FORMULATING AND SOLVING STOCHASTIC TRUCK AND TRAILER ROUTING PROBLEMS USING META-HEURISTIC ALGORITHMS

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FACULTY OF ENGINEERING
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ORIGINAL LITERARY WORK DECLARATION

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Field of Study: Operations Research in Supply Chain Management

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ABSTARCT

Manufacturers and services providers often encounter stochastic parametric scenarios. Researchers have, thus far, considered deterministic truck and trailer routing problems (TTRP) that cannot address the prevailing demand, travel time, service time uncertainties and other pertinent complexities. The purpose of this research is to expand the deterministic TTRP models by introducing stochastic parameters to bring these models closer to the reality. In this research, firstly, truck and trailer routing problems with stochastic demands (TTRPSD) is introduced and modeled. Since the demands are not fixed, the failure may occur when the cumulative demands exceed or attain exactly the truck or vehicle capacities, which is again subject to the types of route. For solving TTRP, a variety of algorithms have been applied earlier but TTRPSD programming has not yet solved. Therefore, multi-point simulated annealing (M-SA), memetic algorithm (MA) and tabu search (TS) algorithms are applied to solve the TTRPSD. Twenty one benchmark-instances have been modified for this case and solved by using the aforesaid algorithms. Afterward, the TTRPSD is extended by considering the time window constraints. Since special operational restrictions or requirements may exist in some real applications such as customer's working period that some customers must be serviced during a specified time interval and there can be no delays in servicing those customers. Therefore, truck and trailer routing problem with stochastic demands and time window (TTRPSDTW) is more realistic and thus modeled. Another purpose of this model is to solve it in a reasonable timeframe by administering the MA, M-SA and TS methods. Here, firstly, two experimental tests have been carried out to show the validity and consistency of the applied algorithms for solving TTRPSDTW. The results is compared with vehicle routing problem with stochastic demands and time window (VRPSDTW) solution obtained by large neighborhood search (LNS) by an earlier researcher. The results indicate that the applied algorithms can generate the useful results. Therefore,

MA, M-SA and TS are found suitable for solving TTRPSDTW as well. Moreover, fifty four benchmark instances have been modified for this case. The initial feasible solutions have been generated for this purpose. The solutions have then been significantly improved by the algorithms. In addition, travel and service times between customers may not be deterministic in real life applications. So, truck and trailer routing problem with stochastic travel and service times with time window (TTRPSTTW) are considered. For solving this problem, the aforesaid algorithms have been applied. One hundred and forty four benchmark instances in six levels have been modified for this study. The initial feasible solutions have been generated for this purpose. The solutions have been significantly improved by the algorithms. This issue has been formulated under chance constrained programming (CCP) model and stochastic programming model with recourse (SPR). Since the CCP model is completely depended on the confidence level and sometimes makes the solutions infeasible, in this case no feasible solution for CCP model is found. Therefore, the problems are only solved within the framework of SPR. Also, all of the aforesaid problems have been tested by sensitivity analysis to understand the effects of parameters as well as to make comparison between the respective best results and sensitivity analysis. Since the differences between the results are insignificant, the algorithms are found appropriate and suitable for solving TTRPSDTW.

All those models have been applied in a real company. This study has been carried out with the collaboration of Pegah Co, a large dairy products distribution company in Iran. One hundred customers with their demands that follow the Poisson distribution are considered for this study. Methods such as MA, M-SA and TS have been applied. The problems are solved by using the MA, M-SA and TS. In addition, these problems also have been tested using the sensitivity analysis.

ABSTRAK

Produsen dan penyedia jasa sering menghadapi scenario stochastik parametric. Para peneliti sejauh ini menganggap bahwa penentuan *truck and trailer routing problem* (TTRP) belum dapat memenuhi permintaan secara umum, waktu perjalanan, ketidak pastian perkhidmatan dan komplesitas lainnya. Tujuan dari penelitian ini adalah untuk memperluas jangkauan model TTRP dengan memperkenalkan parameter stochastic sehingga model ini mendekati keadaan sebenarnya. Dalam penelitian ini, yang utama adalah memperkenalkan dan membuat model routing permasalahan truk dan trailer dengan permintaan stochastic. Selama permintaan tidak tetap, kegagalan dapat saja terjadi ketika permintaan komulatif melebihi atau menyamai dengan kapasitas truk atau kenderaan untuk setiap jenis rute. Untuk menyelesaikan TTRP, beberapa logaritma telah diterapkan sebelumnya tetapi pemograman TTRPSD belum juga terpecahkan. Oleh karena itu, *multi-point simulation annealing* (M-SA), *memetic algorithm* (MA), dan *tabu search algorithm* (TS) diterapkan untuk memecahkan TTRPSD tersebut. Dua puluh satu patokan-kasus telah dimodifikasi untuk kasus ini dan diselesaikan dengan menggunakan algoritma tersebut diatas. Setelah itu, TTRPSD dilanjutkan dengan mempertimbangkan kendala waktu yang dihadapi. Semenjak pembatasan operasional khusus atau persyaratan yang mungkin ada di beberapa aplikasi sebenar seperti masa kerja pelanggan dimana beberapa diantara mereka harus dikhidmatkan dalam interval waktu tertentu dan perkhidmatannya tidak dapat ditunda. Sehingga, *truck and trailer routing problem with stochastic demand and time window* (TTRPSDTW) lebih relistis untuk dimodelkan. Tujuan lain dari model ini adalah untuk menyelesaikannya dalam jangka waktu yang wajar dengan melibatkan metode MA, M-SA, dan TS. Pada tahap awal, dua percobaan telah dilakukan untuk menunjukkan validitas dan konsistensi dari algoritma yang diterapkan untuk memcahkan TTRPSDTW. Hasil yang diperoleh kemudian dibandingkan dengan hitungan di *vehicle routing problem with stochastic demand and time window* (VRPSDTW) yang diperoleh dari *large neighborhood search*

(LNS) dari peneliti sebelumnya. Hasilnya menunjukkan bahwa penerapan algoritma dapat mendatangkan hasil yang bermanfaat. Sehingga, MA, M-SA, dan TS didapati juga sesuai untuk menyelaikan TTRPSDTW. Selain itu, 54 contoh persoalan telah dimodifikasi dalam hal ini. Solusi yang memungkinkan telah disusun untuk tujuan ini. Solusi ini kemudian dinaiktarafkan secara signifikan dengan algoritma. Selanjutnya, perjalanan dan masa perkhidmatan diantara pelanggan tidak diperhitungkan dalm penerapan sebenar. Jadi, *truck and trailer routing problem with stochastic travel and service times with time windows* (TTRPSTTW) dapat dipilih. Algortima tersebut diatas telah diterapkan untk menyelesaikan persoalan ini. Seratur empat puluh empat contoh kasus dimodifikasi dalam enam tingkatan untuk penelitian ini. Solusi awal yang memungkinkan telah ditemukan untuk tujuan ini dan diperoleh peningkatan yang signifikan dengan penggunaan algoritma. Permasalahan ini telah formulasikan menggunakan model *chance constrained programming* (CCP) dan stochastic programming model with recourse (SPR). Dikarenakan model CCP tergantung sepenuhnya pada tingkat kepercayaan and kadang-kadang membuat hasil tidak akurat, dalam hal ini tidak ditemukan solusi yang tepat untuk model CCP. Oleh karena itu, persoalan ini hanya diselesaikan dalam bingkai kerja SPR. Semua persoalan tersebut diatas juga sudah diuji dengan analisa sensitifitas untuk memahami pengaruh dari parameter yang ada serta membuat perbandingan antara hasil terbaik masing-masing dan analisa sensitivitas. Karena perbedaan antara setiap hasil sangat signifikan, maka algoritma adalah yang tepat dan sesuai untuk penyelesaian TTRPSDTW.

Semua model tersebut sudah pernah diterapkan di perusahaan. Penelitian ini dilakukan berkolaborasi dengan Pegah Co, sebuah syarikat distribusi susu terbesar di Iran. Seratus pelanggan dengan permintaan mengikuti posisi arah distribusi menjadi pertimbangan pada penelitian ini. Beberapa metode seperti MA, M-SA, dan TS telah diapplikasikan. Permasalahan dapat diselesaikan dengan menggunakan MA, M-SA, dan TS. Selain itu, masalahini juga telah diuji dengan menggunakan analisa sensitifitas.

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With best wishes to all of them,

Seyedmehdi Mirmohammadsadeghi

Author

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LIST OF ABBREVIATIONS

TTRP	Truck and trailer routing problem
STTRP	Stochastic truck and trailer routing problem
TTRPSD	Truck and trailer routing problem with stochastic demands
TTRPST	Truck and trailer routing problem with stochastic travel times
PVR	Pure vehicle route
PTR	Pure truck route
CVR	Complete vehicle route
TC	Truck customer
TW	Time windows
VRP	Vehicle routing problem
SVRP	Stochastic vehicle routing problem
SDVRP	Site-dependent vehicle routing problem
VRPSD	Vehicle routing problem with stochastic demands
VRPSC	Vehicle routing problem with stochastic customers
VRPST	Vehicle routing problem with stochastic travel times
PSO	Particle Swarm Optimization
ACO	Ant Colony Optimization
GA	Genetic Algorithm
SA	Simulated Annealing
M-SA	Multi-point simulated annealing
MA	Memetic algorithm
VND	Variable neighborhood decent

GRASP	Greedy randomized adoptive search procedures
PR	Path relinking
ILS	Iterated local search
LS	Local search
PS	Populated search
LNS	Large neighborhood search
AMP	Adaptive memory procedures
CCP	Chance constrained programming
SPR	Stochastic programming with recourse
TPE	Two-point exchanging
OPM	One-point movement step
TSP	Travelling salesman problems

CHAPTER 1: INTRODUCTION

1.1 Background

The world has witnessed and experienced two hundred years of unprecedented breakthroughs within the realm of transport system development, vehicle technology, and traffic network extension. Technical advancement happens to be an ongoing process but seems to have come across some confinements such as pollution, congestion, and increasing costs that have been considered as existing impediments, in some parts of the globe, the context of hostility against transportation technology could be a standing example. A climate of hostility does exist when it comes to transportation technology; albeit, mobility is still on the increase.

Recently, more complicated customer demands under mass customization have arisen but that are required to be satisfied by many companies. Therefore, a large number of companies are trying to achieve a high level of reliability, flexibility, and agility in their transportation system for fulfilling different demands. As a result, the subject of supply chain management (SCM) has emerged and become an interesting subject for a lot of companies, seeking for ways of efficiently improving their customers' satisfaction. In a way, according to the position and role, supply chain is categorized into three classes; the inbound, intra company, and outbound supply chain. As the network of supplies begins at the inbound supply chain, the role of this group is transporting the semi-finished products or the raw materials to the site of manufacturing. The main concern of the intra company supply chain, as the intermediary part, is with the flow of material in the site of manufacturing. Finally, the outbound supply chain is concerned with the delivery of final products to the customers. The inventory allocation and transportation are strongly considered in the outbound supply chain for minimizing the cost and satisfying the customers' demands. One significant part of the supply chain management is to provide the services or/and goods from a supply point to different destinations, which have been geographically distributed, with significant implications of economics. Aside from the cost of purchasing the goods, on the average and compared to the other relative activities, a higher percentage of the costs of logistics are absorbed by transportation. Therefore, efficiency improvement through the maximum usage of the necessities of transportation and decreasing the costs of transportation along with the improvement of services for customers are the frequent and significant decision problems. Customers, warehouses, manufacturers, and suppliers are the main elements of the supply chain (SC), carrying the goods from the upstream to the downstream sides of a supply chain.

In a supply chain, there are four main business functions to be performed: distribution, inventory, manufacturing, and purchasing. The function of distribution includes two activities: the shipment of finished products from the companies to the locations of demand, and transportation of parts or raw materials from the suppliers to the companies. The individual management of the supply chain functions is not possible, because they are intensely interrelated by flow of information and materials.

Vehicle routing problem in the supply chain management (VRP-SCM) is introduced by Dondo et al. (2009). Since the VRP-SCM problem allows direct shipment of products from the storages of manufacturers' to the demand locations (customers) and handles multiple items, it is considered as a generalized version of the M-echelon vehicle routing problem.

The vehicle routing problem (VRP) is one of the widely studied and most important combinatorial optimization problems in this field and because of its natural complications and efficacies in a large number of real world and supply chain management applications. The vehicle routing problem (VRP) is a terminology being used in transportation programming. Dantzing and Ramser (1959) first introduced this concept. It is now receiving more attention in the current research than earlier. It is related to transporting manufacturing goods within a plant or factory floor and delivering products to markets or customers. VRP concept is also applied in services sectors. Sometimes it is used to define and solve combinatorial optimization problems (COP) (Dantzig & Ramser, 1959; Gilbert Laporte et al., 2000). The importance of VRP is in transportation, distributions and logistics caused by the plentiful practical applications. Before 1990, most of researchers focused on deterministic vehicle routing problem. However, because of uncertainty in parameters such as stochastic demand, stochastic travel time, stochastic service time and stochastic presence of customers, deterministic VRP is not always practical.

During the last two decades, some constraints were added to the stochastic VRP such as time window, travel and service time. Due to some other practical issues, such as narrow roads and bridges in village or government restrictions, maneuvering a complete vehicle appears to be difficult - the VRP approach is found inadequate and these issues are considered in truck and trailer routing problem (TTRP) model. In general, TTRP is more extensive than VRP and can cover more real life aspects since some limitations in VRP as mentioned above can be considered in TTRP. In TTRP, sometimes trucks pull a trailer to serve the customers, which has a feature of TTRP that is usually ignored in the VRP. However, because of some real-life obstacles as mentioned earlier, only a truck has to serve some of the customers. These constraints are obvious in many practical situations (Derigs et al., 2013; Lin et al., 2009; Villegas et al., 2013). Several researchers have so far contributed in this area. One instance is that of Gerdessen (1996) who worked on VRP with a trailer. He demonstrated two real applications pertaining to TTRP. In one case it was the distribution of dairy products in cities where the distributor face with heavy traffic. The second application was to distribute components of animal feed to farmers. He showed the necessity of considering TTRP by demonstrating the applications.

In this study, the supply chain is considered in terms of transportation and distribution. Due to the complexity, in the past researches, a large number of realistic solutions are yet to be considered. For instance, when the dispatcher is considered to have a number of serving limitations for the customers, stochastic service and travel times and stochastic demands in the model were not taken into account.

1.2 Statement of the problem

In order to manage a supply chain, a large number of business processes need to be carried out and many decisions are required to be made. Particular design versions of these general supply systems and inventory planning problems have been studied for a long time. It is pretty obvious that the main supply chain problems are greatly related. As the time goes by, more companies are awakened about their supply chain performance and how important it is that they improve this performance. They also have become aware of the competitive advantage of distribution operations, inventory, integration and coordination of supplies. One of the main problems in supply chain management and logistics is the routing of a series of vehicles, which are assigned to transport goods from a warehouse to the customers or/and retailers. Since goods are hardly ever produced and consumed in one particular place, transportation is considered as a significant factor in the supply chain management.

Any company in the world currently faces with a number of challenges in serving their customers. Transportation is considered to be the largest logistics expense for a vast number of firms and companies. Transportation is the area where costs can be diminished quickly. This is a very bearing question, how servicing and manufacturing companies could successfully diminish transportation expenses without overshadowing customers' satisfaction.

