.
    III. Route three (56-80 Km/hr.): such as in rural areas and highways leads to the ideal fuel consumption.
    IV. Route Four (81-120 Km/hr.): in this speed limit fuel consumption rises due to high engine Revolutions Per Minute (RPM) which leads to high fuel burning and therefore high consumption. This type of routes includes multi-lane highways.
10. Driving along different type of routes yields to different distances between the same couple of nodes.
11. Limited battery capacity of the electric vehicle is assumed.
12. The electric vehicle must visit a charging station if battery capacity falls below 50%.

13. The location of charging stations is assumed to be fixed.
14. Electric vehicle battery capacity should be 100% charged after visiting a charging station.
15. Electric vehicle energy consumption differs from one route to another, and was classified according to Younes et al. (2013) as follows:
    I. Route 1: 0.14 (kwh/km).
    II. Route 2: 0.12 (kwh/km).
    III. Route 3: 0.1 (kwh/km).
    IV. Route 4: 0.13 (kwh/km).
16. The degree of patient's importance (priority) is based on the complexity of their medical condition, needed care and how they are affected by time of service i.e. time of medication and needed checkups.

3.3.3 Sets and Indices

i	Set of source node, i = 0, 1, ..., N
j	Set of destination node under normal conditions, j = 0, 1, ..., N
j'	Set of destination node under critical conditions, j' = 1, ..., N
p	Index of patient p under normal conditions, p = 1, 2, ..., P, $p \in N$
c	Index of patient c under critical conditions, c = 1, 2, ..., C, $c \in N$
P_C	Index of casual patients, $P_C \in N$
P_U	Index of urgent patients, $P_I \in N$
r	Index of type of route, r = 1,2,3,4

hc Index of caregiver, *hc* = 1,..., HC

d Index of day, *d* = 0,1,..., D

t Index of time slot, *t* = 0,1,….., T

k Index of electric vehicles, $k \in E$

S Set of recharging stations.

S' Set of dummy recharging stations to allow multiple visits.

q Index of quality dimensions, q = 1,2,…..,Q

α , β Index of internal measures of quality of service. α , β =1,2,..,Q

3.3.4 Model Parameters

$Time_d$ Normalized work time at day *d*.

C_{hcd} Costs associated with caregiver *hc*'s workload deviation from the normalized value at day *d*.

K_{hcd} Maximum working time in a single day for caregiver *hc* at day *d*.

S_{HR} Heart rate sensor reading for any patient T.

VEL_{ijr} Velocity of travel between node *i* and node *j* along route *r* (Km/hr.)

V_r The upper speed limit allowed on route *r* (Km/hr.)

e_i Earliest arrival time within time window of service at patient node i.

l_i Latest arrival time within time window of service at patient node *i*.

f_i The duration of service time at patient node *i*.

u'_i The desired time of service at patient node *i*.

ω_i Waiting time at patient node *i*.

PR_i Importance degree of patient at node *i* based on medical status and needed service.

tr_k Total travel time of vehicle *k*.

M Sufficiently large positive number.

σ Constant for violating the hard time windows.

s_{ijr} Travel time from node *i* to node *j* along route *r* ($i, j \in N \cup S'$).

dis_{ijr} Travel distance from node *i* to node *j* along route *r* ($i, j \in N \cup S'$).

δ_k Recharging rate of electric vehicle *k*.

Y_k Battery capacity of electric vehicle *k*.

λ_k Consumption rate of electric vehicle *k*.

$R^{norm}{}_{q\alpha}$ The normalized relationship between the q^{th} service quality dimension and the α^{th} internal measure of service.

$\gamma_{\alpha\beta}$ Presents the dependencies and correlation between internal measures where $\alpha \& \beta \in$ M.

$R_{q\beta}$ The relationship between the q^{th} service quality dimension and the β^{th} internal measure of service.

Pen_q The cost ($) of poor quality of service for the q^{th} dimension of service quality.

WT_{Z_i} Pre-defined target weight for objective function Z_i, set by administrators and decision makers.

$Z_{optimal}$ Summation of all objective functions with their weights (value of the near optimal solution).

3.3.5 Decision Variables

$$x_{ijpr} = \begin{cases} 1, \text{if a caregiver travels from } i \text{ to } j \text{ through route } r \\ \text{serving patients } (p) \text{ under normal conditions} \\ 0, \text{otherwise} \end{cases}$$

$$C_{ij'cr} = \begin{cases} 1, \text{if a caregiver travels from } i \text{ to } j' \text{ through route } r \\ \text{serving patients } (c) \text{ under critical conditions} \\ 0, \text{otherwise} \end{cases}$$

$$SR_{HR} = \begin{cases} 1, \text{if heart rate of a patient is within critical range} \\ 0, \text{otherwise} \end{cases}$$

y_{ik} Battery state of an electric vehicle $k \in E$ at node i.

g_{ik} Battery state of an electric vehicle $k \in E$ after visiting a charging station $i \epsilon S'$.

$tot.load_{hcd}$ The total workload of caregiver hc on day d.

W_{ik} Electric vehicle charging duration$(i \epsilon S')$.

$Sat.exp_q$	Real number where $Sat.exp_q \in [0,1]$ that presents the expected level of customer satisfaction from the q^{th} dimension of service quality.
$Sat.per_q$	Real number where $Sat.per_q \in [0,1]$ that presents the perceived level of customer satisfaction from the q^{th} dimension of service quality.
Ful_α	Real number where $Ful_\alpha \in [0,1]$ that shows the level of fulfillment of the α^{th} internal measure.
$\mu_i(t_i)$	Membership function of patient node *i*.
η_i	Control variable for each patient at node *i*.
at_i	Actual arrival time at patient node *i*.
t_i	Start time of service at patient node *i*.

3.3.6 Defining Equations

$$T` = p \cup c \tag{1}$$

- Equation (1) defines a set T which is the total patients considered in this model including the two types of patients, whether under normal medical conditions (*p*) or under critical conditions (*c*).

$$SR_{HR} = \begin{cases} 1 \; if \; 0 \le S_{HR} \le 60 \\ 0 \; if \; 60 < S_{HR} < 100 \\ 1 \; if \; 100 \le S_{HR} \end{cases} \tag{2}$$

- Equation (2) shows the conversion of heart rate sensor S_{HR} readings to binary numbers where readings between 60 BPM and 100 BPM are in normal range and yields to $S_{HR} = 0$, on the contrary readings below 60 BPM or above 100 BPM are considered critical which results in $S_{HR} = 1$.

$$VEL_{ijrk} \neq 0 \quad \forall\, i,j \in N, r = 1,2,3,4\, , i \neq j, k \epsilon E \tag{3}$$

$$VEL_{ij'rk} \neq 0 \quad \forall\, i,j' \in N, r = 1,2,3,4\, , i \neq j', k \epsilon E \tag{4}$$

- Equations (3) and (4) specify that the velocity parameter doesn't equal to zero when traveling to serve both patients under normal and critical conditions.

$$R^{norm}{}_{q\alpha} = \frac{\sum_{\beta=1}^{M} R_{q\beta}\, \gamma_{\beta\alpha}}{\sum_{\alpha=1}^{M}\sum_{\beta=1}^{M} R_{q\alpha}\gamma_{\alpha\beta}} \tag{5}$$

- Equation (5) defines the normalized relationship between service quality element and a pre-defined internal measure (specified by experts) which was adopted from the work of Khorshidi and Hejazi (2011).

$$Sat.exp_q = \sum_{\alpha=1}^{M} R^{norm}{}_{q\alpha}\, Ful_{\alpha} \quad \forall\, q \in Q \tag{6}$$

- Equation (6) shows the level of the expected customer satisfaction, which is calculated using equation (5) and the degree of fulfillment of a particular internal measure (Khorshidi and Hejazi, 2011).

$$Sat.per_q = \sum_{i=1}^{N} \mu_i(t_i) \quad \forall\, q \in Q \tag{7}$$

- Equation (7) calculates the perceived satisfaction on the provided service, which is measured using the triangular membership function $\mu_i(t_i)$, which on the other hand illustrates the service time windows elements as cited from Ghannadpour and Zarrabi (2019).

$$\mu_i(t_i) = \left(\frac{(at_i + \omega_i) - e_i}{u'_i - e_i}\right).(1 - \eta_i) + \left(\frac{l_i - (at_i + \omega_i)}{l_i - u'_i}\right).\eta_i \ \forall\, i \in P_U \tag{8}$$

$$\mu_i(t_i) = \left(\frac{(at_i + \omega_i) - (e_i - \sigma)}{u'_i - (e_i - \sigma)}\right).(1 - \eta_i) + \left(\frac{(l_i + \sigma) - (at_i + \omega_i)}{(l_i + \sigma) - u'_i}\right).\eta_i \quad \forall\, i \in P_C \tag{9}$$

$$\big(u'_i - (at_i + \omega_i)\big).\eta_i + \big((at_i + \omega_i) - u'_i\big).(1 - \eta_i) < 0 \ \forall\, i \in P_U \cup P_C \tag{10}$$

- Equations (8-10) show how to compute the perceived satisfaction levels for different patients (urgent and casual) using the earliest, latest, desired and actual time of service. The variable η_i is used to control if the start of service is before or after the desired time of service (Ghannadpour and Zarrabi, 2019).

$$Z_{optimal} = \sum_{i=1}^{4} WT_{Z_i}.Z_i \tag{11}$$

- The total near optimal solution is shown in equation (11), which is the summation of the product of each objective function with its pre-determined weight.