Our contemporary universe is so demanding and competitive today. If companies and business entities aim to be sustainable in this competitive atmosphere, they are required to cut down on their costs in order to increase their profit. As mentioned earlier, the cost associated with transportation is a considerable chunk to be taken into account in each and every firm or company. All management teams are willing to decline this expenditure without reduction in the satisfaction level of customers. Consequently, coming up with the best method to ideally optimize this problematic area will assist the copious number of corporations to continue in better manner in this competitive market regime. It is widely accepted principle that firms aiming to service the customers scattered in a vast area should possess a servicing plan if they don't want to waste time and money. One of the best approaches to work out the arising problematic issues is to apply a special and unique method under the title of Vehicle Routing Problem (VRP) and truck and trailer routing problem (TTRP). There are lots of studies which treat the VRP and TTRP in the SC. The problems in supply management that deserves to focus are as follows:

- In practical situations, a dispatcher may not know the demands in advance. Therefore, a company may face a problem of delivering the right volume of products' to customers for these random demands. Consequently, unexpected extra cost might be imposed to the company. These issues can be considered in vehicle routing problem with stochastic demands (VRPSD). Moreover, when facing the limitations and restrictions such as government restrictions, VRPSD cannot cover these issues and need to consider truck and trailer routing problem (TTRP) with stochastic demands (TTRPSD).

- In addition, due to traffic congestion, different weather conditions, level of driver's skills may be influenced by distribution technology, often travel and service times are not really deterministic between two customers and normally follow stochastic distributions. Therefore, due to some limitations in VRP model mentioned above and the necessity of stochastic travel and service times in real-life issues, the truck and trailer routing problem with stochastic travel and service times (TTRPST) need to be considered.

Moreover, often special operational restrictions or requirements may exist such as customer's working period that some customers must be serviced during a specified time interval and there can be no delays in servicing those customers. These issues cause to be considered VRP with time windows. Correspondingly, time windows constraints can be seen in stochastic TTRP applications. These problems are known as stochastic TTRP with time windows. These issues deserve more researches and attentions.

1.3 Objectives

The main focus of this research is to introduce, model and solve stochastic truck and trailer routing problems (TTRPs) by using metaheuristic algorithms without overshadowing customers' satisfaction. This study embarks on the following specific objectives:

1. To improve the TTRP results using the modified memetic algorithm in order to validate the relevance of memetic algorithm in distribution planning.
2. To model and optimize the truck and trailer routing problem with stochastic demand using meta-heuristic algorithms.
3. To model and optimize the truck and trailer routing problem with stochastic demand and time windows using meta-heuristic algorithms.

4. To model and optimize the truck and trailer routing problem with stochastic travel and service time with time windows using meta-heuristic algorithms.

5. To solve and validate the above three models using different meta-heuristic algorithms.

1.4 Methodology

This research has been divided into two parts: formulations of the truck and trailer routing problems with stochastic demands, stochastic travel and service time considering time window constraints for these models. These mathematical models have been solved using different algorithms such as multi-point simulated annealing, tabu search and memetic algorithm . In addition, the problem have been solved by sensitivity analysis to validate the results. In case of both parts, a comperhensive literature review has been carried out. The aforesaid algorithms are coded by MATLAB 7.9.0 using a computer with a 2.4 GHz dual processor and 4 G RAM. To validate the algorithms, the benchmark instances are used and solved by using these algorithms. Furthermore, some experimental tests have been conducted in order to increase the validity of the aforesaid algorithms and to show the consistency of the results.

1.5 Contribution of the research

This research has developed some models in supply chain management that are useful in manufacturing and service organizations. In the proposed models, the stochastic parameters are considered to bring the TTRP model closer to reality and solve the models in a reasonable timeframe by administering the meta-heuristic algorithms. In addition, the real case study has been carried out and the models have been customized for this real case to show the effectiveness of the model in practical situations. Moreover, the meta-heuristic algorithms have been modified to solve the problems.

1.6 Scope and limitations

This is a real case research based on standard research design and related to transportation cost which can be applied in service and manufacturing companies in the prevailing scope of supply chain management (SCM). However, this research also has some limitations.

Firstly, TTRP models should be applied in large companies with vast customers in different areas. Applying this model for a large company may have more efficiency comparing with small one. For instance, a company with limited customers may not need to serve the customers using mathematical models. They may serve their customers manually. Since stochastic TTRP model is a complicated mathematical programming in transportation of goods , therefore, customizing the model to any company needs some expert and time. Therefore, this conditions need to be considered in finding a appropriate case study with at least 100 customers.

Secondly, the initial data for stochastic TTRP model is the information about all customers such as their demands and locations. Therefore, the models can be best fitted to serve and satisfy the customers if large volume of data is used to validate the models. However, often companies are not willing to share the complete data about their customers' demand and travel time to the researchers. In addition, sometimes the customers are also not willing to cooperate in these cases and need to convince them to cooperate.

Thirdly, since the travel and service times are considered stochastic for this model for the first time to bring the TTRP model closer to reality. Estimating the travel and service times between the customers is complicated. In general, finding the complete initial information for this case needs time even if the company and the customers cooperate for this research. Finally, implementation of the models for the company is the main limitation part since it is a big decision for the management and most of the time the transportation system needs to be changed completely and the applier should show the reliability of the model to the management and convince them. In addition, the tangible results cannot be seen quickly and need time to determine.

1.7 Thesis organization

There are seven Chapters in this thesis, which are arranged as follows.

Chapter 1: In this Chapter, the rationale or background of study, problem statements, research objectives, scope and limitations of the work are placed.

Chapter 2: This Chapter contains an extensive literature survey using the articles which are relevant to supply chain management and vehicle routing problems particularly with stochastic parameters and truck and trailer routing problems. In addition, the solution approaches for the aforesaid problems are explained. Finally, the necessary research directions are drawn in its conclusion.

Chapter 3: This Chapter describes the detailed methodology used to accomplish the research objectives. The methods for collecting real data and the relevant benchmarks are also described in this Chapter.

Chapters 4 and 5: In these Chapters, the truck and trailer routing problems with stochastic demands and with stochastic travel and service time model are formulated.

Chapter 6: In this Chapter, the relevant analysis and discussions on results are made based on the models.

Chapter 7: This last Chapter summarizes the research in terms of conclusion and recommendations for further study.

CHAPTER 2: REVIEW OF THE LITERATURE

2.1 Introduction

The Chapter discusses on topics, models, and solution methodologies pertaining to supply chain management (SCM) and transportation of goods in its distribution side.

Truck and trailer routing problems are related to transporting manufacturing goods within a plant or between factory floors and delivering products to markets and/or customers. TTRP is a variant of the conventional vehicle routing problem (VRP). Indeed, VRP has been known as one of the most studied combinatorial optimization problems in this area in the past few decades, due to the fact that it covers certain areas in practice and considers complexities to a reasonable extent (Gilbert Laporte, 1992; Vidal et al., 2013a). This theory was originally derived from travelling salesman problems (TSP) (Vidal et al., 2013a). Over the last two decades, constraints like time windows, travel and service time and depot deadline were added to VRP solutions (Lei et al., 2011; Li et al., 2010).

In TTRP, the customers may be serviced by either a single truck or complete vehicle (truck with a trailer). This feature is usually ignored in VRP. However, because of some obstacles that appear in real life situations, such as road conditions, market locations, government regulations or limited space to maneuver at customer site, only a single truck is needed to serve a few workstations and/or customers.

Literature survey shows no paper on TTRP with stochastic parameters. Only a few articles were published on TTRP with deterministic parameters. Papers published on SVRP are simply large in number. These concepts need to be considered together for formulating stochastic TTRP. Therefore, this section classifies the relevant models in two groups - standard TTRP models with deterministic parameters and VRP with stochastic parameters.

2.2 Supply Chain Management and Transportation

The supply chain includes the entire activities which are related to the transformation and flow of the goods from the stages of raw material to the final customers as well as the related flows of information. Both information and material flow down and up on the supply chain. Basically, a supply chain includes the following factors: finished goods inventory of work-in process, raw material, customers and retail outlets, transportation systems, distribution centers, warehouses, manufacturing centers, suppliers, and information which flows among the various factors.

There are a number of definitions in the literature. The following one has been presented by Simchi-Levi et al. (2004): "The supply chain management is a series of methods that have been used for the integration of stores, warehouses, manufactures, and suppliers in an efficient way, so that the goods are produced and distributed in the proper quantities, at the right time, and to the right destinations, for minimizing the costs in the entire system, while the requirements of the service level is satisfied."

One of the main problems in the field of supply chain management is product coordination and flow of material among the locations. A usual problem includes bearing the minimum cost to bring the goods that have been located at a central facility to geographically scattered facilities. For instance, a supply of goods is located at a distribution center, cross docking center, warehouse or plant and needs to be distributed to the retailers or customers. The transportation activity is a task in most firms that absorbs a major amount of cost. As a result, most of the companies need to have some methods to deal with the significant issues in the transportation such as, shipment consolidations, vehicle routing, carrier routing, and mode selection.

One of the significant aspects in the management of transportation is for the transportation to be coordinated with the remaining tasks in the firm, particularly within customer service and warehouse. Sometimes, the last contact of the sellers with the customer is the transport, thus, the companies need to pay extra attention to the fulfillment of the customer needs and expectations and use this relationship for improving their sales. The transport coordination of the various elements in a supply chain, which is able to change different companies, which can be of significant importance, because all of them presumably benefit by having a fast delivery to a particular customer. Consequently, a large number of issues in integrating the transportation with the other network tasks which could become a challenge to the industrial and academic communities.

Vehicle routing is one of the well-known and basic transportation problems. A series of instructions need to be output by a vehicle routing system to inform the drivers what to deliver, where and when. One of solutions, which is known to be "efficient", is enabling goods to be delivered where and when required at the minimum cost, subject to political and legal constraints.

The legal constraints are the ones that concern with the unloading restrictions, vehicle use and construction regulations, speed limits, and hours of work and so on. Since the sales are growing with the internet use and the times for delivery are often very short, this problem is getting more importance and the customers can be distributed in an area. Everyday a different type of customer emerges and they require very short time-windows for their products to be delivered.

2.3 Transportation and Truck and trailer routing problem

The TTRP is defined as an undirected graph $G = (V, E)$, where $V = \{v_0, v_1, v_2, \dots, v_n\}$ is the set of vertices and $E = \{(v_i, v_j) : v_i, v_j \in V, i < j\}$ is the set of edges. The central depot is represented by 'v_0' and the other vertices in $V \setminus \{v_0\}$ correspond to customers. Each vertex v_i is associated with a non-negative demand d_i to be collected. A customer type t_i is available for all customers, where $t_i = 1$ shows that customer i is truck customer (TC) and can be serviced only by single truck. If $t_i = 0$, a customer i is a vehicle customer (VC) and it can be serviced by single truck or complete vehicle (truck pulling a trailer). $C = (c(v_i, v_j))$ is a symmetric travel cost which is defined on E. It is assumed that all vehicles have the same feature and maintain the same speed (Chao, 2002; Lin et al., 2009; Scheuerer, 2006), so the travel cost is equal to Euclidean distance between v_i and v_j.

A fleet of m_k and m_r number of trucks and trailers are available, respectively. However, some trucks and trailers may not be used in TTRPSD solution. Without loss of generality, it is assumed that $m_k \geq m_r$, as in Chao (2002), Scheuerer (2006) and Lin et al. (2009). The capacity of a truck is Q_k, and that of a trailer is Q_r, where Q_k and Q_r are different (Chao, 2002; Lin et al., 2009; Scheuerer, 2006).

Three types of route are available in TTRP as follow: 1) a pure travel route (PTR). It can be traveled by only a single truck. 2) A pure vehicle route without any sub-tour (PVR). Only complete vehicle can be traveled in this route. 3) Complete vehicle route (CVR). CVR consists of a main tour and at least one sub-tour. A sub-tour starts and finishes at the same vehicle customer (v_r) (trailer is parked in parking place which is called root) and it can be traveled only by a single truck; however, it should be serviced by complete vehicle in the main tour.

In 2002, Chao used the term "Truck and Trailer Routing Problem" for the first time. However, some research has been performed on the related topics from 1993. The first research that can be mentioned on this topic is the research by Semet and Taillard (1993). The motivation of these authors was a real life problem (distribution of food for the supermarkets). Therefore, they conducted their study on a VPR, which included the application of trailers under some restrictions for the accessibility. Unlike the standard TTRP, a sub-tour cannot service the truck customers. Besides, the variable costs, which are vehicle dependent and the time windows have been taken into consideration. A heuristic method has been proposed based on tabu search and clustering.

Semet (1995) has modeled a problem, which is related to TTRP. This problem is called the "partial accessibility constrained VRP". This model is like the model of TTRP. The major differences between them are: 1) there is a restriction for the sub-tours number and it has been set to the maximum of one; 2) in a particular route, the depot is only to be visited for once; 3) all the trucks which are available are used; 4) it is necessary to determine the number of trailers. This problem is formulated as an integer program and the author has proposed a heuristic method with two phases. This model is based on a generalized method of assignment, which was proposed by Fisher and Jaikumar (1981). Gredessen (1996) has also conducted a study on the VRP with trailers. The classical TTRP and this particular TTRP-related problem are different. This difference is due to the assumption that the unit demand is possessed by every customer; Instead of types of customers, the maneuvering costs are assigned to the customers; it is possible to use each one of the customer sites, as an area for parking; every one of the trailers is parked once and once only; diverse speeds for driving has been taken into consideration with or without the trailers. Several procedures of improvement and construction heuristics have been presented.

A similar problem was studied by Chao et al. (1999). This problem was the site-dependent VRP (SDVRP). Here is a variety of different vehicles which are subjected to serve a series of customers that are limited to compatible constraints. The serving of these customers has to be between the type of vehicle and clients. This variety includes different (but limited) types of vehicles and not each vehicle type is able to perform every request of the customers. As an example, a high demand can be related to a customer and it might need a vehicle with large scales; one other customer can be known to be in an area with a restricted access and might need a vehicle with small scales and the other customers (the remaining ones) can be served by vehicles with any scale and with no limitations. Chao et al. (1999) have proposed a solution for this problem. It is a local search with downhill and uphill moves as well as diverse re-initializations. In addition, Cordeau and Laporte (2001) conducted a research on the problem of site dependent routing and modeled the latter as a very particular case of the period VRP and then an algorithm with a base of tabu search was proposed. This algorithm was especially designed for the period VRP for solving the SDVRP. More information on this topic can be found in another study by Lee et al. (2014), in which an algorithm based on the tabu search is proposed for addressing the SDVRP.

Standard TTRP was first proposed by Chao (2002). Then the method mentioned in Chao (2002) was extended by Scheuerer and two novel heuristics of construction were presented as well as a tabu search approach for addressing the same problem. Scheuerer (2006) applied 0 -1 integer programming formulation for solving TTRP. Chao (2002) and Scheuerer (2006) used a 2-phase approach for solving TTRP. They used heuristics to construct the initial TTRP solution in the first phase. In the second phase, Tabu search algorithm was used to improve the initial solution. Chao (2002) followed Fisher and Jaikumar's (1981) construction for vehicle routing problem solving (Fisher and Jaikumar, 1981). Scheuerer (2006) used Chao's (2002) model and improved it by using two-construction heuristics, T-Cluster and T-Sweep, and applied a new Tabu search improvement algorithm for solving TTRP. The results obtained from experiments indicated that the heuristics that were proposed are competitive for the current methods. Scheuerer had studied the TTRP in his 2004 PhD thesis with multiple depots.

A hybrid multi-objective method was presented by Tan et al. (2007), which was an evolutionary algorithm to solve the trailer and truck VRP where both of the required number of trucks and the routing distance need to be minimized. In addition a number of constraints for operations such as the availability of trailers and time windows are to be taken into consideration. The results from the computational experiments indicated that this type of method can be effective for finding the applicable trade off solutions for the TTRP. In the scientific literature, the only study that contributed in the development of exact method for addressing the TTRP is the study by Drexl (2011). In this study an algorithm of branch and price has been presented. The author has considered a particular example of TTRP and presented a path flow based and an arc flow based formula. This formula is characterized by a series of different vehicles, optional transshipment and parking locations, and time windows constraints. Randomly generated instances have been considered and based on a heuristic and exact version of the approach, computational experiments have been performed. The outcomes of the experiments indicate that the only instances that may be optimally solved are the very small ones.

Lin et al. (2009) introduced simulated annealing to solve TTRP and obtained 17 best solutions to the 21 benchmarked TTRP as reported by Lin et al. (2009). Then they applied time windows constraint in TTRP solution for the first time to bring the model closer to the reality (Lin et al., 2011). Villegas et al. (2010) considered single truck and trailer routing problem with satellite depots (STTRPSD). Variable neighborhood descent (VND) and greedy randomized adaptive search procedures (GRASP) were proposed by them for solving TTRP. In addition, they applied GRASP/VND algorithm for multi-depot VRP and improved the previous analysis. Villegas et al. (2011) improved this solution by considering a hybrid algorithm based on the GRASP/VND and a path relinking (PR) algorithm and proved that this hybrid algorithm exceeds in performance in comparison with GRASP/VND. Finally, Villegas et al. (2013) proposed a new hybrid algorithm by considering GRASP and an iterated local search (ILS) and found a new solution for benchmarking, which were considered by Lin et al. (2009) for the first time. Derigs et al. (2013) proposed TTRP without load transfer between truck and trailer for the first time. A hybrid algorithm was applied for solving TTRP problem by considering the large neighboorhood search (LNS) and local search (LS). In addition, time window constraints were also considered for each customer to bring the model closer to the reality.

2.4 Stochastic Vehicle routing: issues and problems

The definition of Stochastic Vehicle Routing problem (SVRP) has emanated from VRP. Some parameters of SVRP are regarded as random variables. Commonly known SVRPs are VRP with stochastic demand, VRP with stochastic customer, VRP with stochastic customer and demand, and VRP with stochastic travel and service time. All variants of SVRP can be considered with time windows, pick up and deliveries and multi-depot. Mostly, classical VRP cannot cover all real issues in the world because some parameters are not deterministic (Gendreau et al., 1996b). These issues can be settled within the framework of stochastic vehicle routing problems (SVRP) (Li et al., 2010). The most common variants of SVRP are as follows:

2.4.1 Vehicle Routing Problem with stochastic demands (VRPSD)

VRPSD is the most popular variant of SVRP. Similar to VRP, the VRPSD is defined as an undirected graph $G = (V, E)$, where $V = \{v_0, v_1, v_2, \dots, v_n\}$ is the set of vertices and $E = \{(v_i, v_j) : v_i, v_j \in V, i < j\}$ is the set of edges. The central depot is represented by v_0 and the other vertices in $V \setminus \{v_0\}$ correspond to customers. Each vertex v_i is associated with a stochastic and non-negative demand ξ_i, which is to be determined. They are splittable and unknown until vehicle arrives at a vertex (Lei et al., 2011; Jorge E. Mendoza et al., 2010).

Tillman (1969) introduced stochastic demand in VRP for the first time to solve some real life problems. He considered a multi-depot VRP and Poisson distributed of demands and modified the work of (Clarke & Wright, 1964) savings algorithm. Laporte et al. (1989) used varying demands in their study. Earlier, most of the researchers assumed a unit demand for each customer. In this research, the location of a depot was also a decision variable. The branch and cut algorithm was used for the chance constrained version of the VRPSD. Bertsimas (1992) demonstrated analytical evidence for stochastic vehicle routing problem and showed that *a priori* and re-optimization strategies are very similar. Laporte and Louveaux (1993) improved L-shaped method and customized it for stochastic programs with recourse. They used relax branch and cut algorithm to add feasible cuts until an integer feasible solution was found. Gendreau et al. (1995) also presented the L-shaped method for stochastic program with recourse and added a penalty cost for return trip to the depot due to route failure. Gendreau et al. (1996a) presented a tabu search algorithm for solving VRP with stochastic demands and customers. The demands followed a known distribution and customers were also presented with a probability. It should be mentioned that the duration constraints are ignored in VRPSD in most of the articles. However, in practical situations, this constraint often occurs because the route has a time limitation for termination and servicing customers after the preset time is not acceptable. Erera et al. (2010) introduced a new solution and used the Tabu search algorithm to solve VRPSD. Laporte et al. (2002) developed the L-shaped method for capacitated vehicle routing problem with Poisson and normal demand distributions. Secomandi (2001) used Neuro Dynamic Programming techniques for VRPSD and considered Re-optimization approach. Then, Novoa and Storer (2009) used dynamic programming algorithm with Re-optimization concept and computed the total distance using the Monte Carlo simulation method. Also, the article computed the cost directly and showed that the computation time using the Monte Carlo algorithm is up to 65 percent shorter than using the direct computation. In addition, Lei et al. (2011) extended VRPSD, and imposed time window constraint to vertices. They solved the vehicle routing problem with stochastic demand and time windows (VRPSDTW) by considering discrete and continuous cases to model the demand. These methods have been improving since 1990 and now can consider a wide variety of VRPSD. However, there are having some limitations that can be resolved for any specific case of SVRP. For example, exact algorithms such as branch-and-bound method should be used for small scale problems. These limitations have been mentioned in subsequent sections.

2.4.2 Vehicle Routing Problem with stochastic customers (VRPSC)

The VRPSC can be demonstrated by an undirected graph $G = (V, E)$, same as the definition of VRPSD. However, each vertex v_i is associated with a deterministic demand d_i and the customers are presented with some probabilities, p_i. It means that the customers are absents with some probabilities $1 - p_i$. The VRPSC can be solved in two stages. In the first stage, the routes are constructed without considering the probability of present customers. The absent customers will be revealed in the second stage

(Bertsimas, 1992; Gendreau et al., 1995; Gendreau et al., 1996b). For example, sometimes the distributor doesn’t know that the customers are present or not (also, if they have any demand or not), therefore, it is possible to predict the probability of customer present. Most of researchers considered VRPSC with unit demand (Bertsimas, 1992) because it is easier to understand. Bertsimas described properties, bound and heuristics for VRPSC (Bertsimas, 1992; Gendreau et al., 1996; Lei et al., 2011). Then, Bent and Van Hentenryck (2004) used Multiple Scenario Approach (MSA) to solve Dynamic VRPTW with stochastic customer. In dynamic VRPTW, customer’s requests are not determined and become available during the service being provided. Although most of the articles wanted to minimize the cost or the distance in VRP, the purpose of the Bent’s article is to maximize the number of serviced customers as much as possible considering all constraints (Bent & Van Hentenryck, 2004; Pillac et al., 2013). In some real life issues, customers are present with probabilities. In addition, their demands are stochastic. Therefore, for these cases VRPSC should consider with stochastic demand which is named as VRPSDC.

2.4.3 Vehicle Routing Problem with stochastic demands and customers (VRPSDC)

Any combination of VRPSD and VRPSC is known as VRPSDC. It means that the demands are stochastic; also the customers are present with probabilities. Jezequel (1985) is the first researcher who worked on this topic. Bertsimas (1992) presented the most accepted definition of VRPSDC. The Bertsimas methodology has two stages. The routes were constructed in the first stage for all customers (present or absent). In the second stage, the absent customers were revealed and considered. Gendreau et al. (1995) used an exact algorithm using the integer L-shaped method for solving VRPSDC and they used Tabu search algorithm for solving VRPSDC in late 1990s (Gendreau et al., 1996b). After this, all researchers who have been working on VRPSC have considered stochastic demand. It means that VRPSC and VRPSDC can be classified into one group. These references may be seen for further information (Bent & Van Hentenryck, 2004; Hvattum et al., 2007; Lei et al., 2011).

2.4.4 Vehicle Routing Problem with stochastic travel and service time (VRPST)

VRPST is one of the most popular variants of SVRP. The VRPST is defined as an undirected graph $G = (V, E)$, where $V = \{v_0, v_1, v_2, \ldots, v_n\}$ is the set of vertices and $E = \{(v_i, v_j) : v_i, v_j \in V, i < j\}$ is the set of edges. The central depot is represented by v_0 and the other vertices in $V \setminus \{v_0\}$ correspond to customers. Each vertex v_i is associated with a deterministic and non-negative demand q_i to be collected. Also each customer has a random variable service time δ_i. Each arc (i, j) is associated with a travel distance, or a travel cost c_{ij} and $C = (c_{ij})$ should satisfy the triangle inequalities (Lei et al., 2011; Li et al., 2010; Zhang et al., 2012). Kenyon and Morton (2003) considered VRPST with a real case study in a service sector in Belgium. This was the first case study in VRPST and could help other researchers to improve their real life problems. The goal of this work was to provide service to all branches of bank and the objective was to minimize the completion time using branch-and-cut algorithm with a Monte Carlo simulation. Li et al. (2010) extended VRPST and studied SVRP in which travel and service times were stochastic with time windows (VRPSTTW) constraint and used tabu search algorithm to solve it. The VRPSTTW was formulated with chance constrained programming (CCP) and stochastic programming with recourse (SPR). Solving a real life problem with CCP concept is easier than SPR; however, CCP concept completely ignores recourse action and the solution cannot be optimized. The objective is to design a set of routes and minimize the corresponding total travel cost considering all constraints in the model. The VRPST can be considered with other constraints such as time windows and service times (Li et al., 2010). Lei et al. (2012) considered CVRP with stochastic service times (CVRPSST) without any limitation in the number of vehicles and used the generalized variable neighborhood search heuristic to solve the problem which was first introduced by Mladenovic and Hansen (1997). In these articles, the insertion and swap methods were used to find a better solution and, indeed, reversion method could be used to find a better neighborhood and better solution. In addition, the CVRPSST becomes more practical if travel time is considered stochastically. Taş et al. (2013) improved VRP with stochastic travel times and worked on VRP with soft time windows and stochastic travel times (VRPTWST). In this article, transportation cost (including travel distances, number of vehicles and over time penalties) and service times were considered in the model and the problem was solved in three phases. An initial solution was constructed in the first stage. In the next stage, the initial solution was improved by tabu search meta-heuristic algorithm. In most of the articles, Meta-heuristic algorithm was the last step for optimization; however, the solution was improved by post-optimization method in the last phase. Post-optimization method tries to modify the departure time of each customer and reduce the service costs to decrease the total cost.

2.5 Differences between stochastic VRP and classical VRP

The classical Vehicle Routing Problem is defined by an undirected graph $G = (V, E)$, where $V = \{v_0, v_1, v_2, \dots, v_n\}$ is the set of vertices and $E = \{(v_i, v_j): v_i, v_j \in V, i < j\}$ is the set of edges. The central depot is represented by v_0 and the other vertices are corresponding to customers or cities. Each vertex v_i is associated with a non-negative demand d_i. Costs are represented by edges. $C = (c(v_i, v_j))$ is a cost matrix, which shows the cost between two vertices for all edges defined on E. The cost can be represented by travel distance; travel costs itself or travel time. The number of vehicles can be considered constant or as a decision variable and it depends on situation that can be changed. All vehicles are assumed to have the same features and have a constant capacity Q. The purpose is to design a set of routes and find the one that minimizes the total cost. In contrast to their CVRP counterparts, SVRP involves some stochastic parameters such as stochastic demand, stochastic travel and stochastic service time. Therefore, the company may face a problem of delivering the products' to customers. Consequently, unexpected extra cost will be imposed to the company.

2.6 Solution approaches

Two main concepts for solving the aforesaid types of problems can be discerned from stochastic programming (Lei et al., 2011). The first one is known as chance constrained programming (CCP). In CCP, a problem is solved by imposing a constraint ensuring that the probability of a route failure is bounded by some parameters, such as time limitation and service time (Lei et al., 2011). This concept attempts to convert the stochastic parameters to the equivalent deterministic values. For instance, the VRPSD can be converted to an equivalent deterministic program. Stewart Jr and Golden (1983) and Laporte et al. (1989) have demonstrated this transformation by considering statistical relationship between the parameters. The second concept is stochastic programming with recourse (SPR). Two main solution strategies are available under SPR. The first one is *a priori* optimization (Bertsimas, 1992; Gendreau et al., 1996; Mendoza et al., 2010; Tan et al., 2007) and the second one is re-optimization (Psaraftis, 1995; Secomandi, 2000; Secomandi & Margot, 2009). In an *a priori* optimization solution, the set of tours and sub-tours is constructed in the first stage. Recourse actions considering the random variables are then revealed. In a re-optimization solution, the customers are serviced until the failure is occurred. Then it comes back to the depot and fills the capacity for the remaining customers; however, the dispatcher decides which customer should be served next, because re-optimization is a dynamic process and the route may be changed during the *en route* service (Pillac et al., 2013; Secomandi & Margot, 2009). During the past few decades different methods and algorithms were applied and developed for solving Stochastic Vehicle Routing Problem. These can be classified into three groups: exact, heuristics and meta-heuristics algorithms. Mostly, exact algorithms are used for small scale problems; however, heuristics and meta-heuristics can be used for large scale cases. Tables 2.1, 2.2, 2.3 show the examples for SVRP, on those approaches.

Table 2.1: Summary on Exact Algorithms to solve SVRP

Method	Short description	Reference papers	Limitation
Dynamic Programming with State Space Relaxation	Considering problems by breaking them down into simpler sub-problems. Performs the recursion on smaller state-space.	(Novoa & Storer, 2009; Nicola Secomandi, 2000; Topaloglu & Powell, 2006)	N < 100 (N is number of customers)
Branch-and-bound	Uses upper and lower estimated bounds on the cost of an optimal schedule	(Kenyon & Morton, 2003; Laporte et al., 1989)	N < 100
Branch-and-cut	Is a hybrid algorithm between branch-and-bound and the cutting plane methods and uses for solving integer linear program	(Karaoglan et al., 2011; G. Laporte & Louveaux, 1993; Valle et al., 2011)	N < 100
Branch-and-cut-and-price	Branch-and-bound with column generation using cutting plane method. Column generation techniques are used to compute linear relaxation	(Christiansen & Lysgaard, 2007; Christiansen et al., 2009)	N < 100
L-shaped algorithm	Is a decomposition method. An important restriction to this method is that all problems should be linear programs	(G. Laporte et al., 1998; Yang et al., 2000)	N < 100

Table 2.2: Summary on Heuristic Algorithms to solve SVRP

Method	Short description	Reference papers	Limitation
Saving method	Tries to improve the initial solutions by combining the customer of two routes and check the feasibility of the routes	(Dror & Trudeau, 1986; Poot et al., 2002; Tillman, 1969)	This algorithm can improve initial solutions and should be combined with other algorithms to find optimal solution
Lagrangian method	The Lagrangian method is based on a ‘sufficiency theorem’. Problems can be formulated for maximization of a concave non-smooth function.	(Stewart Jr & Golden, 1983)	Researchers need to be careful about local minima and maxima to escape from this issue
Sweep method	Able to find near-optimal solutions in large problems at low CPU times	(Goodson et al., 2012)	Researchers should be careful about local minima and maxima to escape from this issue.
Cluster method	The purpose is to gather customers in small group to find optimal solution in reasonable time	(J.E. Mendoza et al., 2011; Yang et al., 2000)	The customers cannot easily be categorized
Clarke and Wright heuristic	Tries to find initial solution then merges two routes for decreasing the travel or distance cost	(Mendoza et al., 2011)	Should be used with other algorithms until the solution reach to an optimum level.