3.3.7 Objective Functions

$$\min Z_1 = \sum_{i=0}^{N}\sum_{r=1}^{4}\left(\sum_{j=1}^{N}\sum_{p=1}^{P}\left(s_{ijr}\, x_{ijpr}\,(1-SR_{HR})\right) + \sum_{j\prime=1}^{N}\sum_{c=1}^{C} s_{ij\prime r}\;\; C_{ij\prime cr}\, SR_{HR})\right) \quad (12)$$

- First objective function is shown in equation (12) which aims at minimizing the overall travelled time, which was adopted and modified from Erdem and Koç (2019) research. The left hand side of equation (12) minimizes the travel time between a set of predefined patients under normal medical conditions which is judged by the reading of the employed sensor. However, the right hand side minimizes the travel time between predefined patients whenever any of them experience abnormal critical medical condition.

$$\max Z_2 = \sum_{i=0}^{N}\sum_{r=1}^{4}\left(\sum_{j=1}^{N}\sum_{p=1}^{P}\left(VEL_{ijr}\, x_{ijpr}\,(1-SR_{HR})\right) + \sum_{j\prime=1}^{N}\sum_{c=1}^{C}(VEL_{ij\prime r}\;\; C_{ij\prime cr}\, SR_{HR})\right) \quad (13)$$

- Second objective function is presented in equation (13) which aims at maximizing the travel speed from one node (patient) to another. Similar to equation (12) the left hand side of this objective function maximizes the travel speed when visiting stable patients, on the other hand, the maximization of speed when serving un stable patients is shown in the right hand side of equation (13), the decision of serving either stable or unstable patients is made based on the heart rate sensor readings. Note that this objective function was adopted from the work of Hosseini-Nasab and Lotfalian (2017) and modified to match and fit in the developed model.

$$\min Z_3 = \sum_{i=0}^{N} \sum_{r=1}^{4} \sum_{d=1}^{D} \sum_{hc=1}^{HC} \Big(\sum_{j=1}^{N} \sum_{p=1}^{P} (C_{hcd} . \left| Time_d . x_{ijpr} - tot.load_{hcd} \right| (1 - SR_{HR})) + \sum_{j\prime=1}^{N} \sum_{c=1}^{C} (C_{hcd} . \left| Time_d . x_{ijpr} - tot.load_{hcd} \right| \; C_{ij\prime cr} \, SR_{HR}) \Big) \quad (14)$$

- The third objective function is shown on equation (14), which aims at minimizing the costs related to having a deviation from the average daily workload for a caregiver, which results in economic and behavioral disputes between HHC companies and caregivers. A deviation more or less than the average workload will cause costs in form of overtimes or not adequately allocate workload among employees.

$$\min Z_4 = \sum_{i=0}^{N} \sum_{r=1}^{4} \sum_{q=1}^{Q} \left(\sum_{j=1}^{N} \sum_{p=1}^{P} ((Sat.exp_q - Sat.per_q) PR_i . Pen_q . x_{ijpr} \; (1 - SR_{HR})) + \sum_{j\prime=1}^{N} \sum_{c=1}^{C} ((Sat.exp_q - Sat.per_q) PR_i . Pen_q \, . C_{ij\prime cr} \, SR_{HR}) \right) \quad (15)$$

- Equation (15) presents the fourth objective function that aims at minimizing the cost of poor quality of service, which is the product of penalties of poor service and the difference between patient's expected and perceived satisfaction on the provided health service. Similar to the first two objective functions, the left hand side considers patients under normal status and the right side shows patients under risky state.

3.3.8 Constraints

$$\sum_{i=0}^{N} x_{ijpr} = 1 \ \forall j \ \in N, p \in P \ r \ = 1, \dots, 4, i \neq j \tag{16}$$

$$\sum_{i=0}^{N} C_{ij'cr} \ = 1 \ \forall j' \ \in N, c \in C \ r \ = 1, \dots, 4, i \neq j' \tag{17}$$

$$\sum_{j=1}^{N} \sum_{p=1}^{P} \sum_{r=1}^{4} x_{ijpr} = 1 \ \forall i \ \in N, i \neq j \tag{18}$$

$$\sum_{j'=1}^{N} \sum_{p=1}^{P} \sum_{r=1}^{4} C_{ij'cr} \ = 1 \ \forall i \ \in N, i \neq j' \tag{19}$$

$$\sum_{p=1}^{P} \sum_{r=1}^{4} x_{ijpr} \leq 1 \ \forall i, j \in N, i \neq j \tag{20}$$

$$\sum_{c=1}^{C} \sum_{r=1}^{4} C_{ij'er} \leq 1 \ \forall i, j' \in N, i \neq j' \tag{21}$$

$$\sum_{i=0}^{N} \sum_{r=1}^{4} x_{ilpr} - \sum_{j=0}^{N} \sum_{r=1}^{4} x_{ljpr} = 0 \ \forall l \in N, p \in P \ , i \neq j \neq l \tag{22}$$

$$\sum_{i=0}^{N} \sum_{r=1}^{4} C_{ilcr} - \sum_{j'=0}^{N} \sum_{r=1}^{4} C_{lj'cr} = 0 \ \forall l \in N, c \in C \ , i \neq j' \neq l \tag{23}$$

$$\sum_{j=1}^{N}\sum_{p=1}^{P}\sum_{r=1}^{4} x_{ijpr} \leq 1 \; \forall j \in S' \tag{24}$$

$$tot.load_{hcd} \leq K_{hcd} \qquad \forall \; d, t \in T \tag{25}$$

$$at_i + \omega_i + f_i + s_{ijr} - (1 - x_{ijpr})M \leq tr_k \quad \forall \, i, j \in N, r = 1,2,3,4, i \neq j \tag{26}$$

$$at_i + \omega_i + f_i + s_{ijr} - (1 - x_{ijpr})M \leq at_j \quad \forall \, i, j \in N, r = 1,2,3,4, i \neq j \tag{27}$$

$$e_i \leq at_i + \omega_i \leq l_i \qquad \forall \, i \in P_U \tag{28}$$

$$e_i - \sigma \leq at_i + \omega_i \leq l_i + \sigma \qquad \forall \, i \in P_C \tag{29}$$

$$at_i + (s_{ijr} + f_i + \omega_i)x_{ijpr} + W_{i'k} \leq at_j + \delta_k Y_k (1 - x_{ijpr}) \; \forall \, i, j \in N, i' \in S' \; p \in P, r = 1,2,3,4 \,, i \neq j \tag{30}$$

$$0 \leq y_{jk} \leq y_{ik} - s_{ijr}\lambda_k x_{ijpr} + Y_k \left(1 - x_{ijpr}\right) \forall \, i, j \in N, k \in E \,, p \in P, r = 1,2,3,4 \,, i \neq j \tag{31}$$

$$0 \leq y_{jk} \leq g_{i'k} - s_{ijr}\lambda_k x_{ijpr} + Y_k \left(1 - x_{ijpr}\right) \forall \, i, j \in N, k \in E, i' \in S', p \in P, r = 1,2,3,4 \,, i \neq j \tag{32}$$

$$y_{jk} \leq g_{ik} \leq Y_k \; \forall \, j \in N, i \in S', k \in E \tag{33}$$

$$w_{ik} \geq \delta_k \left(g_{ik} - y_{ik}\right) \; \forall \, i \in S', k \in E \tag{34}$$

$$VEL_{ijr} \leq V_r \, x_{ijpr} \; \forall i, j \in N, p \in P \; r = 1, \ldots, 4, i \neq j \tag{35}$$

$$x_{ijpr} + C_{ij'cr} = 1 \; \forall \, i, j, j' \in N, p \in P, c \in C, r = 1,2,3,4 \,, i \neq j \neq j' \tag{36}$$

$$x_{ijpr} \in \{0,1\} \tag{37}$$

$$C_{ij'cr} \in \{0,1\} \tag{38}$$

$$y_{ik} \geq 0, t_{ik} \geq 0 \;\; \forall\, i \in N, k \in E \tag{39}$$

$$g_{ik} \geq 0, w_{ik} \geq 0 \;\; \forall\, i \in S', k \in E \tag{40}$$

$$0 \leq Sat.exp_q \leq 1 \;\; \forall\, q \in Q \tag{41}$$

$$0 \leq Sat.per_q \leq 1 \;\; \forall\, q \in Q \tag{42}$$

$$0 \leq Ful_\alpha \leq 1 \;\; \forall\, \alpha \in M \tag{43}$$

3.3.9 Equations description

Equations (16) and (17) shows constraints which specify that from patient node *i* any patient could be visited in both normal and critical conditions. Constraints which guarantee that each patient is visited once only are shown in equations (18) and (19). Moreover, the Constraints shown in equations (20) and (21) ensure that under normal and critical conditions only one route must be selected to travel from one patient to another. The law of flow conservation and the continuity of paths are shown on equations (22) and (23). The constraint in equation (24) states that a charging station could be visited or not and it is not mandatory to recharge the vehicle. Furthermore, equation (25) restricts caregivers from exceeding a predefined workload so that a maximum daily working hours is not encroached. The maximum allowable travel time of each vehicle is restricted and controlled using the constraint presented in equation (26). The arrival times as well as the service time windows are defined in equations (27-29). Note that time windows for urgent patients is shown in equation (28), whereas time windows for casual patients is defined in equation (29). On the other hand, constraint (30) safeguards time feasibility but differs from constraint (27) by considering recharging duration of electrical vehicles. The battery status is shown in constraints (31) and (32) where consumption is restricted to be between nodes. Equation (31) shows battery levels at patient *j* after visiting patient *i* considering consumption rate and battery capacity; in addition equation (32) shows battery level at patient *j* after visiting charging station and restricts energy consumption to be between the patient and the charging station. Constraint (33) restricts battery capacity levels to be less than or equal (doesn't exceed) maximum capacity after visiting charging station, yet it restricts capacity levels to be greater than or equal to the node before visiting charging station. Constraint (34) shows the charging duration considering energy consumption of electric vehicle *k* and the difference in battery capacities before and after visiting the charging station. Equation (35) defines a constraint that limits the speed of travel when serving stable patients to the upper speed limit of the selected route. on the other hand, constraint (36) implies that a caregiver travels to serve either patients with normal conditions or patients with critical conditions. The domain of decision variables is shown in Constraints (37) and (38). Constraint (39) and (40) restricts a positive value of battery level, charging duration of vehicles and service time. Finally the constraints in equations (41-43) define the boundaries of the variables, note that those variables are real numbers between 0 and 1 i.e. $\in [0,1]$.

Chapter Four

Solution Methodology

Chapter Four
Solution Methodology

4.1 Chapter Overview

In this chapter, the methodology used to translate the mathematical model to programming codes and then numerical results is presented and discussed. This methodology was carried out using a metaheuristic algorithm; which was shown and explained including each stage of the process in this chapter. This chapter shows the methodology used including the software used for coding and other hardware specifications, in addition to sub-sections to present the used algorithm. The next chapter presents the obtained results with sub-sections that discuss each aspect of the model.

4.2 Optimization Methodology

As mentioned in previous chapters, due to the complexity of the problem at hand, using exact methods to generate solutions for the proposed model is infeasible. Therefore, in this research approximate optimization methodology is used, mainly by using a metaheuristic algorithm that combines and based on Ant Colony Optimization algorithm (ACO) and non-dominated sorting (NDS) approach. The use of the proposed Non-dominated Sorting Ant Colony Optimization (NS-ACO) algorithm is due to the need of a metaheuristic algorithm that deals with the dynamism of the proposed model in addition to the multi-objective functions. Such algorithm will generate near-optimal solutions compared to the exact optimization methods which produce global optimal solutions (Rader, 2010). The use of NS-ACO algorithm is justified by its appropriateness in solving multi-objective complex NP-hard optimization problems including VRP, as shown in many researches in the literature (Bagherinejad & Dehghani, 2016; Gupta & Garg, 2017; Kalhor et al., 2011). As discussed in previous chapters, the nature of the presented SSHHCVRP model requires a decision to be made after each visited node to select which node to visit next, depending on the condition of patients which is transmitted continuously by the employed sensors, as well as, the energy level of the vehicle. However, this is not the only issue to be solved by the proposed algorithm; the presence of multi-objective functions must be considered. Therefore, ACO is used to handle the issue of dynamic vehicle routing that arises in two situations, first when changing the planned routing path depending on the medical condition of patients (normal or critical), and the second situation is related to the energy levels of the electric vehicle to make a decision to visit a charging station or not. Whereas, the NDS technique is used to find and sort the best solutions generated from ACO algorithm, and thereby, presenting the Pareto front solutions. The proposed NS-ACO algorithm was coded using Matlab software along with a personal computer with windows 10 operating system, 3.00 GHz CPU, Intel i5 processor, and 8.00 GB of RAM.