Table 2.3: Summary on Meta-heuristic Algorithms to solve SVRP

Method	Short description	Reference papers	Limitation
Tabu search (TS)	Tries to find good neighborhood to decrease the cost using a tabu list to avoid repetition	(M. Gendreau et al., 1996; Hu & Liu, 2011; Ismail & Irhamah, 2010; Taş et al., 2013)	Time taken to solve the problem may be more than other meta-heuristics particularly population search algorithm.
Simulated annealing (SA)	Based on annealing in metallurgy, tries to find good neighborhoods with this technique to improve the solutions	(Goodson et al., 2012; Suman & Kumar, 2005)	Time taken in SA is more than population search algorithms and highly dependent on the parameters. They must be defined precisely.
Genetic algorithm (GA)	Based on natural evolution, tries to generate and improve solutions using crossover and mutation techniques	(Ismail & Irhamah, 2010; Tasan & Gen, 2012; Xie & An, 2006)	The effectiveness of GA is fully dependent on the parameters. They must be defined precisely.
Neural networks (NN)	Based on biological neurons, tries to simulate some properties of biological neurons and find and improve solutions	(Bullnheimer et al., 1999; Ghiani et al., 2003; Ismail & Irhamah, 2010; Nygard et al., 1990; Tasan & Gen, 2012; Xie & An, 2006)	Time taken in NN is more than population search algorithms which must often be matched with incredible amounts of CPU.
Ant colony optimization (ACO)	To generate and improve the solution based on the behavior of ants seeking	(Bianchi et al., 2006; Bullnheimer et al., 1999)	Researchers need to be careful about the local minima and maxima to find real optimal solutions.
Adaptive memory procedure (AMP)	AMP is a series of suitable and proper solutions, which during the search process, gets updated dynamically.	(Bent & Van Hentenryck, 2004)	TS is mostly embedded in AMP to empower the algorithm.

Particle Swarm Optimization (PSO)	Tries to find optimal solution based on organism's behavior such as flocking of birds.	(Shanmugam et al., 2011)	PSO is sensitive to the system of coordinates and researchers need to be careful about this issue.
Memetic algorithm (MA)	Similar to GA; however, MA uses local search method to generate and improve solutions.	(Mendoza et al., 2010)	Researchers need to be careful about the local minima and maxima to find real optimal solutions.
Adaptive large neighborhood search	Uses different simple heuristic algorithms to cull and repair the current solution	(Gilbert Laporte et al., 2010; Lei et al., 2011)	The algorithms for culling and repair should be chosen accurately for empowering the algorithm.

Table 2.3 continued

2.6.1 Heuristic and Meta-heuristic algorithms

Heuristic indicates a series of problem solving techniques that are experience-based. In addition to problem solving, they are also used for learning and discovery. These techniques find a solution that is not guaranteed to be the optimal solution, but it is proper enough for a given series of goals. Heuristic methods are applied where the exhaustive search is not practical. They are applied for speeding up the process of finding a good enough solution through mental shortcuts to simplify the decision making cognitive load. In a more precise way, heuristics are strategies using readily accessible information (though loosely applicable) for controlling the problem solving in machines and humans.

A meta-heuristic is a procedure at a higher level or it is considered as a heuristic designed procedure to select, generate, or find a heuristic or procedure at a lower level (partial search algorithm) that can provide a good enough solution for a problem of optimization, especially with imperfect or incomplete information or restricted capacity of computation. There may be some assumptions made by the Meta-Heuristics about the optimization problem, which is being solved and therefore they might be applicable for various problems. Meta-heuristics search over a large set of feasible solutions and through this search, they are usually capable of finding proper solutions through lower computing efforts than simple heuristics, iterative methods, or algorithms. Over the last two decades, most of researchers have focused on the development of heuristics and meta-heuristics algorithms to solve VRPs. It is indeed, not possible to solve all variants without considering heuristic approaches, particularly in large scale problems. For instance, dynamic programming algorithm can only be used for less than 100 customers otherwise the performance of the algorithm will be decreased. Heuristic algorithms such as the sweep algorithm (Goodson et al., 2012), saving method (Dror & Trudeau, 1986), the Fisher and Jaikumar algorithm (1981) and cluster algorithm (Mendoza et al., 2011) emphasize to obtain a feasible solution quickly. It depends on the type or complexity of SVRP, some heuristic algorithms may be appropriate. Mostly, these algorithms may be used to construct initial solutions and these solutions can be improved by meta-heuristic algorithms.

Meta-heuristics use two principal methods to improve the solution from that of heuristic in terms of different performance criteria. These methods are known as local search method (Hu & Liu, 2011; Lei et al., 2011; Liu et al., 2008) and population search method (Ismail & Irhamah, 2010; Vidal et al., 2013b). When using the local search methods, one should know that a thorough search of the solution space is implemented by moving at each step from the existing solution to another likely solution in its neighborhood. Tabu search (TS) and simulated annealing (SA) (Suman & Kumar, 2005) are the most well-known algorithms in this area. The population search includes upholding a pool of good parent solutions and then re-associating them to create new offsprings. Genetic algorithm (GA) and adaptive memory procedures (AMPs) and particle swarm optimization (PSO) are the three main examples in this principle. The other famous meta-heuristic algorithms are ant colony optimization, evolutionary strategy, artificial immune system and neural networks. Genetic algorithm is a classic example in population search method. If several parents are used to produce several descendants, this method can be identified as an adaptive memory procedure (Cordeau et al., 2002). AMP can cover more space than GA, therefore AMP has more chance to find an acceptable solution; however, this method is more complicated than GA because AMP has more parameters and needs enough experience to customize the method into the corresponding problem. Some meta-heuristics algorithms which may use for solving SVRP and STTRP are reviewed more specifically.

1- Genetic algorithms

Genetic algorithms (GAs) are the population search algorithms, which are based on the genetics and the natural selection evolutionary ideas. In fact, what they represent is a random search intelligent exploitation that has been applied for solving the optimization problems.

The procedure of GA is to simulate the fittest survival among individuals for the following generation to solve a problem. Every one of the generations includes a character string population, which are similar to the chromosome that exists in the human DNA. In a search space, possible solutions and the points are represented by each individual.

Then, an evolution process needs to be performed for the individuals of the population. The base of the GA is an analogy with a structure of genetics and the chromosomes behavior in an individual population, using the foundations that are mentioned as follows (Goldberg & Holland, 1988):

- In a population, each individual competes with others for mates and resources.
- More offspring is generated by the individuals that are most successful in the competitions than the ones with a poor performance.

- The spread of genes from superior individuals is throughout the population in a way that sometimes a better offspring is produced by the good parents that is superior to either parent.
- Therefore, each following generation will be more adapted for the surrounding environment.

For a GA, a population of individuals is kept among the space of search and a possible solution is represented by each one of them for a particular problem. Usually the alphabet of binary {0, 1} is used as a term of variables or finite length vector of components for coding each individual.

For contenting the analogy of genetic, a connection has been made between these individuals and the chromosomes and the variables are similar to the genes. Therefore, it is genes (variables) that make a chromosome (solution). In order to represent the capabilities of a particular individual in competing, a score of fitness is assigned to every solution. The individual that has the near optimal or the optimal score is looked for. The objective of the GA is to apply the selective solution breeding for the production of better offspring than the parents by mixing the chromosomes information. A population including n chromosomes is maintained by the GA and this population includes the associated fitness values as well. According to the fitness of the parents, they are chosen to mate resulting to produce offspring through a plan of reproduction. As a result, more opportunities are given to the solutions with a high fit to reproduce so that the characteristics from each individual parent are inherited by the offspring. Since there is a static size for the population, room has to be generated for the new offspring as the parents mate (Holland, 1975).

In the population, the individuals die and their replacements are the new solutions. When all the mating possibilities are exhausted, eventually a fresh generation is created. The hope is that in the following generations more improved solutions are generated and the solutions with less fitness die out. New generations are produced as the solutions which include improved genes than a usual solution in a previously created generation. Each one of the following generations includes improved solutions than the one that was generated right before this current generation. At the end, when the population in no longer in the process of producing improved offspring compared to the previous generation, it is concluded that the algorithm is converged to a series of solutions for the objective problem (Goldberg, 1989). An improved GA was proposed by Nagendra et al. (1996) for finding the most appropriate sequence of stacking of the stiffeners laminate and the skin. In addition, GA was used by Xie et al. (2008) for the best design of the heat exchangers of plate fin. The total annual cost and minimizing this cost was the consideration of the authors and it was considered as the objective function and the constraint for this objective function was the pressure drop. In order to perform the second law based optimization for the heat exchangers of the plate fin cross flow, GA was used by Mishra et al (2009). The GA flowchart is drawn in Figure 2.1.

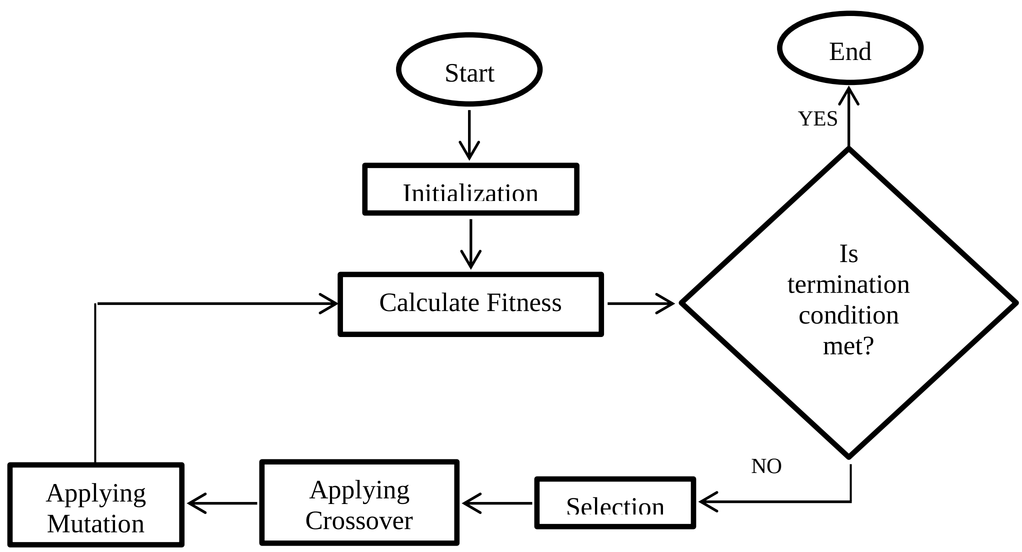

Figure 2. 1: Genetic algorithm flowchart

2- Ant colony optimization

Ant colony optimization (ACO) is an example for the design of meta-heuristic algorithm for the combinatorial optimization problems. In 1991, the very first algorithm that could be categorized in this type of framework was proposed by (Dorigo et al., 1991a). After that, it has been expanded from the basic principle.

In fact, a low level solution, which is also constructive, is driven by the ACO algorithms. However, these algorithms include the solution in a framework population and the construction is randomized in a Monte Carlo method. In addition, GAs also suggests the different solution elements with a Monte Carlo combination. However, in the ACO case, the distribution of probability is defined clearly by the solution components that have been previously obtained.

The basic idea of the Ant Colony was inspired by the ants' behavior in real life. Their parallel search on several computational threads, which are constructive and the search is based on the data about the local problem and a structure for dynamic memory that includes information about the quality of the results that have been previously achieved. The interactions among the different search threads have led to the emergence of collective behavior. This behavior has been proved to be effective for solving the problems of combinatorial optimization (CO).

The ACO has been very successful in many problems of combinatorial optimization such as vehicle routing problem (Bell and McMullen, 2004), and travelling salesman problem (TSP) (Dorigo et al., 1991b). The ACO flowchart is drawn in Figure 2.2.

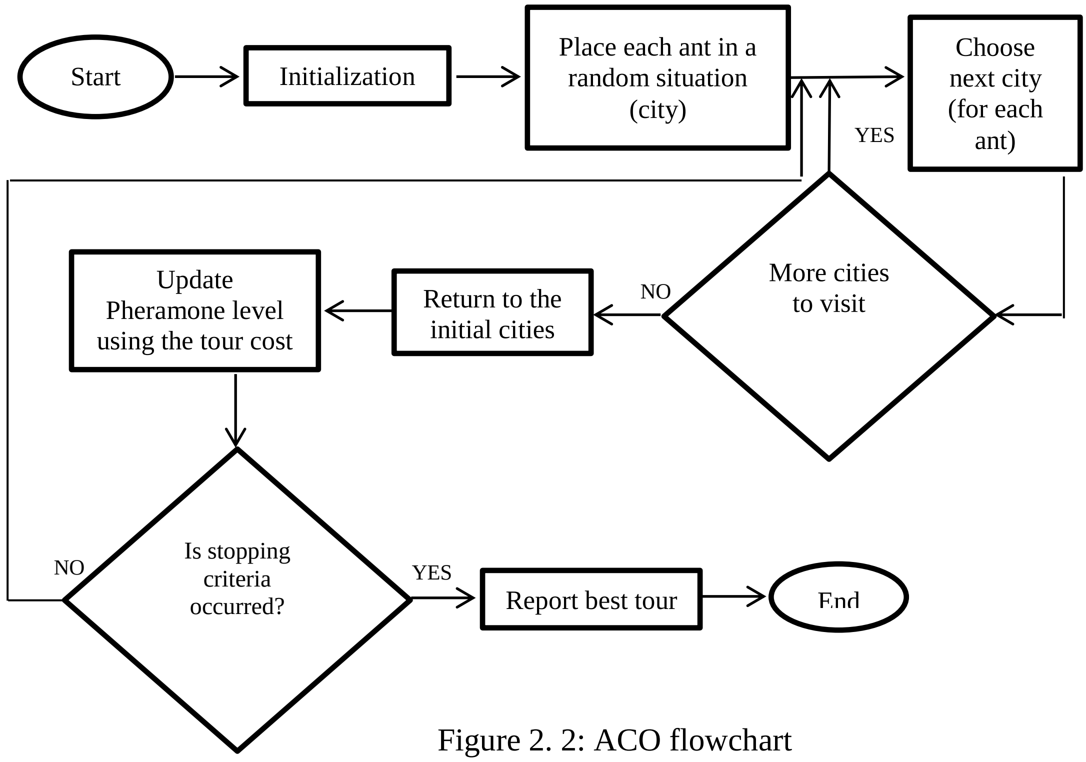

Figure 2. 2: ACO flowchart

3- Particle swarm optimization

The Particle Swarm Optimization or so called PSO is a technique for optimization which is stochastic and population based and it has been developed by Kennedy and Eberhart (1995). The inspiration of this method is by the social behavior of fish schooling or bird flocking. There are many similarities that the PSO shares with the computation techniques of evolutionary such as Genetic Algorithms. The initialization of the system is by a random solutions population and it tries to search for the optima by performing updates for generations.