4.2.1 Ant Colony Optimization (ACO)

ACO is categorized as one of the optimization techniques that follow the swarm intelligence optimization methodology. Swarm intelligence optimization approaches were developed based on the observed behavior of insects such as bees and ants. The surprisingly socially coordinated behavior of such insects inspired scientists to develop algorithms that solve complex real life problems by simulating the social structure and activities of insects. Therefore, ACO is a meta-heuristic optimization approach that provides solution for complex problems based on and aided by the behavior of ants, in terms of their team work and travel from their nest (colony) to food sources in different unique paths. In ACO artificial ants are assumed to travel from one node to another and thereby, each ant produces a solution for the problem at hand. In real world ants use a unique system for gathering food and traveling from nest to food source and back, however, ants can’t communicate with each other and plan the process. Each ant leaves the nest to take one of many routes to reach food. Each ant selects randomly the route to follow, and this random selection of routes continues ant each junction until reaching food. Logically, each route has different travel distance than other routes; therefore, each ant covers different travel distance compared to other ants. While traveling ants deposit a chemical substance called pheromones which used for communication between ants to tail and follow the optimal path. As mentioned, ants select route randomly, but when sensing pheromones they will follow the route which contains pheromones, as the process continues shorter (faster) route will possess the largest amount of pheromones since ants will leave nest and return more often compared to other ants taking longer routes. Therefore as the number of ants taking the same route increases, the probability of other ants to join the same route increases due to the large amount of pheromones in those routes. This form of communication between ants using pheromones enables this species of insects to survive and get food, as well as, solve problems whenever a barrier appears between them and food. In addition, pheromones evaporates as the probability of taking the longer route by ants decreases, thus, the level of pheromones in this route decreases and the existing pheromones evaporates. However, the random selections of routes remains but with lower probability. This random selection of routes enables ants to survive and helps them in the process of finding and navigating alternatives route when obstacles appear. This trail selection process is the foundation of ACO to solve complex real life problems, especially problems where each node in the routing plan owns different importance than other nodes and must be given a higher probability for the vehicle (in case of VRP) to visit. According to Bell and McMullen (2004), the first implementation of ACO in VRP was introduced by the doctoral dissertation of Dorigo (1992), and with time the use of ACO in solving VRP continues with various and continuous improvements in the algorithm (Wang et al., 2019; Zheng et al., 2020). Figure 4.1 shows the ACO algorithm flowchart as shown in the work of Khanna et al. (2015).

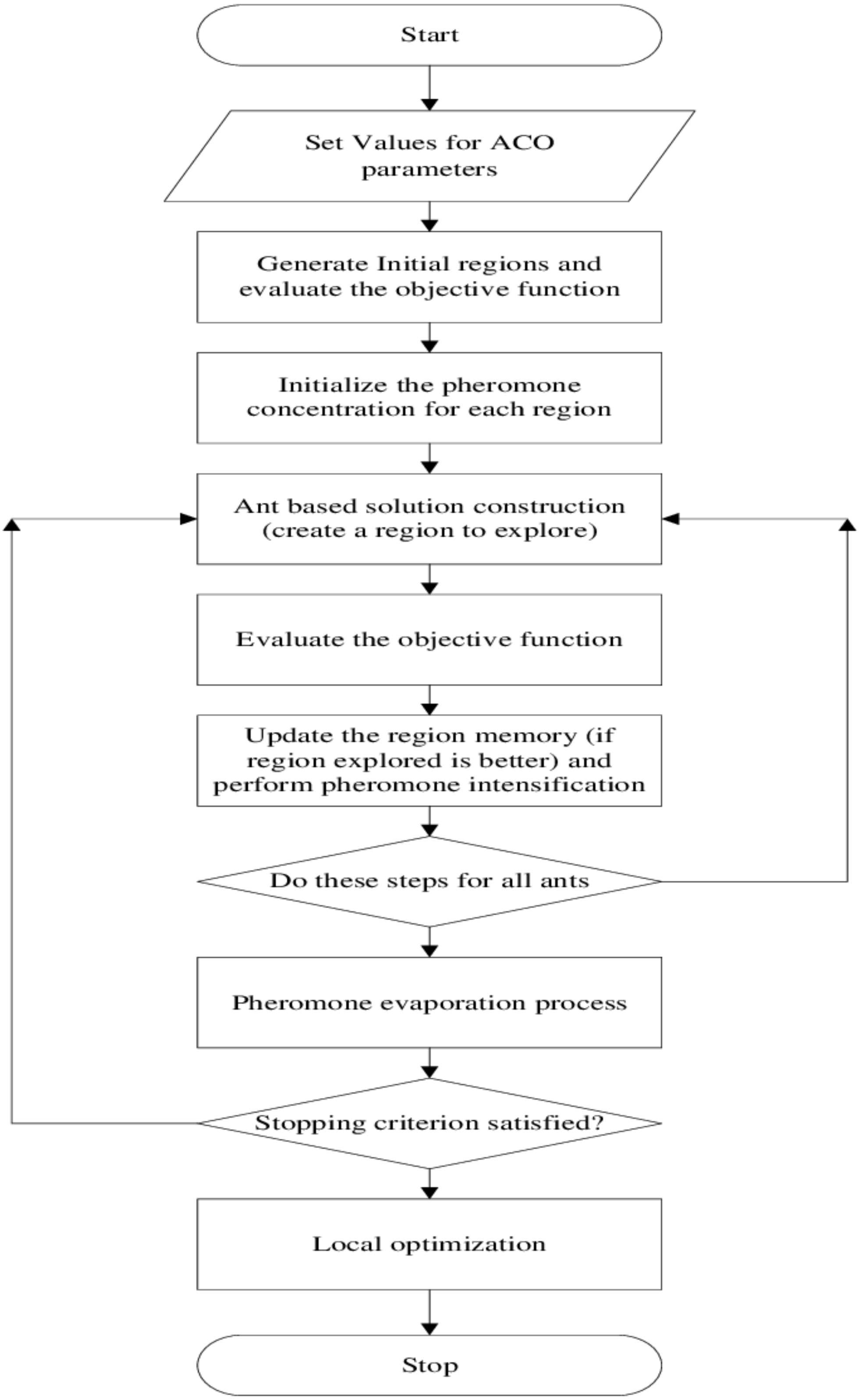

Figure 4.1: ACO algorithm flowchart (Khanna et al., 2015)

4.2.2 Non-dominated Sorting

Non-dominated sorting (NDS) is a technique used in optimization problems to sort solution based on their dominance according to the principle of Pareto. This technique doesn't provide one optimal solution for the problem; it rather delivers Pareto-Optimal solutions at each irritation. In NDS a Pareto-optimal solution exists for the multi objective problem where those solutions are not dominated by any other solution and can't be enhanced without worsening at least one of the other objectives. These solutions are led by the most feasible solutions referred to as Pareto front solutions. According to Deb et al. (2000) the NDS process consists of two stages, non-dominated sorting and crowding distance. NDS starts with non-dominated sorting stage to rank each solution in the population by comparing it with other solutions in the same population to find if it is dominated by other solution or not. The process continues until finding the first class (Pareto front) solutions, the other ranks are done by removing the Pareto front and repeat the same process above. The next and final stage is crowding distance which is used to rank solutions of the first front (Pareto front) solutions which is based on the density of solutions that border a particular point as shown in Figure 4.2, where Pareto front solutions are presented in solid circles and the crowding distance is shown as a dashed cuboid. Therefore, the rank and selection of solutions is based on the fitness of the solution and the crowding distance if two solutions have the same rank (lower crowding distance solution is selected).

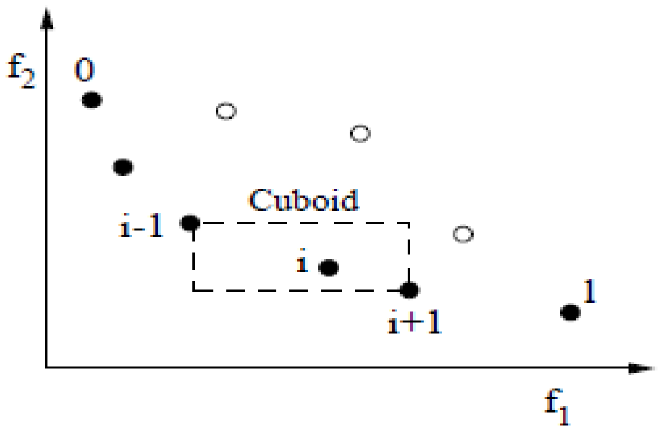

Figure 4.2: Crowding distance process (Deb et al., 2000)

4.2.3 Solution Presentation

As discussed earlier, in the proposed SSHHCVRP model caregivers will travel from a depot to serve a predefined set of patients and return back to the depot, while considering the condition of patients through the information provided by a heart rate sensor, and the decision to visit a charging station or not. This situation creates uncertainty when planning the routing plan and must be solved as a dynamic routing problem. Generally, the proposed problem should be presented as a five dimension matrix that includes depot node, normal condition patient's destination node, critical condition patient's destination node, charging station node and route type. However, in the suggested metaheuristic algorithm the problem can be presented by a two dimension matrix. The solution for our optimization problem starts with ACO algorithm to generate a population of feasible solutions for the problem, the nature of ACO helps to overcome the dynamic routing problem. Then, NDS takes place to provide the best possible solutions for the problem.

The first step of the solutions is constructing different routes. At each repetition of the algorithm, an ant which represents a vehicle will travel from the depot node to visit different nodes that represent patients. After visiting each node, the ant will make a decision to visit another node based on the level of pheromones, where higher levels of pheromones results in a higher probability of taking that route. The probability of selecting the destination node is calculated using the following formula.

$$j = \arg\max\{(\tau_{iu})(\eta_{iu})^{\beta}\} \; for\ u \notin M_k\ , if\ q \leq q_0\ , otherwise\ S \qquad (44)$$

Where τ_{iu} is the level of pheromones between the current node i and the possible destination node u, η_{iu} is the inverse of the distance between nodes i and u, β is a parameter that shows the importance of pheromone levels compared to distance. Moreover, M_k represents the memory of the ant where visited nodes are memorized and can't be visited twice. q is a random number $\in [0,1]$, whereas, q_0 is a predefined parameter where $0 \leq q_0 \leq 1$. In a situation where $q \geq q_0$ a random variable S will be selected by the ant to be the next patient based on the following probability (p_{ij}).

$$p_{ij} = \frac{(\tau_{ij})(\eta_{ij})^{\beta}}{\sum_{u \notin M_k}(\tau_{ij})(\eta_{ij})^{\beta}} \;\; if\ j \notin M_k\ , 0\ otherwise \qquad (45)$$

Therefore, the travelling ant may follow a desirable route (exploitation) that had been established, or it could take a new random route (exploration) based on the probability is equation 45 that favors higher pheromone levels and shorter distance. However, in our proposed model, a higher probability must be given to critical condition patients (if there is one) and chagrining stations if the energy level is low. For the purpose of ensuring that the algorithm will prioritize critical condition patients and charging nodes whenever needed. To do so, the level of pheromones must be altered at routes leading to those nodes, and thereby guarantees that the virtual ants (vehicles) will follow those routes. Equation 46 shows the specified probability of taking the aforementioned routes in different situations.

$$\tau_{ij} = \begin{cases} 0.1 & , if\ (S) is\ not\ critical\ and\ energy\ level > minimum \\ 0.9 & , if\ (S)\ is\ critical\ and\ energy\ level > minimum \\ 1 & , if\ (S)\ is\ charging\ station\ and\ energy\ level < minimum \end{cases} \tag{46}$$

From equation 46, when a critical node is found, the level of pheromones will increase to 90% which in return will increase the probability in equation 45 for the vehicle to take the shortest route to that node. Similarly, when the node is not critical and energy levels are above minimum, the level of pheromones will be 10% and the probability of selecting different routes will depend in the distance between nodes. Finally, when the energy levels are below the minimum allowable level, the pheromone levels will be 100% directed to the route which leads to a charging station. Note that at each iteration the level of pheromones is updated at each route depending on the status of patients and energy levels.

The next step is trial updating where the level of pheromones is updated continuously in each route. The process consists of two types of trial updating, local and global updating. After the generation of solutions, local updating is used to lower the levels of pheromones at each route to show the idea of pheromone evaporation and ensuring that no solution is too dominant. Local trial updating is shown in equation 47.

$$\tau_{ij} = (1-\alpha)\tau_{ij} + (\alpha)\tau_0 \tag{47}$$

Where α is the speed of pheromone evaporation and τ_0 is the initial level of pheromone at each route. Moreover, global trial updating is used to add more levels of pheromones in the best (near optimal) route which was taken by one of the ants as shown in equation 48, where L is the value of the best solution.

$$\tau_{ij} = (1-\alpha)\tau_{ij} + \alpha(L)^{-1} \tag{48}$$

After creating different solutions for the problem using ACO algorithm, the next step is selecting the Pareto front solutions which are the fittest ones using NDS and crowding distance operator. In addition to finding Pareto front solutions, NDS is used to deal with the multi-objective functions in the model. Figure 4.3 shows a detailed flowchart that illustrates how the ACO algorithm was conducted, where sets *m*, *N*, *J* and *T* correspond to the set of ants, node number, destination nodes and iteration number, respectively. In addition, patient's condition and vehicle's energy level are continuously-updated, and possess the highest priority when needed as shown in Figure 4.3. Moreover, a process flowchart that presents the steps of conducting the proposed NS-ACO algorithm is shown in Figure 4.4.

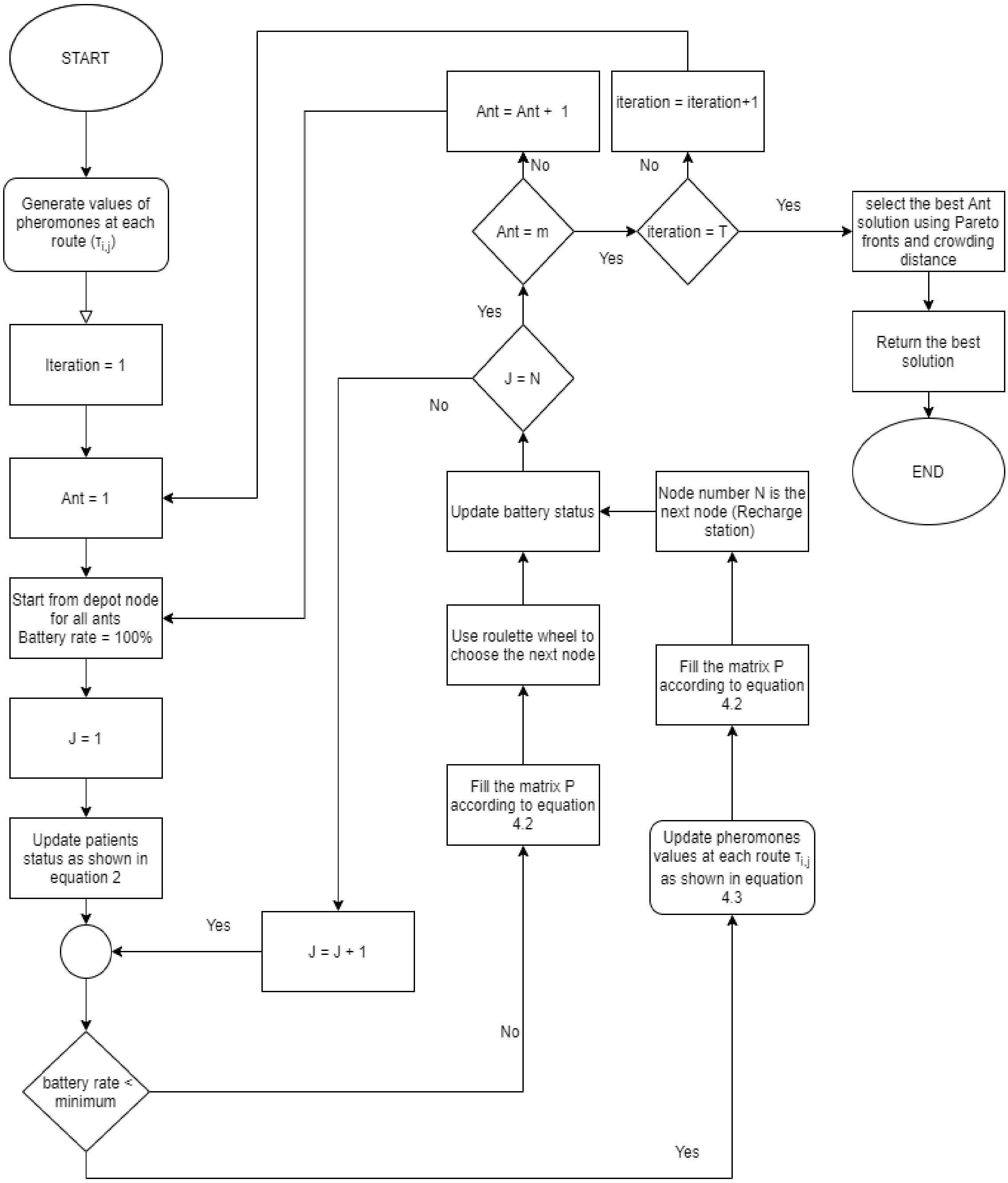

Figure 4.3: ACO algorithm flowchart for the proposed SSHHCVRP

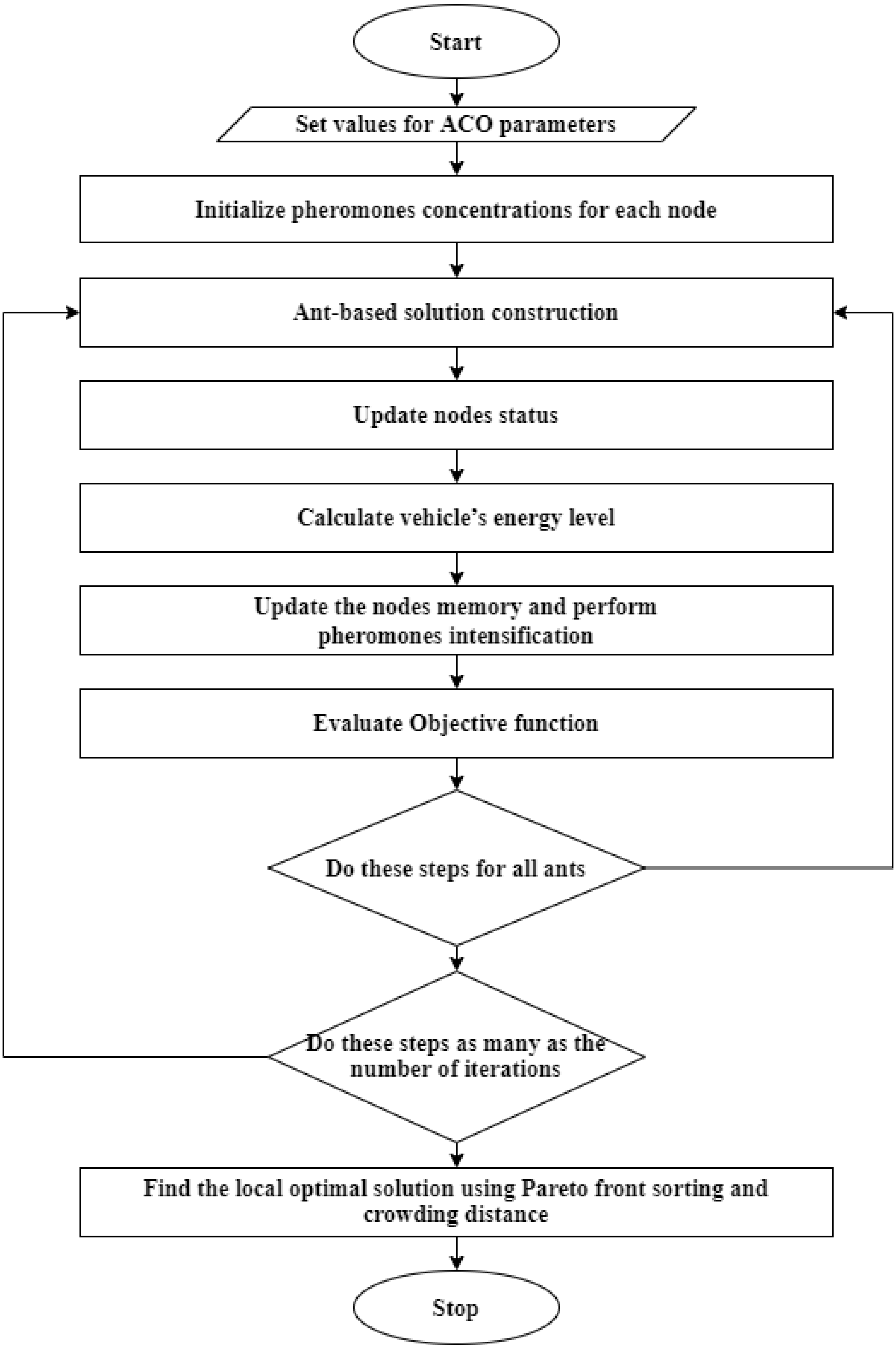

Figure 4.4: NS-ACO flowchart

Chapter Five

Research Results

Chapter Five
Research Results

5.1 Chapter Overview

In this chapter, the obtained results after solving the proposed SSHHCVRP are presented, discussed and explained. First, the numerical data used in solving the model is presented. Then the obtained results are shown including routing plan, costs functions, workload and quality of service.