However, not similar to the Genetic Algorithm, there are no operators of evolution for PSO. Some instances of these operators can be mentioned as the mutation and the crossover operators. The potential solutions of the PSO are known as the particles and they follow the current optimum particles to fly and go through the space of the problem. In the problem space, the coordinates of each particle is maintained by the particles themselves. However, only the coordinates, which are related to the best fitness (solution) that the particle has obtained so far are maintained (the value of the fitness is stored as well). This particular value is known as the *pbest.* In addition, there is another "best" value that the optimizer of the particle swarm tracks and it is the best value that has been achieved by any other particle in the neighborhood of the particle. This location of this neighborhood is called the *lbest.* At the time that a particular particle receives all of the population as the neighbors of topological location, the best achieved value is best globally and it is known as the *gbest.*

At each step of time, the concept of PSO includes the change in the each particle's velocity (accelerating) toward the locations of its *lbest* and *pbest* (the PSO local version). A random term weights the acceleration. Random numbers are separately generated for getting closer toward the locations of *lbest* and *pbest* (Kennedy & Eberhart, 1997).

Particles in the PSO are in a multidimensional search space and they can fly around. During the time of flying, the position of each one of the particles is adjusted by the particle itself according to the own experience of the particle and the experience of a particle in the neighborhood. This adjustment is in a way that the particle will be able to make use of the best position that its neighbor or itself has encountered (Bergh & Engelbrecht, 2006). Therefore, the local search is combined by an algorithm of PSO with the global methods of searching and it attempts to make a balance for the exploitation and the exploration. For the methods that can be applied in a wide range of applications, the PSO has been used. The PSO flowchart is drawn in Figure 2.3.

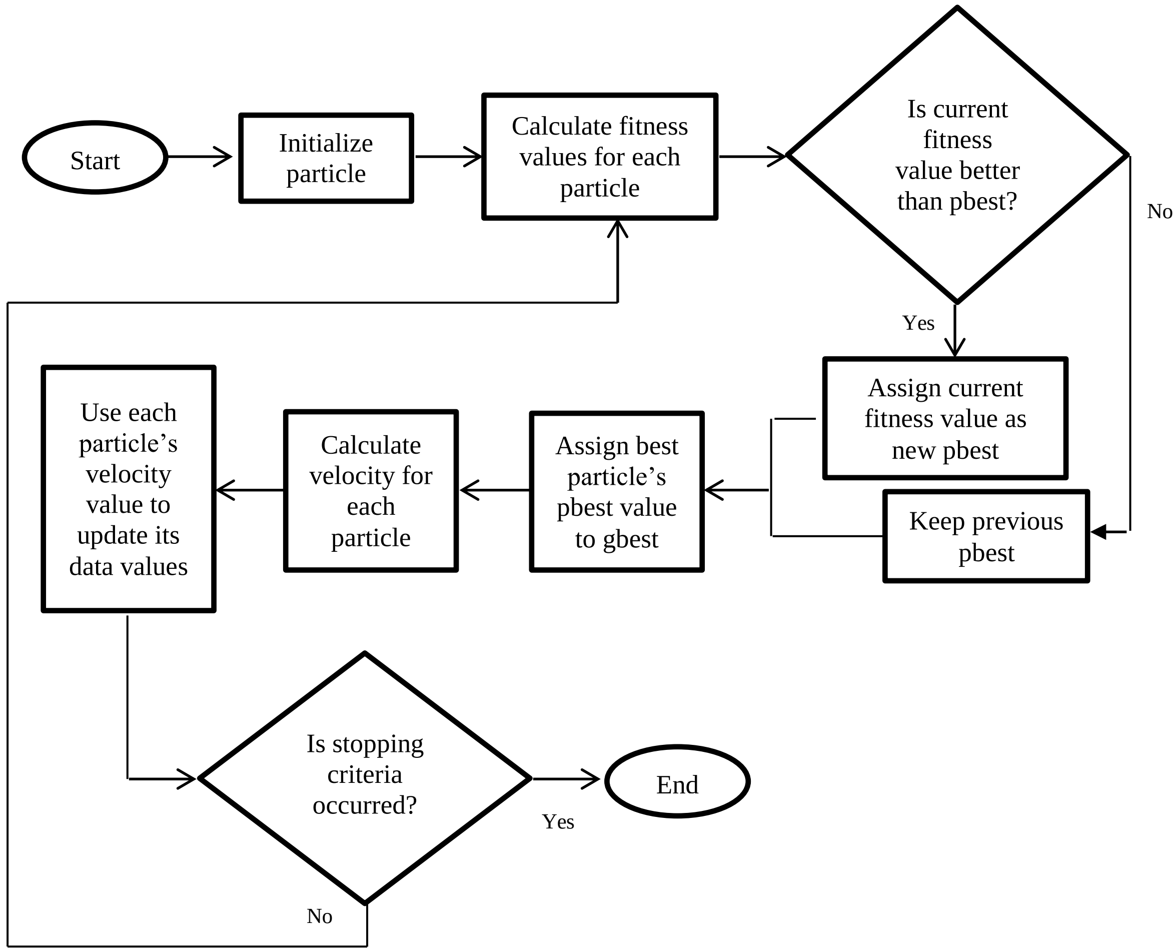

Figure 2.3: PSO flowchart

4- Simulated annealing

Simulated annealing (SA) is one of the most famous local search heuristics. It can be applied to a wide variety of combinatorial optimization problems (Lin et al., 2011; Van Breedam, 1995). It was introduced (Metropolis et al., 1953). When using the local search methods, one should know that a standard SA thoroughly searches a solution space by moving from an existing solution to another likely solution in its neighborhood. However, due to increase the possibility of finding better solution, the standard SA needs to be modified. Therefore, a multi-point version of SA can be considered for this study. At first, the number of predetermined initial solutions should be produced and it is known as best solutions. In each iteration, the algorithm produces some new solutions from the neighborhood of the current solutions and finds the best one between them and chooses this as a new solution. If a new solution appears to be better than the current solution, this new solution is termed as a best solution and the procedure is continued. In this process, the number of predetermined iterations is applied in each temperature level to improve the possibility of a set of appropriate solutions. However, sometimes the algorithm occurs in local optima. The procedure may escape from this issue by accepting worse solution with some conditions. This new solution with a worse objective function value can be accepted as the current solution with a small probability determined by the Boltzmann function, $exp(-\Delta/KT)$, where K is a predetermined constant and T is the current temperature in Boltzmann function (Lin et al., 2011). The M-SA flowchart is drawn in Figure 2.4.

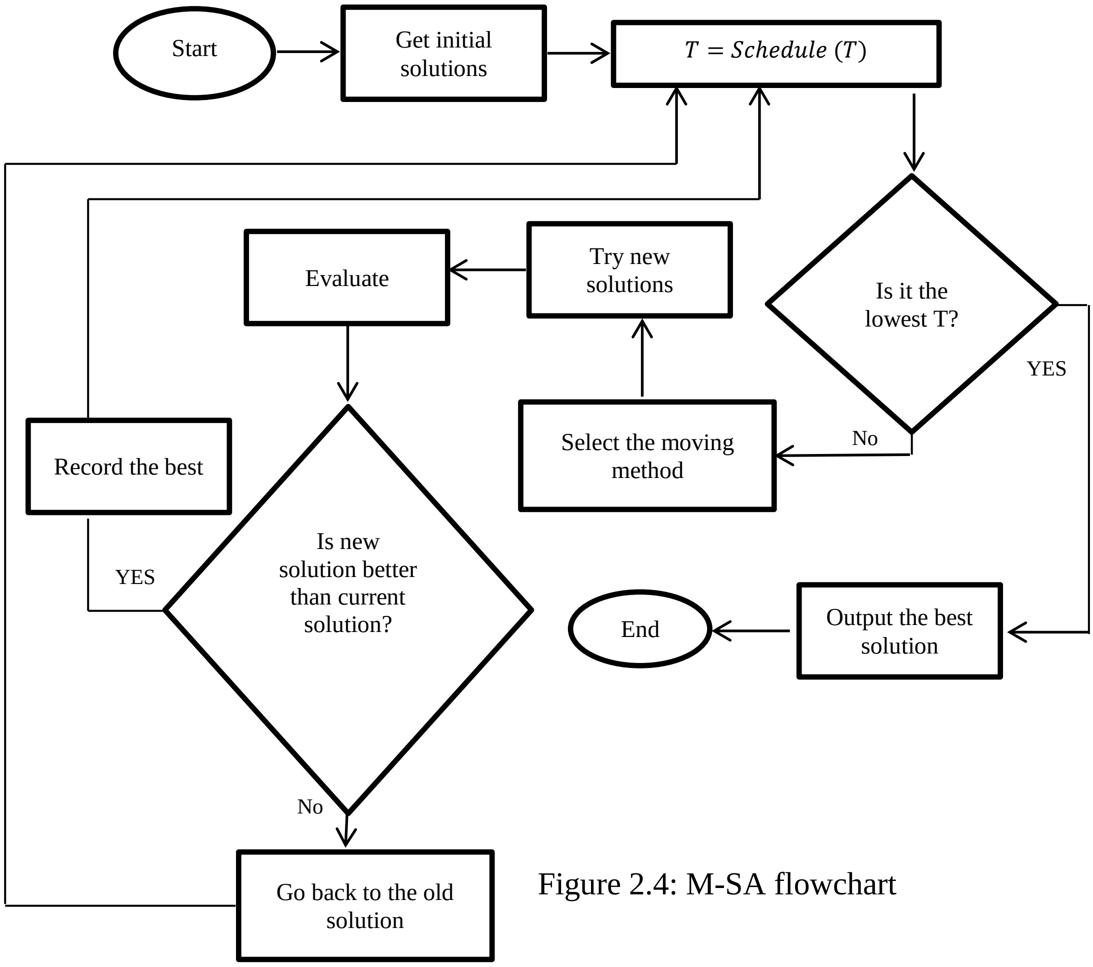

Figure 2.4: M-SA flowchart

5- Tabu search

Tabu search (TS) is a famous iterative local search heuristics. It can be applied to a wide variety of combinatorial optimization problems (Li et al., 2010). It was introduced by Glover (1986). A comprehensive version of TS was developed by (Glover & Laguna, 1993). At each iteration, the algorithm explores the solution space and produces a new solution from the neighbourhood of the current solution. Even if, the objective function value becomes worse with this new solution. A tabu mechanism is put in place to prevent the process from cycling over a sequence of solutions. An intuitive way to prevent cycles is to forbid the process from returning to previously encountered solutions, which is achieved by exploiting excessive bookkeeping. Some attributes of the past solutions are registered and any solution possessing these attributes may not be considered, and temporarily declared tabu for number of iterations (it is called tabu tenure). The TS flowchart is drawn in Figure 2.5.

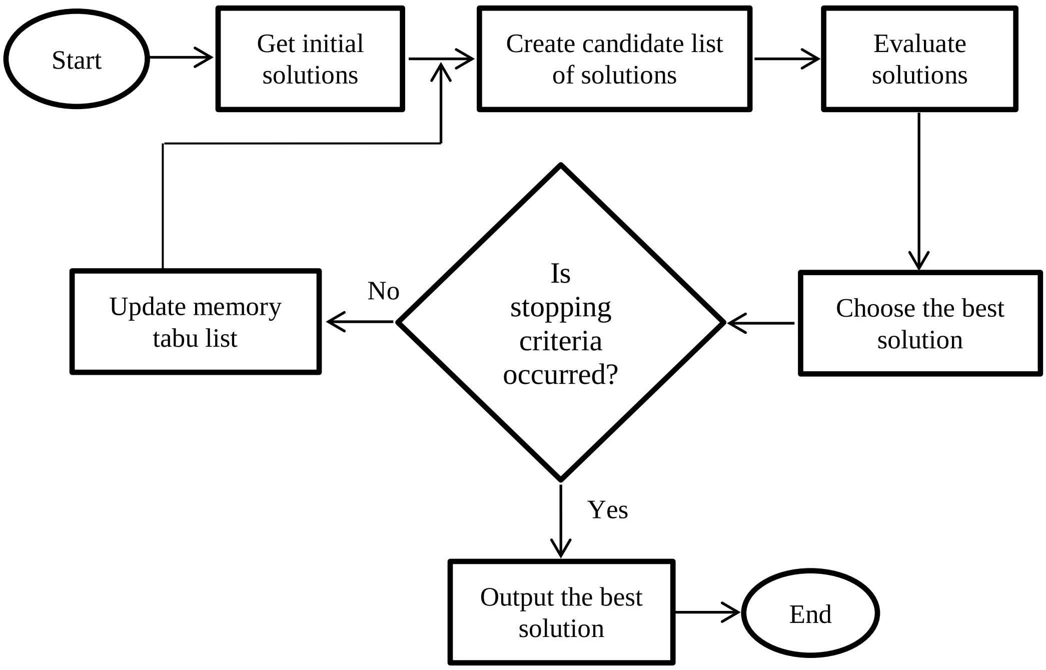

Figure 2.5: TS flowchart

6- Memetic algorithm

Memetic Algorithms (MAs) fit into the category of the evolutionary algorithms (EAs) where local search procedures are used to distribute the search area and enhance the search to refine individual. In fact, MA is a hybrid algorithm which combines the population and local search procedures to improve the initial solutions. The inspiration for MA has been realized from the adaptation models in the natural systems. These models combine the lifetime learning of an individual with the populations' evolutionary adaptation (Tavakkoli-Moghaddam et al., 2006). Besides, another inspiration of the MAs was obtained from the concept of meme from Dawkin. A cultural evolution unit is represented by this concept and it can indicate the local refinement (Tavakkoli-Moghaddam et al., 2006) and can be applied for solving TTRP.

In proposed MA, the population P consists of a set of individuals which are generated randomly. Each individual is called a 'chromosome', which is simply a permutation of the set of n nodes (customers) $\{1,2,\dots,n\}$ and N dummy zeros (artificial store or the root of sub-tour). This idea was initially proposed by (Beasley, 1983) as part of a route-first cluster-second heuristic, and was then used by (Prins, 2004). Recently, this method was applied to other versions of the VRP, such as heterogeneous fleets (Prins, 2009) and pickup and delivery vehicle routing problem (Velasco et al., 2009). The MA flowchart is drawn in Figure 2.6. All heuristic and meta-heuristic algorithms can be assessed based on five criteria: accuracy, speed, flexibility, simplicity and consistency (Cordeau et al., 2002). Accuracy measures the differences between the value which is obtained from heuristic and meta-heuristic algorithms and the actual optimal value. In addition, computational speed is important in SVRP, because sometimes solving a variant of SVRP with a particular algorithm consumes a lot of time and researchers might prefer to use another algorithm. Therefore, after solving SVRP, the time taken should be calculated. Mostly, accuracy and speed are against each other.