5.2 Results and Discussion

This section presents the obtained numerical results after solving the developed model. Hypothetical data was used to solve the model, which was adopted from literature or generated randomly using MATLAB software. Due to the use of hypothetical data rather than real world scenarios, different sized instances were tested to validate and verify the solvability of this model. First, small instances were used to present results, while medium to large instances were shown later on this chapter.

5.2.1 Numerical Data

As mentioned earlier, the set of numerical data used is either adopted from literature or generated randomly. In this section, the adopted data were presented for the purpose of evaluating the developed model compared to previous work in the literature. In addition, the inclusion of numerical data previously used in validated models will improve the robustness of our model. Table 5.1 shows the used numerical data used in the model. The numerical data used for the velocity of vehicle and the distance of travel from one node to another through one of the assumed routes was adopted from the work of Hosseini-Nasab and Lotfalian (2017). The velocity and distance follows a uniform distribution ranging from 10-50 km and 1-120 km/hr. respectively, where the decision regarding the near optimal velocity and distance is done by the model based on the selected route to follow. Moreover, the values of electric vehicle consumption rate and battery capacity are in consistence with (Statista Research Department, 2018; Younes et al., 2013). Also, with respect to battery capacity, the threshold at which a charging station must be visited was set to 50% of total battery capacity. In addition, the cost of deviating from the average workload per working day for each caregiver, was set hypothetically to 30 $/hr. In addition, the penalty of poor service where patient's perception doesn't meet the expectations was set to 100 $. Also, the priority of service PR_i is defined to be between 1 and 5 (i.e. $\in \{1,2,3,4,5\}$), where the value of 1 shows a patient with the least priority in service, whereas 5 is the highest as discussed in previous chapters. Finally the workload was set to 8 hours per working day, whereas the maximum workload was proposed to be 10 hours per working day. Note that due to the nature of HHC services, three shifts should be planned to cover a continuous 24 hours of service, however, in this research one shift of 8 hours will be considered and the same analysis applies to the remaining shifts. With regard to routes, Table 5.2 summarizes the characteristics of each route type in terms of maximum allowable velocity, maximum length and energy consumption.

Table 5.1: Numerical data used in the proposed SSHHCVRP model

Parameter	Value
dis_{ijr}	U [10,50] km
VEL_{ijr}	U [1,120] km/hr.
λ_k	≥ 0.1
Y_k	43 kwh
Y_k Threshold	50%
C_{hcd}	30 $/hr.
Pen_q	100 $
PR_i	∈ {1,2,3,4,5}
Workload ($Time_d$)	8 hours
K_{hc}	≤ 10 hours

Table 5.2: Assumed characteristics of each route

Route type	$r = 1$	$r = 2$	$r = 3$	$r = 4$
V_r (Km/hr.)	30	55	80	120
Maximum dis_{ijr} (km)	10	20	30	50
λ_k (kwh/km)	0.14	0.12	0.1	0.13

5.2.2 Numerical Results

After solving the developed model, the results regarding the near optimal route, parameters, decision variables and objective functions were presented and debated. A network of thirteen patients, single depot and two charging stations was assumed. Figure 5.1 reveals the optimal routes for serving a pre-defined number of patients. In the aforementioned figure, the depot and charging stations are assumed to be number 1, 15 and 16 nodes respectively, where both nodes are presented by symbols as shown in the legend.

Moreover, normal condition patients are presented along with natural sensor sign, whereas, critical patients are distinguished with red sensor sign. Note that at each node the model updates the condition of patients and battery status and the updated information is used to make a decision about the next node to be visited. As shown in Figure 5.1 the first caregiver started with patient 2 since the data transmitted from the sensors showed a critical argent condition, after that the route continues to serve patients 4, 6 and 14 until another critical condition arises at patient node 9 and so on. In addition, after visiting node 13 the model makes a decision to visit a charging station (node 15) since the battery capacity dropped below the minimum predefined level which was presented in details later on in this section. Moreover, as shown in the route followed by EV 2, the model made a decision to visit patient 12 after patient 8 due to his/her critical condition, rather than visiting patient 11 who is closer and visiting him/her directly would resulted in saving time and money, however, patient’s well-being is the first priority.

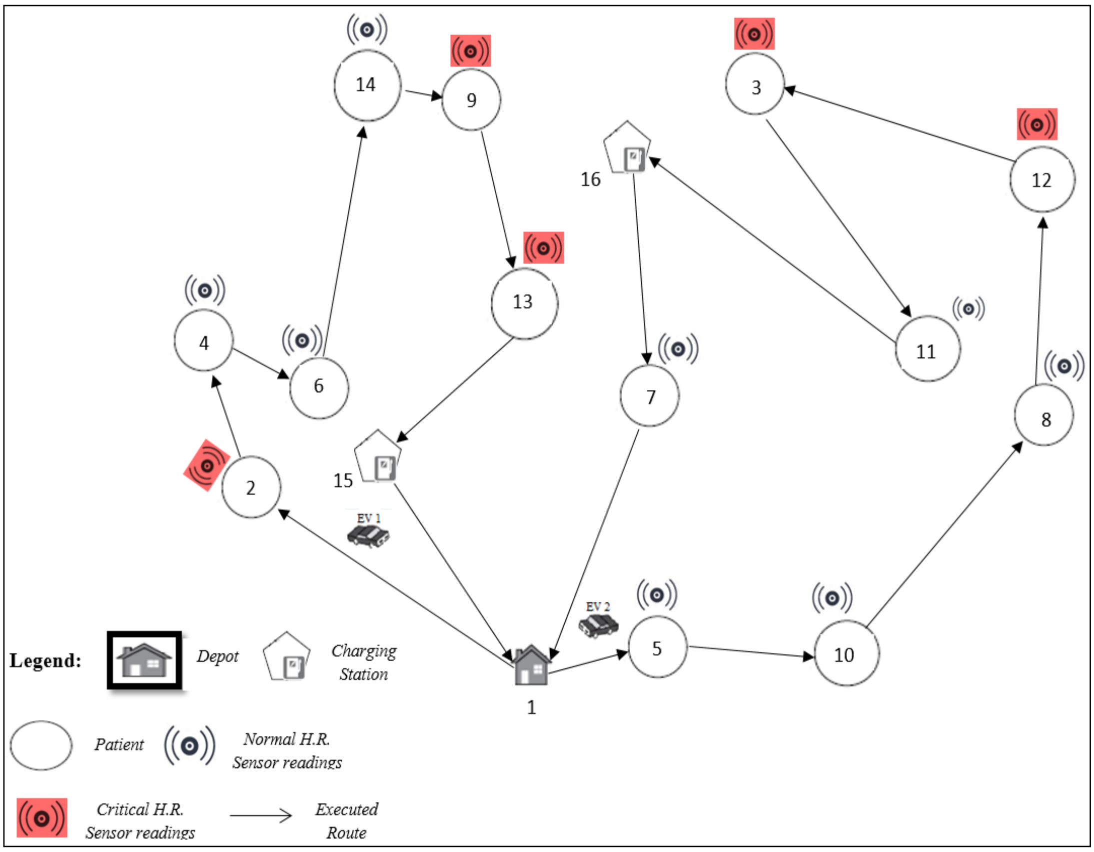

Figure 5.1: Near optimal route for the developed SSHHCVRP model

On the other hand, along with the near optimal route, Table 5.3 spotlights on the arrival and departure times into and from different patient's nodes, in addition to the battery status after each visited node. Be noted that the battery capacity drains as the electric vehicle travel from one patient to another until a certain threshold point where visiting a charging station must be done. It was assumed in the proposed model that the battery capacity shouldn't drop below 50% of total capacity; therefore, as shown in Table 5.3 the decision to visit a charging station wasn't done until after visiting patient node 13 (in route 1) and patient 11 (in route 2), where battery status was 21.24 kWh and

21.06 kWh respectively. Changing the abovementioned threshold will result in more or less visits to charging station. After visiting each node, the model updates and checks the battery status to alter the routing plan if needed, which illustrates the dynamism of our proposed model. Moreover, the time constraint variables are shown in the table in terms of arrival and departure times, which follows a pre-defined time schedule for visits. Additionally, the relationship between the number of patients, time windows and working hours must be planned carefully, to ensure an adequate time of service within the daily working hours. Such relationship was discussed in the following chapter. Finally, the patient's condition is included in Table 5.3, where a value of 1 indicates a critical conditioned patient.

Table 5.3: Near optimal route results with arrival/departure times and battery status

Source Node	Destination Node	Patient's Condition SR_{HR}	Arrival Time at_i (hr.)	Departure Time b_i (hr.)	Battery Status y_{ik} (kwh)
1	2	1	8:51	9:03	34.30
2	4	-	9:13	9:53	32.62
4	6	-	10:22	10:52	30.22
6	14	-	11:40	12:12	24.76
14	9	1	12:34	12:46	23.64
9	13	1	13:20	14:30	21.24
13	15	-	15:04	15:34	43.00
15	1	-	16:08	-	38.45
1	5	-	8:40	8:52	38.32
5	10	-	9:14	9:26	37.62
10	8	-	10:19	10:31	31.77
8	12	1	11:09	11:33	29.07
12	3	1	12:05	12:17	26.91
3	11	-	13:01	13:19	21.06
11	16	-	13:53	14:25	43.00
16	7	-	15:02	15:17	38.71
7	1	-	15:48	-	33.51

Furthermore, Tables 5.4 and 5.5 demonstrate the near optimal route along with decision variables and parameters linked with each route. Specifically, the near optimal velocity, route type, travel time and energy consumption which are incorporated with each route as shown in Table 5.4. For example, the route from patient node 8 to patient node 12 (using EV 2) was executed due to the critical condition of patient 12 and therefore a higher service priority was given. The near optimal velocity for this route was 78 km/hr. and the travel time between the two patients was 0:32 hr., also the electric vehicle consumed 2.70 kWh of energy. Note that the velocity, distance and energy consumption are consistent with the pre-defined characteristics of each route. On the other hand, Table 5.5 shows the variables linked with each route at which a decision is made to travel from one patient node to another. For each path between two nodes, eight decisions could be made in terms of route type and the status of patients which are shown in the table. As an example at the trip between nodes (4, 6) a decision was made to travel from node 9 to node 13 through route type 2 to service patient number i.e. $x_{4602} = 1$, whereas other variables are 0's.

Table 5.4: Near optimal values of the model parameters and variables

Source Node	Destination Node	Energy Consumption (kwh)	Route type (r)	VEL_{ijr} (Km/h)	s_{ijr} (hr.)
1	2	2.70	3	73	0:20
2	4	1.68	2	67	0:29
4	6	2.40	2	56	0:56
6	14	5.46	4	103	0:22
14	9	1.12	1	22	0:34
9	13	2.40	3	72	0:30
13	15	2.60	3	90	0:32
15	1	4.55	4	102	0:39
1	5	1.68	1	27	0:22
5	10	0.70	2	59	0:54
10	8	5.85	4	95	0:38
8	12	2.70	3	78	0:32
12	3	2.16	3	81	0:44
3	11	5.85	4	96	0:34
11	16	5.2	4	100	0:36
16	7	4.29	4	108	0:34
7	1	5.2	4	90	0:28

Table 5.5: Near optimal route and patient's condition decision variables

Served Destinations	Route Type and Patient's Condition							
	x_{ijp1}	x_{ijp2}	x_{ijp3}	x_{ijp4}	$C_{ij'c1}$	$C_{ij'c2}$	$C_{ij'c3}$	$C_{ij'c4}$
(1,2)	0	0	0	0	0	0	1	0
(2,4)	0	1	0	0	0	0	0	0
(4,6)	0	1	0	0	0	0	0	0
(6,14)	0	0	0	1	0	0	0	0
(14,9)	0	0	0	0	1	0	0	0
(9,13)	0	0	0	0	0	0	1	0
(13,15)	0	0	1	0	0	0	0	0
(15,1)	0	0	0	1	0	0	0	0
(1,5)	1	0	0	0	0	0	0	0
(5,10)	0	1	0	0	0	0	0	0
(10,8)	0	0	0	1	0	0	0	0
(8,12)	0	0	0	0	0	0	1	0
(12,3)	0	0	0	0	0	0	1	0
(3,11)	0	0	0	1	0	0	0	0
(11,16)	0	0	0	1	0	0	0	0
(16,7)	0	0	0	1	0	0	0	0
(7,1)	0	0	0	1	0	0	0	0

Table 5.6 shows the arrival and departure times at each visited patient's node, for the purpose of measuring the total workload on each day for the assigned caregiver. The difference between the average and actual workload is shown in the table and multiplied with the cost of workload deviation C_{hcd} to find the total costs of workload deviation. For instance, Table 5.6 presents two different trips, where each trip is executed by two different drivers (driver 1 and driver 2). For instance, the second trip resulted in total workload of 9 hours and 5 minutes (9:05) for driver 1 and a total workload of 7:38 hours for driver 2. In this trip the deviation from average workload for driver 1 was 1:05 hours, which resulted in 33 $ of cost due to deviating from the average workload. Whereas for driver 2 the deviation from average workload was 0:22 hours resulting in 11 $ of cost. Similarly in trip 1, where the workload was 8:08 hours and 7:48 hours for driver 1 and driver 2 respectively. Note that costs will be incurred in both situations where the total workload is more or less than the average, as a mean to achieve resources utilization, as well as, fairness between caregivers and HHC companies. Moreover, Table 5.7 presents the results of patients satisfaction levels at each node in addition to the costs related to dissatisfaction from the provided service. As shown in the table, the model assumes five levels of priority where 5 and 1 have the highest and the lowest priority respectively. Note that different priority levels represent different patient's conditions in terms of needed monitoring and care in addition to the excessive need of precision in service times.

Table 5.6: Workload deviation results and costs.

Driver 1	**Patient's node**	1	2	4	6	14	9	13	15	1	-	**Deviation from avg. workload (hr.)**	0:08
	Arrival time	-	8:51	9:13	10:22	11:40	12:34	13:20	15:04	16:08	-	**Total Cost ($)**	4
	Departure time	8:12	9:03	9:53	10:52	12:12	12:46	14:30	15:34	-	-	**Total working hours (hr.)**	8:08
Driver 2	**Route**	1	5	10	8	12	3	11	16	7	1	**Deviation from avg. workload (hr.)**	0:12
	Arrival time	-	8:40	9:14	10:19	11:09	12:05	13:01	13:53	15:02	15:48	**Total Cost ($)**	6
	Departure time	8:12	8:52	9:26	10:31	11:33	12:17	13:19	14:25	15:17	-	**Total working hours (hr.)**	7:48
Driver 1	**Route**	1	8	7	9	4	11	15	3	5	1	**Deviation from avg. workload (hr.)**	1:05
	Arrival time	-	8:39	9:01	10:47	11:14	12:37	13:40	15:20	16:05	17:05	**Total Cost ($)**	33
	Departure time	8:12	8:51	10:27	10:59	12:05	13:02	14:15	15:45	16:33	-	**Total working hours (hr.)**	9:05
Driver 2	**Route**	1	10	12	2	14	6	13	16	1	-	**Deviation from avg. workload (hr.)**	0:22
	Arrival time	-	8:30	9:10	10:02	10:47	12:08	13:40	14:40	15:38	-	**Total Cost ($)**	11
	Departure time	8:12	8:49	9:37	10:27	11:40	13:10	14:10	15:10	-	-	**Total working hours (hr.)**	7:38

Table 5.7: Patient's satisfaction and quality costs

Patient's node	**Urgent / Casual**	SR_{HR}	PR_i	at_i	ω_i	u'_i	e_i	l_i	$\mu_i(t_i)$	$Sat.exp_q$	**Quality costs ($)**
2	Urgent	1	4	8:51	0:06	8:45	8:30	9:00	100%	80%	0
4	Urgent	0	4	9:13	0:01	9:15	9:00	9:30	93%	86%	0
6	Casual	0	3	10:22	0.09	10:30	10:00	10:45	73%	85%	36
14	Urgent	0	4	11:40	0.02	11:45	11:30	12:00	80%	75%	0
9	Casual	1	2	12:34	0:03	12:30	12:15	13:00	100%	86%	0
13	Casual	1	3	13:20	0:06	13:30	13:00	13:45	100%	84%	0
5	Casual	0	2	8:40	0:03	8:45	8:30	9:15	86%	80%	0
10	Casual	0	2	9:14	0:08	9:15	9:00	9:45	77%	86%	18
8	Urgent	0	5	10:19	0:06	10:30	10:15	10:30	67%	75%	40
12	Casual	1	2	11:09	0:05	11:15	10:45	11:30	100%	84%	0
3	Urgent	1	4	12:05	0:04	12:00	11:45	12:15	100%	70%	0
11	Casual	0	3	13:01	0:03	13:00	12:30	13:15	73%	90%	51
7	Casual	0	1	15:02	0:01	15:00	14:45	15:30	90%	75%	0

Different parameters and variables related to the arrival times at patient's nodes and time windows of service are shown in the table, where higher priority (levels 4 &5) urgent patients are served with a restricted time windows compared with the soft ones applied to lower priority (levels 1-3) casual patients. As discussed in previous sections, $\mu_i(t_i)$ shows patient's satisfaction by measuring the deviation from the desired time of service using equations (8) and (9). However, when a critical condition arises a caregiver skips other patients (temporarily) to serve critical ones, and therefore the satisfaction was assumed to be 100% as shown at patient's nodes 2, 9, 13, 12 and 3. On the other hand, the expected satisfaction $Sat.exp_q$ was calculated as shown and explained in Equation (6). And so, the gap between the perceived and expected satisfaction was calculated and the incurred costs which presents the costs of poor quality of service were shown in the last column of Table 5.7. It's worth mentioning that in addition to serving critical condition patients first whenever needed, our model prioritize higher priority patients for service.

Chapter Six

Sensitivity Analysis

Chapter Six
Sensitivity Analysis

6.1 Chapter Overview

For the sake of revealing the effect of different patient's priority levels on different variables of the model including routing plan, time windows of service and quality costs, this chapter presents the results of the conducted sensitivity analysis on different patient's priority levels. In addition a sensitivity analysis was performed on having different weights of the introduced objective function, for the purpose of understanding the effect of each objective function on the total near optimal solution. The following sections present the results of the conducted sensitivity analysis.

6.2 The Effect of Using BSNs (Heart Rate Sensor)

To assess the effectiveness and the efficiency of the followed approach and the developed model, two scenarios were tested and analyzed in this section to reveal how model variables are sensitive to the employment of the proposed heart rate sensor. Where scenario 1 shows a situation that includes the employment of heart rate sensors that transmit real-time data for the purpose of route planning. On the other hand, scenario 2 presents a situation where heart rate sensors weren't used. In this situation, a predefined routing plan was assumed and no real-time data was considered. Table 6.1 shows the results when solving the model, while considering scenario 1 and 2. The results shown in Tables 6.1 are the average results after solving the model for five runs. As shown in the table, the value of the first objective function Z_1 showed a 22 minutes more travel time in scenario 1 compared to scenario 2, since the presence of critical conditions requires a detour from the planned near optimal route, thus more travel time will be incurred. With regard to the velocity of the EV shown in Z_2, the average velocity of the five tested runs was considered, where the near optimal value was 78.3 km/hr. for scenario1 and 93.7 km/hr. in scenario 2. Such difference in velocities is because of the availability of different route types, as well as, the presence of critical conditions which results in following different routes in each scenario. In addition the results related to cost functions were as follows: the workload deviation costs presented by Z_3 showed a slight difference between the two scenarios with a 3--$ increase in such costs when using sensors. On the other hand, quality costs shown in the fourth objective function Z_4 were significantly affected the employment of sensors. As shown in Table 6.1, in scenario 1 quality costs were 69.2 $, however, in scenario 2 where sensors wasn't considered, quality costs noticed a significant leap to reach 375.2 $. The major difference between quality costs is justified by the advantage of using the heart rate sensor which allows caregivers to serve critical condition patients immediately, and thereby ensuring a 100% satisfaction from those patients (thus, zero poor service quality costs). Figure 6.1 shows the incurred quality costs in each of the five tested runs for each scenario. Finally, the last column in Table 6.1 shows the energy consumed by the EV. In both scenarios, the amount of consumed energy while routing is almost the same, therefore, using sensors have no clear effect on the energy consumed. The results of this sensitivity analysis, especially the results related to quality costs, proved the benefits of employing sensors which provides continuous data about patient's condition.