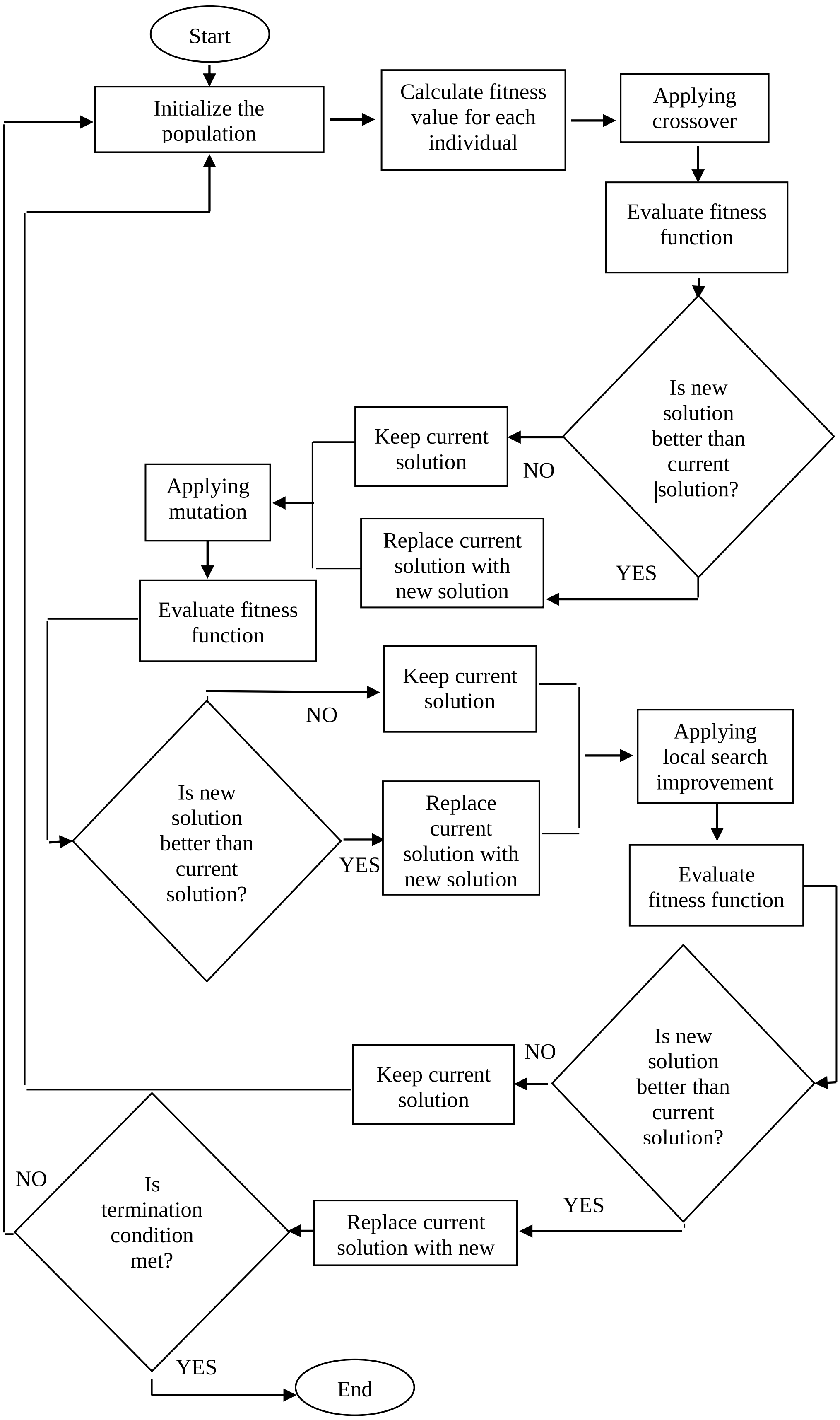

Figure 2. 6: MA flowchart

If the speed of algorithm is increased by changing the parameter such as temperature in simulated annealing by an operator, the accuracy may decrease and vice versa. In SVRP, most of algorithms cannot solve a problem for the optimal value. Hence, researchers compare their solutions with benchmark instances such as Christofides and Solomon benchmarks (Christofides et al., 1979; Solomon, 1987) and try to improve the best known values for each benchmark instance. In addition, consistency which is relevant to accuracy is important in heuristic algorithms particularly in SVRP. Researchers prefer algorithms which implement well for all models rather than algorithms which perform better for most of the time; however, some algorithms may have a poor performance over others (Cordeau et al., 2002).Also users prefer to get best values at an early stage to decrease the computing time whenever the speed is a priority; however, it depends on the case under the study where this strategy may be changed whenever accuracy is more important than speed. Flexibility and simplicity are two other important criteria in all heuristics, particularly in SVRP. Some of the algorithms are seldom used to solve the SVRP because they are too complicated or have too many parameters, and operator should have a confidence to customize these algorithms with problem. Hence it is difficult to understand and most researchers are not likely to use them (Cordeau et al., 2002). Therefore, some algorithms which have more flexibility can be appropriate for solving SVRP, because users should accommodate the algorithm after stochastic parameters are revealed. Because of that, most researchers define a penalty cost in their model to increase the flexibility of the algorithm. Some heuristic algorithms such as saving method, lagrangian method, sweep method, cluster method and Clarke and Wright and meta-heuristics such as tabu search, simulated annealing, genetic algorithm, neural network, ant colony, particle swarm optimization, adaptive memory, memetic algorithm and adaptive large neighborhood search have been proposed to solve variants of SVRP. In general, the accuracy and flexibility in meta-heuristics are higher than heuristics. However, meta-heuristics can involve more parameters but needs user confidence or experience (Cordeau et al., 2002). The heuristics and meta-heuristics algorithms are evaluated in Tables 2.4 and 2.5.

Table 2.4: Evaluation of some of the main SVRP heuristic algorithms

Heuristic algorithms	Accuracy	Speed	Flexibility	Simplicity	Consistency
Saving method	Medium	Medium	Low	Easy	Medium
Lagrangian method	High	Medium	Medium	Difficult	Medium
Sweep method	Medium	High	Medium	Easy	Medium
Cluster method	Medium	High	Low	Easy	Medium
Clarke and Wright	High	High	Low	Medium	Medium

Table 2.5: Evaluation of some of the main SVRP meta-heuristic algorithms

Meta-heuristic algorithms	Accuracy	Speed	Flexibility	Simplicity	Consistency
Tabu search	High	Medium	High	Medium	High
Simulated annealing	Very high	Medium	High	Medium	High
Particle swarm optimization	High	High	High	Medium	Medium
Genetic algorithm	Very high	High	High	Medium	High
Memetic algorithm	Very high	High	Very high	Medium	High
Neural networks	Very high	Medium	High	Difficult	Medium
Ant colony	Very high	Medium	High	Difficult	Medium
Adaptive memory	Very high	High	High	Difficult	Medium

2.6.2 Exact algorithms

Exact algorithms for SVRP can be classified into three groups: tree search method (Christiansen & Lysgaard, 2007; Laporte et al., 1989), integer linear programming (Laporte et al., 2002) and dynamic programming (Novoa & Storer, 2009; Pillac et al., 2013). In tree search methods, the purpose is to limit the constraints by calculating lower and upper bounds. Branch-and-bound, Branch-and-cut and Branch-and-cut-and-price are the three well-known methods in this group. Dynamic programming is used for optimization and re-optimization and can be formulated as a stochastic shortest path (SSP) approach (Novoa & Storer, 2009). In this method, service and routing decisions need to be made simultaneously and such decisions are made on the current system state. Each time the vehicle reaches at a location and observes the demands, the system state is then updated. In this system, there is no pre-planned course or which customers to be visited next and should be considered at each stage. The other decision to minimize the expected routing costs is whether or not to send the vehicle to the depot for replenishment (Pillac et al., 2013). Exact algorithms can be studied by four criteria: speed, flexibility, simplicity and scale. The number of customers which can be addressed by the algorithms in a reasonable time in SVRP is called scale. In exact methods, users do not consider accuracy as an important criterion because the most significant difference between exact and heuristics is that the first one gives a precise solution; however, the heuristics produce a proximate solution. So accuracy is not an important criterion in exact methods. In past few decades, many different exact algorithms have been proposed. All of them have some positive and negative aspects. For most researchers, speed and scale of the algorithms are more important criteria than others. If the number of customers is increased in SVRP, users should consume more time to find an appropriate solution and researchers should consider speed and scale of algorithm together. In addition, flexibility and simplicity are two other criteria that should be considered in these algorithms. Researchers compare their solutions with the benchmark instances and try to improve their algorithms by using wider instances (Novoa & Storer, 2009). Some exact algorithms such as dynamic programming, branch and bound, branch and cut (Gounaris et al., 2011), branch and cut and price (Bettinelli et al., 2011; Christiansen & Lysgaard, 2007) and L-shaped algorithms (Laporte et al., 2002; Lei et al., 2011) have been used in SVRP. In general, an exact algorithm is designed for a special case, so it might not have a good flexibility. However, among the exact algorithms, dynamic programming can provide the highest flexibility. Based on the main criteria of evaluation, different exact algorithms are compared and are placed in Table 2.6.

Table 2.6: Evaluation of some of the main SVRP exact algorithms

Exact algorithm	Speed	Flexibility	Simplicity	Scale
Dynamic Programming	Medium	High	Difficult	Medium
Branch-and-bound	Medium	Low	Easy	Small
Branch-and-cut	Medium	Low	Easy	Small
Branch-and-cut-and-price	Medium	Low	Medium	Medium
L-shaped algorithm	Medium	Medium	Medium	Large

2.7 TTRPs and solution algorithms

The level of activities on the subject of VRP and the variations of VRP has been very high in the last decades. However, as far as it's known, the attention that has been given to the subject of TTRP and its applications is limited. Table 2.7 indicates that some of the practical applications have also addressed the TTRP. One of the most related ones is the raw milk collection. For more details about this application, the reader might be referred to (Derigs et al., 2013; Villegas et al., 2013).

Table 2.7: Classification of truck and trailer routing problem (TTRP)

Authors	**Algorithm**	**Specific features and limitations**
Semet and Taillard (1993)	Tabu search	Time windows, vehicle-dependent variable costs; Cannot consider sub-tour
Semet (1995)	Two-phase heuristic based on Fisher and Jailumar (1982)	The number of trailer needs to be determined; Maximum one sub-tour can consider
Gredessen (1996)	Two-phase heuristics: construction and improvement	Each customer must have unit demand
Chao (2002)	Construction heuristics and Tabu search	Standard TTRP
Scheuerer (2006)	Construction heuristics and Tabu search	Standard TTRP
Hoff and Løkketangen (2007)	Tabu search	Standard TTRP
Lin et al. (2009)	Simulated annealing	Standard TTRP
Lin et al. (2009)	Simulated annealing	A relaxation of TTRP
Lin et al (2009)	Simulated annealing	TTRP with time windows
Villegas et al. (2010)	Variable neighborhood descent (VND) and greedy randomized adaptive search procedures (GRASP)	Single TTRP with satellite depots
Villegas et al. (2011)	A hybrid algorithm based on the GRASP/VND and a path relinking (PR) algorithm	Single truck and trailer routing problem with satellite depots
Villegas et al. (2013)	A hybrid algorithm based on the GRASP and an iterated local search (ILS)	Single truck and trailer routing problem with satellite depots
Derigs et al. (2013)	A hybrid algorithm based on large neighboorhood search (LNS) and local search (LS)	TTRP without load transfer between truck and trailer with time window

2.8 SVRPs and solution algorithms

SVRPs are classified into three groups: VRP with stochastic demand, VRP with stochastic customers, and VRP with stochastic travel and service time. Also it may be partitioned into single depot, multi depot and multi compartments. Table 2.8 considers the algorithms which are used to solve a variety of stochastic VRP real-life problems. Researchers have to decide the suitability of an algorithm for solving SVRPs.

Table 2.8: Classification of stochastic vehicle routing problems (SVRP)

Authors	VRPSD	VRPSC	VRPST	Algorithm	Specific features and limitations
Tillman (1969)	Not exactly SVRP but is helpful for introducing SVRP	----------	----------	Clarke and Wright	Single depot, consider only the basic concept
(Golden & Stewart, 1978)	Introduced VRPSD considering the penalty cost for return trips	----------	----------	Clarke and Wright	Single depot, considered only the basic concept
(Dror & Trudeau, 1986)	VRPSD with single depot	----------	----------	Savings algorithm	Presented new recourse action method in 1986
(Laporte et al., 1989)	consider stochastic location routing problem with single depot	----------	----------	Integer linear programs	The recourse action need to be calculated completely
(Bertsimas, 1992)	Modeled with single depot and recourse action	Modeled with single depot and recourse action	----------	Branch-and-bound	Use the basic concept of recourse action that could be used as a good reference for SPR
(Teodorović & Pavković, 1992)	VRPSD with single depot	----------	----------	Simulated annealing	Recourse action and route fauilare need to be considered in the model
(Laporte & Louveaux, 1993)	Consider stochastic integer programming with recourse action	----------	----------	Integer L-shaped	Only binary variables are considered
(Gendreau et al., 1995)	VRPSD with single depot and recourse action	VRPSC with single depot and recourse action	----------	Integer L-shaped	Need to be considered with multi depot and for large scale problems.
(Gendreau et al., 1996b)	VRPSD	VRPSC	----------	-------	explained variants and algorithms of SVRP in 1996
(Gendreau et al., 1996a)	VRPSD with single depot and recourse action	VRPSC with single depot and recourse action	----------	Tabu search	Can be considered with multi depot or heterogeneous fleet vehicle

Table 2.8, continued: Classification of stochastic vehicle routing problems (SVRP)

Authors	VRPSD	VRPSC	VRPST	Algorithm	Specific features and limitations
(Secomandi, 2000)	VRPSD with single depot	----------	----------	Neuro-dynamic programming	Can be considered with multi depot and cost-to-go estimation.
(Yang et al., 2000)	Single and multi VRPSD with single depot	----------	----------	Tabu search	Can be considered with multi depot and for large scale
(Protonotarios et al., 2000)	VRPTWSD with single depot and heterogeneous fleet vehicle	----------	----------	Genetic algorithm	The paper considered customer satisfaction
(Bianchi et al., 2004)	VRPSD with single depot	----------	----------	SA, GA, TS, ACO	Some meta-heuristic algorithms are Compared
(Bianchi et al., 2006)	VRPSD with single depot	----------	----------	SA, GA, TS	Hybrid algorithm is considered in this paper
(Tan et al., 2007)	Multi-objective VRPTWSD with single depot	----------	----------	Evolutionary algorithm	Consider routing schedules, driver remuneration, and number of vehicles
(Haugland et al., 2007)	VRPSD with single depot	----------	----------	Tabu search	designing districts for vehicle routing problems with stochastic demands is introduced
(Christiansen & Lysgaard, 2007)	VRPSD with single depot	----------	----------	Branch-and-price	Can be considered with meta-heuristic algorithms and multi depot
(Hvattum et al., 2007)	VRPSD with single depot	VRPSC with single depot	----------	Branch-and-Regret, dynamic programing	Real life issue in Norway. Consider dynamic and stochastic vehicle routing problems.
(Liu et al., 2008)	VRPSD with single depot	----------	----------	Tabu search	Tabu search and genetic algorithm are compared in this paper
(Novoa & Storer, 2009)	Single VRPSD using cost-to-go estimation	----------	----------	Dynamic programming	Can only considered single VRPSD with unit distribution demands
(Secomandi & Margot, 2009)	Single VRPSD with single depot under re-optimization concept	----------	----------	Partial reoptimization	Consider a finite-horizon Markov decision process
(Shen et al., 2009)	Considered VRPSD under CCP	----------	Considered stochastic travel times	Tabu search	Considered stochastic demand and travel times simultaneously