Table 6.1: Sensitivity analysis on the employment of heart rate sensor

Experiment Number	Z_1 (hr.)	Avg. Z_2 (km/hr.)	Z_3 ($)	Z_4 ($)	Energy Consumption (kwh/km)
Scenario 1 (with heart rate sensors)	9:13	78.3	19.5	69.2	48.2
Scenario 2 (without heart rate sensors)	8:51	93.7	16.8	375.2	49.8

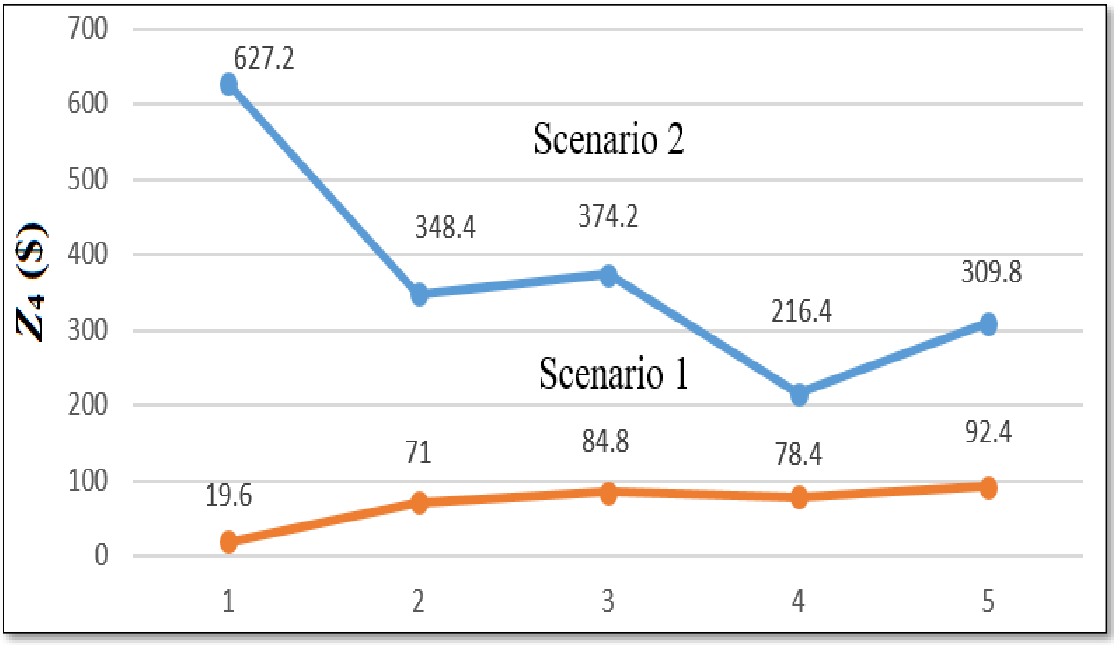

Figure 6.1: The difference in quality costs between the two proposed scenarios

6.3 The Effect of Different Patient's Priority Levels

To understand the effect of having different patient's importance level, four different scenarios were proposed which are: 1) all patients have neutral importance levels i.e. there is no priority given to any patient ($PR_i = 1$); 2) all patients possess low importance levels i.e. priority levels are 1, 2 and 3 which corresponds to casual patients; 3) a combination of low and high importance levels are assumed in this scenario, where patient's levels are uniformly distributed; 4) all patients enjoy high importance levels i.e. priority levels are 4 and 5. Indeed, altering the patient's importance levels and thereby the priority in serving those patients, will directly affect the total quality costs shown in the fourth objective function (Z_4), therefore, such relationship must be analyzed perceptively to ensure an optimal trade-off between patient's satisfaction and the service provider's satisfaction. In addition to costs, different priority levels results in different time windows of service and routing plan. As shown in Table 6.2, the four proposed scenarios of different patient's importance (priority levels) are presented. Those scenarios are presented along with the executed route, total quality cost of the route, average deviation from the desired time of service (triangular membership function) and the percentage of change between different scenarios. As expected, when relaxing the model from service priority levels i.e. $PR_i = 1$ as shown in scenario 1, results showed the least quality costs compared to other scenarios (127.8 $). Such results are justified by the absence of strict / hard time windows to service high importance patients whom if not served urgently within desired times, quality costs will be incurred. On the other hand, the results when assuming lower importance patients whom aren't prioritized in service compared to higher importance ones, yields in quality costs of 372.9 $ as shown in scenario 2 with a 192% increase compared to the first scenario. However, in scenario 3 the patients are assumed to follow a uniform distribution in terms of the priority of service, in a sense that different importance levels will be presented (i.e. 1-5) including urgent and casual patients, as shown in Table 6.2 scenario 3 resulted in a 548.6 $ of quality costs with a 47% escalation compared to scenario 2. Finally, when all patients are assumed to enjoy high levels of importance as shown in scenario 4, quality costs are increased by 23% compared to scenario 3, resulting in 677.2 $ of costs.

Table 6.2: The effect of different patient's importance level on the quality cost's function

Experiment Number	Patient's Importance level	Route	Z_4 ($)	Avg. $\mu_i(t_i)$	Percentage of Change of Z_4 (%)
Scenario 1	1	EV1: 2→5→4→9→7→6→15 EV2: 3→13→10→8→12→16→14→11	127.8	86 %	-
Scenario 2	1,2,3	EV1: 5→3→12→4→10→15 EV2: 14→7→9→13→6→8→16→11	372.9	83 %	192%
Scenario 3	1,2,3,4,5	EV1: 2→5→3→12→4→10→15 EV2: 14→7→9→13→6→8→16→11	548.6	81 %	47%
Scenario 4	4,5	EV1: 2→12→5→3→9→15→13 EV2: 10→4→11→7→8→15→6→14	677.2	80 %	23%

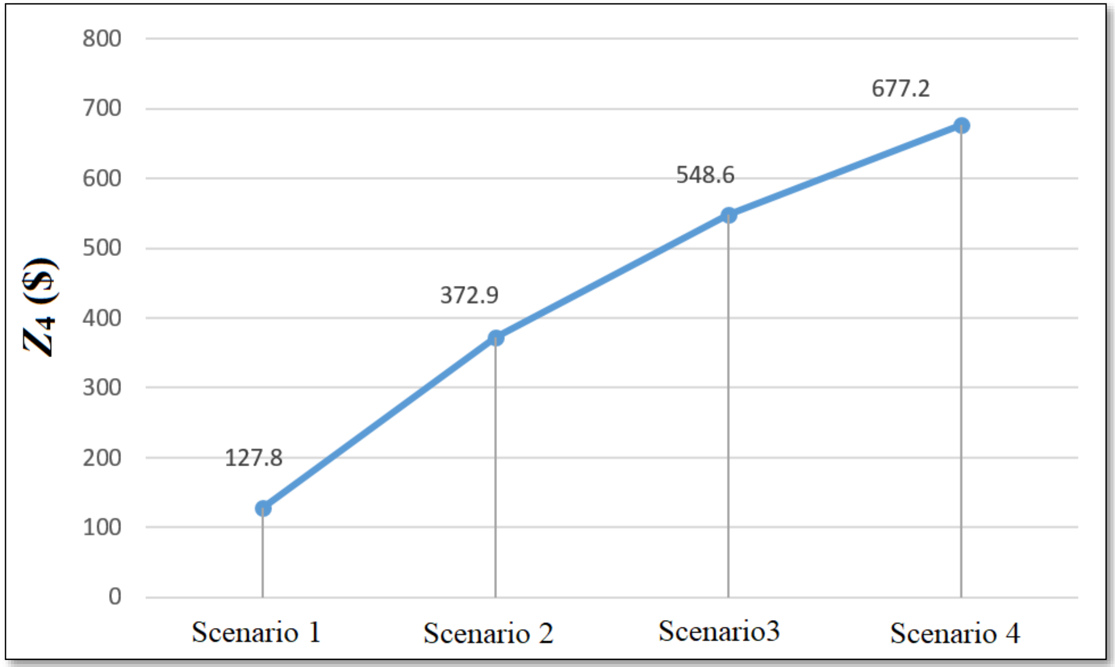

Figure 6.2: The relationship of the effect of different patient's importance levels on the quality cost function

Moreover, Figure 6.2 graphically presents the resulting quality costs when changing importance level. The explored relationship between patient's importance level and quality costs could be interpreted by the scheduled time windows of service, where higher importance patients are prioritized in service with more strict time windows. In other words, as the time window becomes tighter, any deviation from the desired time of service will yield in more costs compared to softer tie windows due to its tied margin of error. Note that the presented quality costs are strongly associated with the penalty of poor quality of service Pen_q as shown in equation (15). Due to the lack of references of such parameter (Pen_q) in the literature of HHCVRP, it was assumed that 100 $ is the penalty of poor quality of service. Therefore, altering this value will result in different quality cost function possibly to more realistic values if the aforementioned penalty was measured adequately.

6.4 The Effect of Altering Objective Functions Weights

To realize the effect of each single objective function on the total near optimal solution, the weights of the objective functions will be changed alternately, by assigning a higher weight for each function at a time. Table 6.3 shows the results of the total near optimal solution when varying the weights of the four objective functions. As shown in the table, five scenarios were suggested including equivalence status where all functions have the same weight.

Table 6.3: Sensitivity analysis on the effect of different objective function weights on the near optimal quality cost's function

Experiment Number	WT_{Z_1}	WT_{Z_2}	WT_{Z_3}	WT_{Z_4}	$Z_{optimal}$ ($)
Scenario 1	1	1	1	1	1220.92
Scenario 2	2	1	1	1	1230.14
Scenario 3	1	2	1	1	2343.92
Scenario 4	1	1	2	1	1240.42
Scenario 5	1	1	1	2	1290.12

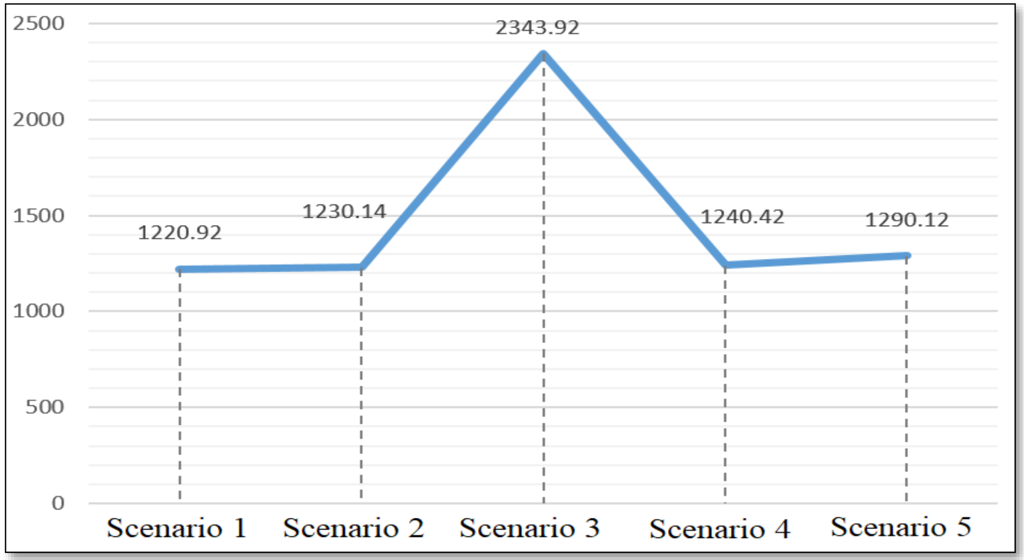

Figure 6.3: The effect of different objective function weights on the near optimal quality costs function

Upon analyzing the obtained results, it was found that the second objective function which aims at maximizing the velocity when serving normal and critical condition patients has the highest effect on the total near optimal solution where $Z_{optimal} = 2343.92$ $, in contrast to other objective functions which caused a minor non-significant change on the total near optimal solution. Figure 6.3 describes the track of the near optimal solution when altering the weights of the objective functions. It is apparent that objective functions Z_1, Z_3 and Z_4 which aim at minimizing travel time, workload deviation from the normalized workload, and quality costs, respectively, merely change the value of the solution when doubling their weights individually at a time. On the other hand, objective function Z_2 had a significant impact of the solution when changing its weight, where the value of the total solution $Z_{optimal}$ went from 1220.92 $ to 2343.92 $. Therefore, HHC companies should emphasize on the velocity of the vehicle while serving patients. Moreover, the velocity of the proposed EVs in our model is directly related to the consumed energy as shown and interpreted by Younes et al. (2013), thus, series attention that should be placed on the velocity function is due to two reasons. First, optimizing energy levels will result in satisfied HHC companies due to the saving in energy and thus reducing operational costs of the service. Second, maximizing the velocity will increase the probability of reaching patients at the exact desired time of service which is specified by the patients, hence ensuring satisfied and healthy patients which is the core goal of any HHC company. In addition, proper decisions must be made when selecting routes to follow, since each route type corresponds to different speeding ranges depending on its nature and traffic volume. Furthermore, the minor effect of cost functions (Z_3 and Z_4) is an opportunity for HHC companies to allow overtimes for caregivers within the allowable working hours specified by laws and regulations. Such opportunity will enable HHC companies to serve additional patients or current patients but with more flexible working times without the need for other caregivers and thus saving costs, since paying overtimes is more economically feasible compared to assigning a new caregiver or piecework pay. However, although quality costs shown in the fourth objective function Z_4 don't crucially affect the total near solution, neglecting such costs will result in tremendous subsequences of unsatisfied patients and accumulated costs of poor quality of service.

6.5 Managerial Insights

In many countries especially western ones where the management of aging societies and HHC services has a great interest and needs special concern, presenting simple HHC models with simplified objectives is not feasible and unsatisfactory. Therefore, in this research, a smart and sustainable HHCVRP model that considers patient's condition, quality of service and employs the use of technology was developed, to answer the complexity of real world applications and thus be prepared for practical implementation. Practicality requires a rich model with multi-objectives and constraints that simulate reality, as well as, validity to provide managerial insights that support decision making. In that context, the results and the conducted sensitivity analysis in our research can be used to support such decision making process. Therefore, practically, the results of the conducted sensitivity analysis spotlight on the benefits of implementing such HHCVRP model. First and foremost, the results shown in Table 6.1 and Figure 6.1 reveal the added value and advantage when using BSNs compared to a situation where such sensors aren't used. The main advantage is seen in the significant reduction in quality costs when using heart rate sensors to monitor patient's health status. Indeed, serving patients immediately when an emergency occurs will improve the quality of service and results in satisfied and healthy patients. Furthermore, no clear benefits were noticed related to other variables such as time of travel and workload deviation costs when using the proposed sensors. However, the trade-off between variables is inevitable in real-life practices, in addition, it is well-known that quality of service is critical and any degradation in quality will result in many other incurred costs. Therefore, the improvement in quality of service associated with the implementation of our model is an advantage point even if it's associated with extra travel time or overtime costs. Moreover, in Table 6.2 and Figure 6.2 at which the relation between patient's importance level and quality costs is presented, provides supportive suggestions for HHC companies in terms of balancing patient's satisfaction and costs. Such suggestion may include allocating and grouping patients in a way that combines different importance (priority) levels to avoid a situation where satisfaction will cause significant costs, since in typical HHC system a caregiver (or more) is assigned to a group of patients. Finally, a sufficient attention must be placed on the velocity of the EV due to its significant impact on the total routing solution compared to other objectives as shown in Table 6.3 and Figure 6.3. Actions such as selecting the optimal route type to follow based on velocity and the resulting energy consumption rate of EVs will optimize the total solution further, although the use of EVs was due to its ability to save energy and protect the environment from GHG.

Chapter Seven

Conclusions

Chapter Seven
Conclusions

7.1 Summary

In this research, a SSHHCVRP was developed and presented that promotes the use of technology, as well as, aims at achieving the three pillars of sustainability for the well-being of Patients, environment and the profitable HHC companies. In addition, different patient's importance levels were considered which is correlated with prioritizing higher important patients in service. The importance of patients were set depending on only the medical condition, where higher importance indicates a medically critical status which should be prioritized in service. Moreover, a novel approach was introduced which includes a function that aims at measuring and minimizing the gap between expected and perceived quality of service. The expected part was measured using internal measures (related to time of service) by experts and then the degree of fulfilling such measures by the HHC service provider formulated the expected quality of service. Whereas, the perceived quality of service was measured using a triangular membership function that calculated the deviation from the desired time of service. Due to the consideration of patient's condition (critical or normal), EV battery levels and the complexity of the model to simulate reality, a dynamic programming approach was adopted using NS-ACO algorithm, to ensure a continuous update of data and therefore updating the routing plan at each node. The total near optimal solution resulted from this model could be optimized further by grouping patients with different importance levels to avoid a situation where all patients are important with strict time windows of service, and thereby minimizing costs of poor quality of service. In addition, planning which route to follow between the 4 types of routes will optimize the near optimal solution. Furthermore, due to the significant effect of the second objective function (velocity maximization) on the total solution, such suggestion is justified by the limited ranges of velocities at each route type.

7.2 Thesis Contributions

This research contributes to the literature of VRP in general and HHCVRP in particular mainly in two dimensions. First, the use of technology directly in planning the routing path for vehicles, since the proposed heart rate sensors are used to transmit real time data to show the medical status of patients, and the collected data is used to update the routing path. To the best of our knowledge, the use of technology especially body sensors in VRP hasn't been considered before. The second contribution is the novel approach of integration of measuring the gap in expected and perceived service quality, customer satisfaction level and penalty of poor quality of service. Generally, the above mentioned gap is measured using a structured questionnaire; however, such approach is impractical in terms of effort, time and patient's status in HHC services. Therefore, in our research the perceived level of service is calculated and the expected service was set by experts using specific internal measures as explained in previous sections, for continuous and more applicable assessment of quality of service as cited by

Khorshidi and Hejazi (2011). Such approach wasn't pursued by any researcher in the literature of VRP to the extent of the researcher's knowledge.

7.3 Imitations

Despite all the attempts to develop a realistic model that tackle real-life applications and complexities, some limitations were found that may hinder the practicality of the model. The model limitations are:

- Hypothetical data: although most of the data used to solve the proposed model were driven from the literature, however, some data was assumed hypothetically. Applying real-world data and instances from the literature (if available), will improve the model and enhance its applicability.
- BSNs challenges and limitations: the heart rate sensor plays a significant role in the flow of the proposed model. However, it was assumed that the sensors are flawless and no risk on the functionality of those sensors was included in the model. Some of the possible challenges that may occur while using BSNs are debated by Hao and Foster (2008).

7.4 Future work

For future researches, this study could be extended and enhanced to answer to real world applications by many improvements to the proposed model. Such improvements may include adding caregivers driving behavior in terms of being risk taker, risk averse or neutral risk taker. Such approach was introduced for the first time in VRP by Abu Al Hla et al. (2019), and wasn't considered in HHCVRP yet. Adding the driving behavior of caregivers will improve the reality of the model, in addition to improving the total near optimal solution by linking the behavior to other functions especially quality cost function. Moreover, in addition to the assumed costs in our model shown in Z_3 and Z_4, the consideration of other operational costs such as the presented in the work of Wang et al. (2021) that includes fixed, transportation, energy consumption and damage costs is a solid addition to our model. Such financial parameters are important for the HHC companies to analyze the feasibility of the provided service, as well as, linking those costs with the customer satisfaction aspect in our model where a trade-off between cost, customer satisfaction and quality of service is clarified and be available for decision makers, again for the purpose of providing a robust and realistic model.

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جامعة النجاح الوطنية

كلية الدراسات العليا

مشكلة توجيه مركبات الرعاية الصحية المنزلية الذكية مع مراعاة حالة المريض وجودة الخدمة

إعداد

أحمد رياض أسعد

إشراف

د. محمد عثمان

قدمت هذه الأطروحة إستكمالاً لمتطلبات الحصول على درجة الماجستير في الإدارة الهندسية في كلية الدراسات العليا، في جامعة النجاح الوطنية، نابلس فلسطين.

2021

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د. محمد عثمان

الملخص

زاد الطلب على خدمات الرعاية الصحية المنزلية بشكل كبير مؤخرًا ، بسبب تصاعد نفقات خدمات الرعاية الصحية التقليدية والتشخيص المتكرر لمرضى الأمراض المزمنة. وبالتالي، يهدف هذا البحث إلى حل نموذج مشكلة توجيه مركبات الرعاية الصحية المنزلية الذي يأخذ في الاعتبار الركائز الثلاث للاستدامة، والتي يمكن تنفيذها في المدن الذكية. علاوة على ذلك، يهدف نهجنا إلى الاستفادة من التكنولوجيا المتاحة في المدن الذكية ، من خلال وضع أجهزة استشعار للجسم على المرضى لمواصلة تحديث حالتهم الصحية وإعطاء الأولوية للظروف الحرجة في الخدمة. بالإضافة إلى الديناميكية وعدم اليقين الناجمين عن التباين في حالة المريض، فإن نهجنا يوسع واقعية النموذج المقترح من خلال اضافة عوامل ثابتة و متغيرة و التي تهدف الى تعزيز قابليته للتطبيق، مثل افتراض مستويات مختلفة من الأهمية (الأولوية) للمريض. علاوة على ذلك، لضمان التدفق المستدام للأعمال ، يأخذ النموذج في الاعتبار المركبات الكهربائية التي ستؤدي إلى توفير تكاليف الوقود والحفاظ على البيئة من غازات الاحتباس الحراري. أيضًا، تمت معالجة الجانب الاجتماعي من خلال زيادة رضا المرضى والموظفين من خلال تحسين جودة الخدمة وإدارة عبء العمل على التوالي. تم حل النموذج باستخدام نهج خوارزمية metaheuristic، و تحديداً عبر خوارزمية Ant Colony Optimization جنبًا إلى جنب مع تقنية Non-dominated Sorting نظرًا لقدرة هذا المزيج على العمل مع النماذج الديناميكية المتغيرة و التي تتضمن أهداف متعددة. أظهر تحليل الحساسية فوائد استخدام مستشعر معدل ضربات القلب في النموذج المطور خاصة في تحسين جودة الخدمة. بالإضافة إلى ارتفاع تكاليف الجودة عند زيادة مستويات أهمية المرضى ، ومن بين الوظائف الموضوعية المقترحة ، يكون لوزن وظيفة السرعة التأثير الأكبر على الحل شبه الأمثل. يأتي تطبيق هذا النموذج في قطاع الرعاية

الصحية بميزة كبيرة لمقدمي الخدمات، بسبب المراقبة المستمرة لحالة المريض، وكذلك تصنيف مستويات أهمية المريض (بناءً على الحالة الطبية)؛ وبالتالي، ضمان رضا المرضى، وتوفير إرشادات لتخطيط المسار في حالات عدم اليقين في حالة المريض.