Table 2.8, continued: Classification of stochastic vehicle routing problems (SVRP)

Authors	VRPSD	VRPSC	VRPST	Algorithm	Specific features and limitations
(Ismail & Irhamah, 2010)	VRPSD with single depot	----------	----------	Genetic algorithm, tabu search	real life case in waste collection, need to be considered with SPR recourse action
(Mendoza et al., 2010)	VRPSD with multi-compartment	----------	----------	Memetic algorithm	An extension of VRP with multi-compartment
(Li et al., 2010)	----------	----------	Consider VRPSTTW with CCP and SPR concept single depot	Tabu search	Multi-depot can be considered to transform the problem into more practical form than what single depot can do
(Lei et al., 2011)	Consider VRPSDTW with SPR concept with single depot	----------	----------	Adaptive large neighborhood	capacitated VRPSD and time windows is modeled and introduced
(Mendoza et al., 2011)	Multi compartment VRPSD	----------	----------	Clarke and Wright, memetic algorithm	Restocking can be considered for extention of this paper
(Hu & Liu, 2011)	Multi objective VRPSD with single depot	----------	----------	Tabu serach	Considered routing distance and number of vehicles
(Goodson et al., 2012)	VRPSD with single depot	----------	----------	Simulated annealing	Try to expand the problem considering multi depot or heterogeneous fleet vehicle
(Lei et al., 2012)	----------	----------	VRP with stochastic service time with single depot	Generalized variable neighborhood	Service cost can be considered in the model for further research
(Moghaddam et al., 2012)	VRPSD with single depot	----------	----------	Particle swarm optimization	Can be considered with multi depot and heterogeneous fleet vehicle
(Agra et al., 2013)	-----------	----------	VRPST with time windows and single depot	Dynamic programming, robust linear programming	The paper uses robust approach and considers real instances from maritime transportation
(Taş et al., 2013)	----------	----------	VRPST with single depot	Tabu search	Considering total distance traveled, number of vehicles used costs
(Marinakis et al., 2013)	VRPSD with single depot	----------	----------	PSO	Considered PSO algorithm with the 2-opt and 3-opt local search algorithms

Table 2.8 illustrates that many researchers preferred to improve their initial solutions with meta-heuristics algorithms, particularly preferred to utilize local search algorithms such as tabu search and simulated annealing. This preference was given with a view to achieve an appropriate solution in a reasonable time length using these algorithms (Cordeau et al., 2002). However, population search algorithms such as GA, ACO and PSO are used for SVRP. Indeed, these meta-heuristics algorithms are used for combinatorial optimizations and for using them, a user needs to customize the algorithm for SVRP.

As said earlier, some researchers used exact algorithms such as dynamic programming and integer programming. They preferred to see the problems mathematically. So they modeled their problems precisely and used the dynamic and integer programming algorithms to solve SVRP. For using meta-heuristic algorithms, the problem is not necessarily to be modeled mathematically.

In addition, it should be mentioned that most of the researchers in this area prefer to consider SVRP with stochastic demands. However, the common real life issues such as traffic jam or road conditions may affect service performances. Consequently, those issues may change the travel and service times (Li et al., 2010). Therefore, various aspects of VRPST such as soft or hard time windows, service time and service cost with different constraints need to be considered. And, different algorithms may be recommended for solving VRPST in order for comparing the results and coming up with the best solution.

2.9 Research Direction

It is obvious that very little research has been conducted in TTRP. These days truck and trailer routing problem (TTRP) solving in broader perspectives are gaining extensive attention in research and applications than earlier. Therefore, its variants and solution approaches need to be reviewed to cope up with the research advancements and the real-world needs. From the above literature review, the following research directions or conclusions can be considered as follows:

1. TTRP model is only solved by a few algorithms; however, this problem can be solved using other algorithms to improve the results.
2. TTRP with stochastic demands model needs to be considered. Due to prevent unexpected extra cost to the company since the company may face a problem of delivering the right volume of products' to customers for these random demands.
3. TTRP with stochastic travel and service time needs to be considered. Due to prevent unexpected extra cost to the company since route duration may exceed the threshold of a driver duration and driver may need to work more than the predetermined working hours.

CHAPTER 3: METHODOLOGY

3.1 Introduction

This Chapter presents a short research methodology. The detailed methodology of formulation of each model is given in the following Chapters. The research frameworks and mathematical formulations were done based on extensive literature review in area of supply chain management (SCM) and transportation. This work was conducted based on the necessity of stochastic transportation cost in SCM. The models can be divided into two types, TTRP with stochastic demands and TTRP with stochastic travel and service time. These are relevant in modeling the stochastic truck and trailer routing problems (STTRPs). The proposed models were tested by real-life data. Also, some benchmark instances were modified for each case. In addition, the problems were tested using sensitivity analysis to understand the effects of the parameters. Finally, the method of data collection is explained in this Chapter.

3.2 Sources of Theoretical Information

Inevitable authentic knowledge sources were considered for required review for locating the further needs of research. Currently, the internet is considered as one of the most important information sources, which includes theoretical material. Some of the search engines such as ISI Web of Knowledge, Google, Springer, Science Direct, ProQuest and Emerald were used for downloading authentic papers for this research as reliable information. After probing the papers, an inclusive reference of the literature about the variant of SCM, VRP and TTRP and their related solution approaches was achieved. In addition, the papers, which were published in edited books, proceedings, and peer-reviewed journals, were gathered. The conduct of the search about the literature review was based on the following key words: “trailer and truck routing problem", "Stochastic vehicle routing problem", and "vehicle routing problem". Initially, each paper was fully reviewed so that the unrelated articles to the SCM, VRP and TTRP and their related solution methods could be separated. Unpublished working papers, doctoral dissertations, and conference papers were rarely included. However, it was probable that a few numbers of the published papers were not included. At last, close to 110 authentic papers were utilized from more than twenty journals. The selected papers were thoroughly reviewed for stochastic methods of TTRP. In the literature review chapter, the relevant contents to the research topic and the content of this work have been presented.

3.3 Approach applied in the research

This research has been done since September, 2011. The literature review phase can be divided into four sections. The first one discussed about the necessity of considering transportation cost in SCM. As vehicle routing is one of the well-known and basic transportation problems, a series of instructions need to be taken into account by a vehicle routing system in order to inform the drivers what to deliver, where and when. The second and third parts studied stochastic vehicle routing problem, truck and trailer routing problem and their variants. These parts were used for formulating the proposed models. In the last part, the algorithms which may be used for solving stochastic truck and trailer routing problem were classified.

This work was conducted based on the theories and concept involving SCM and stochastic TTRP for establishing efficient mathematical models, which can be used in real-life SCM problem. The expansion of the literature review is for introducing a number of essential issues that manufacturers are facing. However, the past researchers in the area have not sufficiently considered these issues. The methodological flowchart of this research is shown in Figure 3.1.

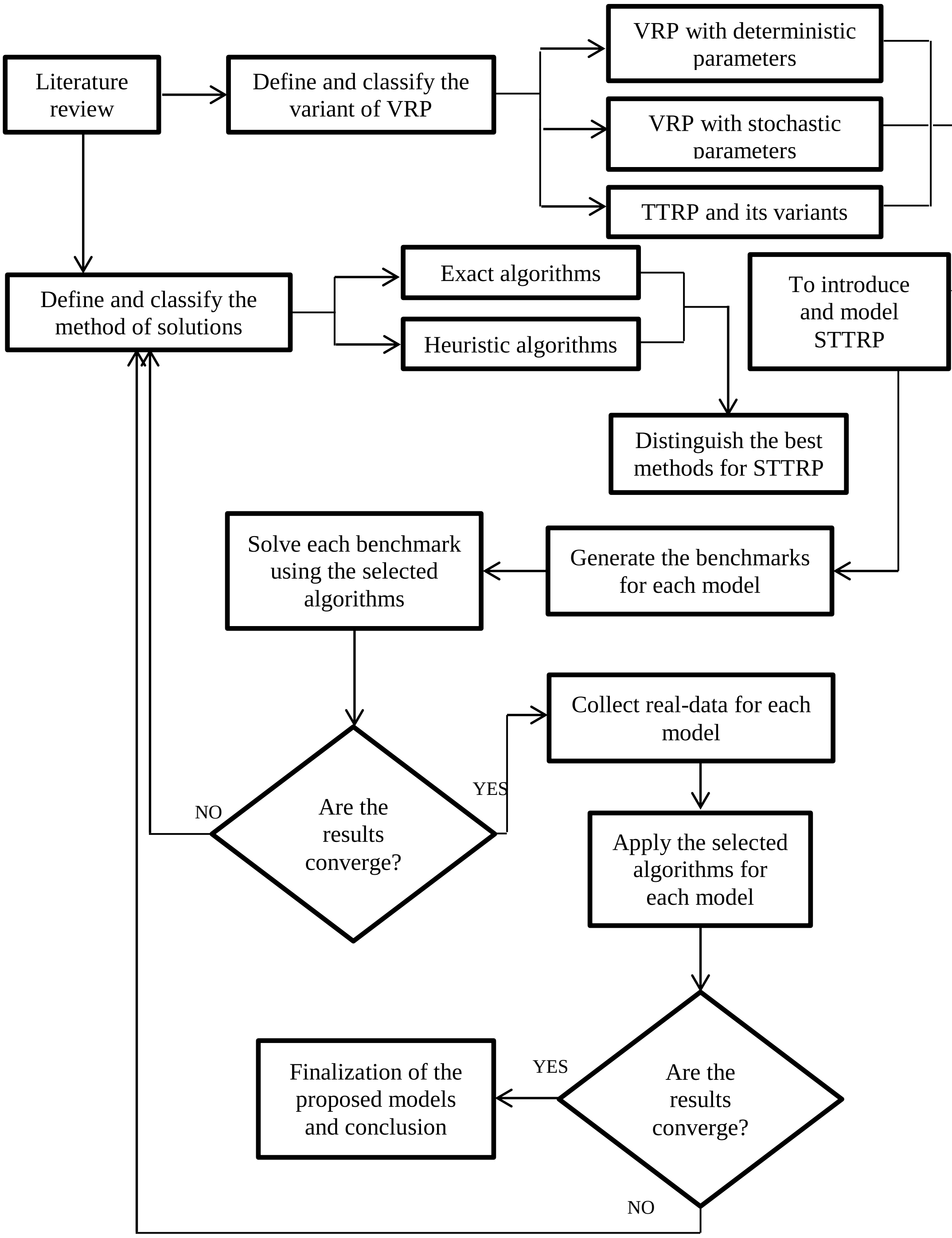

Figure 3.1: Methodological flowchart of this research

3.3.1 Benchmark instance problems

For TTRP problem, 21 benchmark instance problems were generated by Chao (2002). Since stochastic TTRP is considered in this research, no benchmark instances are available to compare the solutions that are used in solving stochastic TTRP. As three new models have been considered in this research, three set of benchmarks were modified for this purpose. The first benchmark is for TTRP with stochastic demand. The special 21 TTRPSD benchmark instances have been modified which are derived from Chao (2002) for the truck and trailer routing problem with deterministic demands (TTRP). The coordinates of vertices are the same as in the Chao's instances. The customer demands are stochastic and are generated with Poisson distributions having a mean value equal to the customer average demand. However, due to increasing possibility of failure on the route, the capacity of the truck and trailer is less than Chao's benchmark, because the failure has rarely occurred with its capacities.

The second benchmark is for TTRPSDTW. To generate the benchmark for TTRPSDTW, the special 54-benchmark-instance problems are modified in three different classes, as derived from Lin (2011). The numbers of customers are 50, 100 and 200 in the first, second and third classes, respectively. The coordinates of the vertices are the same as in Lin's (2011) instances. The customers' demands are stochastic and were generated with Poisson distributions having a mean value equal to the customers' average demand. However, same as TTRPSD benchmarks, due to the increasing possibility of failure on the route, the capacity of the truck and trailer is less than Lin's benchmarks because failure has rarely occurred with its capacities.

The third benchmark is for TTRP with stochastic travel and service time with time windows (TTRPSTTW). One hundred and forty four benchmark instances in six levels have been produced for this study. Firstly, some instances with different properties have been selected from the basic test problem of Li et al (2010) with 50 and 100 customers and three different scheduling horizons, i.e., R1, R2, and R3. The problem in R1, R2 and R3 have short, medium and long scheduling horizons, respectively (Li et al., 2010). Then each problem were converted into three new TTRPSTTW problems by the following description. The distances between each customer and its nearest customer is calculated and symbolized as A_i. Sixty percent of the customers with the largest A_i values are put as TCs in the first problem. This is decreased to forty and twenty percents for the second and third problems, respectively. The remaining customers were specified as VCs. The coordinates of vertices and demands were the same as in the Li's instances. Also the number of trucks and trailer and their capacities were customized for this problem. In addition, the travel and service times between customers are stochastic with normal distributions $(\mu_{ij}, \sigma_{ij}^2)$ having a mean value equal to deterministic travel times from Li et al. (2010). Furthermore, σ_{ij}^2 is a randomly generated integer value taken from $[1,4]$. All distances and travel times are considered in meters and minutes, respectively. Also the time window constraints are same as Li et al (2010) and the capacity of trucks and trailers are 300 and 200, respectively.

3.3.2 Data Collection method

A real case study from an Iranian dairy company has been considered for this Research. It is Pegah Co, a large dairy distribution company in Iran, whose products are distributed to more than 50,000 retailers (customers) in Iran and some other countries. Iran Dairy Industries Co. (IDIC) is the largest dairy producer in Iran with "PEGAH" brand. This factory produces some dairy products such as Pasteurized and UHT milk, flavored milk, pasteurized and UHT cream, a variety of cheese (process, slice, pizza, UF), different kinds of yoghurt, probiotic products (such as yoghurt, cheese, ice cream), and drinking yoghurt (see Appendix-A).

For case study, the data were collected through two methods. With securing the formal permission from university and company sides, the company documents were collected. To augment the data available through these documents, customers were interviewed. Repeated contacts were made with the company and customers to get the right data in terms of volume and authenticity (see Appendix-B). To implement the TTRPSD model for this case, 100 customers were selected based on their stochastic demands and the types of customers. To select the customers, the last 20 demands of each customer were realized and the customers of stochastic demands with the Poisson distribution were selected for this research (see Appendix-C). Then the customers' locations were determined to compute the travel distance matrix between the customers and the depot. Furthermore, the type of each customer was distinguished and the truck customers (TCs) and the vehicle customers (VCs) were classified into their respective groups, where 30 customers were TC and the remaining customers were VC. The demands were measured based on their weights. The company considered 5 trucks and 3 trailers to serve these customers. The capacity of a truck and a trailer are 2000 and 3000 kilograms, respectively. Also, this method was used to implement the TTRPSDTW and TTRPSTTW models.

3.4 Model assumptions

In the mathematical programming, it is inevitable to make the pertinent assumption. It is assumed that $m_k \geq m_r$, as considered by Chao (2002), Scheuerer (2006) and Lin et al. (2009). It is assumed that all trucks and all trailers have their respective constant capacities, such as Q_k and Q_r, respectively.

The assumptions relevant to TTRP with stochastic demands are as follow:

1. All demands are independent random variables with known distributions.
2. Each demand ξ_i is a non-negative random variable and never exceeds the truck capacity. So, since each demand must be less than the truck capacity, $P\{\xi_i \leq Q_k\} \cong 1 (v_i \in V \backslash \{v_0\})$.

3. A maximum of one return trip to the root is possible during any sub-tour (ST) and a maximum of one return trip to the depot can be allowed on any main tour (in a complete route). Because more than one failure is impossible on any kind of route r_k.

$$P\{\sum_{v_i \in r_k} \xi_i < 2(Q_k + Q_r)\} \cong 1 \qquad \text{If } r_k \in \text{PVR and CVR}$$

$$P\{\sum_{v_i \in r_k} \xi_i < 2(Q_k)\} \cong 1 \qquad \text{If } r_k \in \text{PTR and ST}$$

This failure means that the demand of a customer cannot be satisfied while serving the customers since the vehicle does not have enough capacity to serve the respective customer and has to come back to the depot (or parking place) and fill the capacity and return to the respective customer to serve it completely. This assumption is considered to ensure that this failure may occur a maximum once. Therefore, the cumulative demand of the customers must be less than twice the route capacity in the worst case.

4. Customers whose time windows are violated must be served by a single trip from the depot, which imposes an additional cost equal to the distance between a customer and the depot multiplied by two. Each customer with this condition is serviced with a special single trip.

The assumptions relevant to TTRP with stochastic travel and service time are as follow:

1. Each customer is associated with a deterministic and non-negative demand q_i that has to be met.
2. Time windows constraints are considered for each customer and a stochastic service time is imposed when visiting a customer
3. The travel times between customers are considered stochastic.

CHAPTER 4: FORMULATION ON TTRP WITH STOCHASTIC DEMANDS

4.1 Introduction

This Chapter discusses on formulation and solution of a truck and trailer routing problem in which demands are stochastic (TTRPSD) in nature. This work is an advancement of the well-known truck and trailer routing problem (TTRP). TTRP is a variant of the vehicle routing problem (VRP). In general, TTRP is more extensive than VRP and can cover more real life aspects since some limitations in VRP as mentioned in Chapter 1 can be considered in TTRP.

4.2 Formulation on TTRP with stochastic demand

TTRPSD is defined as an undirected graph $G = (V, E)$, where the set of vertices is $V = \{v_0, v_1, v_2, \ldots, v_n\}$ and $E = \{(v_i, v_j) : v_i, v_j \in V, i < j\}$ is the set of edges. The central depot is represented by 'v_0' and the other vertices in $V \setminus \{v_0\}$ correspond to customers. Each vertex v_i is associated with a stochastic and non-negative demand ξ_i. They can be split and are unknown until the vehicle arrives at the vertex. A customer type t_i is available for all customers, where $t_i = 1$ shows that customer v_i is a truck customer (TC) and can be serviced only by a single truck. If $t_i = 0$, a customer i is a vehicle customer (VC) and it can be serviced by a single truck or a complete vehicle (truck pulling a trailer). $C = (c(v_i, v_j))$ is a symmetric travel cost, which is defined on E. It is assumed that all vehicles are the same and have a unit speed, so the travel cost is equal to the Euclidean distance between v_i and v_j. Say a fleet of m_k and m_r, trucks and trailers, respectively, is available. However, some trucks and trailers may not be used at any time in the TTRPSD solution. Without loss of generality, it is assumed that $m_k \geq m_r$, as in Chao (2002) and Scheuerer (2006) and Lin et al. (2009). All trucks have the same capacity Q_k, and all trailers also have the same capacity Q_r, where Q_k and Q_r are different.

Three types of route are available in TTRPSD as follows: 1) a pure travel route (PTR), which can be travelled by only a single truck; 2) a pure vehicle route without any sub-tours (PVR), which can only be travelled by a complete vehicle; 3) complete vehicle route (CVR), which consists of a main tour and at least one sub-tour. A sub-tour starts and finished at the same VC (v_r) (the trailer is parked in a parking place which is called the root) and it can be travelled only by a single truck; however, it should be serviced by a complete vehicle in the main tour. It is assumed that shifting demand loads between the truck and the trailer is possible at the parking places. In addition, it should be mentioned that there may be a lack of capacity in serving the customers since the customers' demands are stochastic. Therefore, the vehicle must return to the depot or to the parking place (while the truck is delivering on the sub-tours) and re-fill to capacity to serve the remaining customers. This is the so-called failure in the route.

The TTRPSD can be cast as stochastic programming. Two main solution concepts for solving the aforesaid types of TTRPSD can be discerned from stochastic programming (Lei et al., 2011). The first is known as chance constrained programming (CCP). In CCP, the problem can be solved by imposing a constraint ensuring that the probability of route failure is bounded by some parameters, such as time limitation and service time (Li et al., 2010; Lei et al., 2011). This concept attempts to convert stochastic parameters to equivalent deterministic values. For instance, the TTRPSD can be converted to an equivalent deterministic program. Stewart and Golden (1983) and Laporte et al. (1989) demonstrated this transformation by considering the statistical relationships among the parameters. The second concept is stochastic programming with recourse (SPR). Two main solution strategies are available under SPR. The first is known as *a priori* optimization (Bertsimas, 1992; G. Laporte et al., 2002; Jorge E.

Mendoza et al., 2010; Tan et al., 2007) and the second is re-optimization (Psaraftis, 1995; Secomandi & Margot, 2009). In an *a priori* optimization solution, the set of tours and sub-tours is constructed in the first stage. Recourse actions considering random variables are then revealed. The common recourse policy in TTRPSD is as follows: if the cumulative demand exceeds the vehicle capacity on the main tour (it means that the cumulative demand exceeds the summation of capacities of truck and trailer on the main tour up to a vertex), the vehicle returns to the depot to unload, fills the capacity (truck and trailer) and then comes back to the last visited vertex. However, if the vehicle capacity is reached exactly for any vertex on the main tour (it means that the cumulative demand is equal to the summation of capacities of truck and trailer on the main tour up to a vertex), the vehicle should return to the depot, fills the capacity and then start servicing from the next vertex along its route. But if the cumulative demand exceeds the truck capacity on the sub-tour, the vehicle should return to its root to upload, use the remaining trailer capacity and return to the last visited vertex on the sub-tour. In addition, if the truck capacity exactly reached the customer demand for any vertex on the sub-tour (it means that the cumulative demand on the sub-tour is equal to the truck capacity up to a vertex), the truck returns to the root, using the remaining trailer capacity to fill the truck and comes back to the next vertex on the sub-tour.

The TTRPSD consists of designing the first-stage routes, including the truck route, vehicle route and complete route, satisfying all constraints and if a failure occurs, a recourse action is applied. The purpose is to minimize the sum of the total distance of the first-stage routes and the expected recourse costs.

4.2.1 The expected cost of a solution

Since all trucks and trailers in their respective groups are the same, each having its own features in terms of capacity and associated unit speed, the cost is associated with the distance travelled. Initially, the expected recourse cost (distance) is computed under the assumptions mentioned in Chapter 3. These assumptions have been used to generate the TTRPSD benchmarks and the recourse costs will be computed based on these assumptions. This assumption is considered to ensure that this failure may occur at most once in a route. Therefore, the cumulative demand of the customers must be less than twice the vehicle capacity in a worst case scenario. Then the total cost is computed.

4.2.2 Mathematical estimation of the total expected cost

It should be considered that TTRPSD has three different types of route. Each route is planned in the first stage of the solution $R = (r_1, r_2, \dots, r_m)$, where $r_k = (v_0^k = v_0, v_1^k, \dots, v_{n_k}^k, v_{n_k+1}^k = v_0)$. Objective function $T(R)$ is the summation of two terms: $\Phi(R)$ and $\theta(R)$, where $\Phi(R)$ is the deterministic cost of the planned routes and $\theta(R)$ is the expected cost of recourse.

$$T(R) = \Phi(R) + \theta(R) \tag{4.1}$$

The computation of $\Phi(R)$ is easy. The cost of each route should be found and the costs of all routes that are planned in the first-stage should be computed. Refer to Lin et al. (2009), the estimation of $\theta(R)$ is complicated and will be computed later in this section. First of all, the probability of failure should be computed.

The probability of the cumulative demand up to the customer v_i^k, on a route r_k, can be calculated by the following recursive equation. This equation is an extension from (Lei et al., 2011), where $P_{\xi_0^k}(t)$ is a boundary condition for this equation and $P_{X_i^k}(t) = P\{X_i^k = t\}$.

$$P_{X_i^k}(t) = \sum_{d=0}^{t} P_{X_{i-1}^k}(t-d)\mathrm{P}_{\xi_i}(d) \tag{4.2}$$

For instance, considering $P_{X_0^k}(t) = P_{\xi_0^k}(t)$, $P_{X_4^k}(3) = P_{X_3^k}(3)\,\mathrm{P}_{\xi_4}(0) + P_{X_3^k}(2)\mathrm{P}_{\xi_4}(1) + P_{X_3^k}(1)\mathrm{P}_{\xi_4}(2) + P_{X_3^k}(0)\,\mathrm{P}_{\xi_4}(3)$. This means that the cumulative demand up to customer 4 can be three if the cumulative demand up to customer 3 is three and the demand of customer 4 is zero, or the cumulative demand up to customer 3 is two and the demand of customer 4 is one, or the cumulative demand up to customer 3 is one and the demand of customer 4 is two, or the cumulative demand up to customer 3 is zero and the demand of customer 4 is three. Therefore, the probability of these cases should be summed to calculate the total cumulative demand up to customer 4.

If the failure occurred at vertex v_i^k on a route r_k as follows, then $X_{i-1}^k < Q_k$ and $X_i^k \geq Q_k$, if failure occurred in a pure truck route or ST or $X_{i-1}^k < Q_k + Q_r$ and $X_i^k \geq Q_k + Q_r$, if failure occurred in a pure vehicle route or a main tour. Then depending on the type of route, the probability P_i^k can be computed. The probability of route failure P_i^k at customer v_i^k on a route r_k can be computed (Lei et al., 2011) as

$$P_i^k = \begin{cases} \sum_{d=0}^{Q_k-1} P_{X_{i-1}^k}(\mathrm{t}) - \sum_{d=0}^{Q_k-1} P_{X_i^k}(t) & \text{if failure occurred in PTR or sub tour,} \\ \sum_{d=0}^{Q_k+Q_r-1} P_{X_{i-1}^k}(\mathrm{t}) - \sum_{d=0}^{Q_k+Q_r-1} P_{X_i^k}(t) & \text{if failure occurred in PVR, main tour,} \\ 0 & other\ wise. \end{cases}$$

(4.3)

For example, if the failure occurs on the main tour of CVR, the probability P_i^k can be computed as

$$P_i^k = P\{X_{i-1}^k < Q_k + Q_r \text{ and } X_i^k \geq Q_k + Q_r\}$$

$$= 1 - P\{X_{i-1}^k \geq Q_k + Q_r\} - P\{X_i^k < Q_k + Q_r\}$$

$$= P\{X_{i-1}^k < Q_k + Q_r\} - P\{X_i^k < Q_k + Q_r\}$$

$$= \sum_{l=0}^{Q_k+Q_r-1} p_{X_{i-1}^k}(\mathrm{t}) - \sum_{l=0}^{Q_k+Q_r-1} p_{X_i^k}(t)$$

4.2.3 The expected cost of the recourse

Failure can happen in different situations. First, failure may occur in the PTR, PVR or main-route on the CVR; second failure may occur in an ST on the CVR. For instance, the failure types 1 and 3 occur when the cumulative demands up to customer *i* is exactly equal to the capacity. Therefore, dispatcher can serve customer *i*; however, the vehicle does not have any available capacity to serve the next customer. Thus, it has to come back to depot, fill the capacity and go to customer *i+1* to continue serving the remaining customers. Failure types 2 and 4 occur when the cumulative demands up to customer *i* is more than the capacity. Then the dispatcher cannot serve customer *i* and must come back to depot, fill the capacity and return to customer *i* to continue serving the remaining customers. Therefore, the recourse cost can be computed according to four failure types as follows:

1- Type 1: $H_i^k = c(v_i^k, v_r^k) + c\left(v_r^k, v_{i+1}^k\right) - c(v_i^k, v_{i+1}^k)$, if $X_i^k + \xi_i^k = Q_k$, if failure occurred in the PTR or ST

2- Type 2: $G_i^k = 2c(v_i^k, v_r^k)$, if $X_i^k + \xi_i^k > Q_k$, if failure occurred in the PTR or ST

3- Type 3: $F_i^k = c(v_i^k, v_0^k) + c\left(v_0^k, v_{i+1}^k\right) - c(v_i^k, v_{i+1}^k)$, if $X_i^k + \xi_i^k = Q_k + Q_r$, if failure occurred in the PVR, main tour

4- Type 4: $E_i^k = 2c(v_i^k, v_0^k)$, if $X_i^k + \xi_i^k > Q_k + Q_r$, if failure occurred in the PVR, main tour.

The expected cost of a recourse for route r_k can be computed as

$$E[\theta(r_k)] = \sum_{i=2}^{n_k} (A_i^k \left(H_i^k\right) + (B_i^k\left(G_i^k\right) + (C_i^k\left(F_i^k\right) + (D_i^k(E_i^k) \qquad (4.4)$$

where $A_i^k, B_i^k, C_i^k, D_i^k$ are the probabilities that the first, second, third and fourth failure types occur, respectively. Considering Eqs. 4.2 and 4.3, the four probabilities can be written as (Lei et al., 2011).

$$A_i^k = \begin{cases} \sum_{l=1}^{Q_k} p_{\xi_i^k}(l) P_{X_{i-1}^k}(Q_k - l) & \text{if failure occurred in PTR or sub tour,} \\ 0 & \text{other wise.} \end{cases} \tag{4.5}$$

$$B_i^k = \begin{cases} \sum_{l=1}^{Q_k-1} P_{X_{i-1}^k}(t) - \sum_{l=1}^{Q_k-1} P_{X_i^k}(t) - A_i^k & \text{if failure occurred in PTR or sub tour,} \\ 0 & \text{other wise.} \end{cases}$$

(4.6)

$$C_i^k = \begin{cases} \sum_{l=1}^{Q_k+Q_r} p_{\xi_i^k}(l) P_{X_{i-1}^k}(Q_k + Q_r - l) & \text{if failure occurred in PVR, main tour}, \\ 0 & \text{other wise.} \end{cases}$$

(4.7)

$$D_i^k = \begin{cases} \sum_{l=1}^{Q_k+Q_r-1} P_{X_{i-1}^k}(t) - \sum_{l=1}^{Q_k+Q_r-1} P_{X_i^k}(t) - C_i^k & \text{if failure occurred in PVR, main tour}, \\ 0 & \text{other wise.} \end{cases}$$

(4.8)

Four failure types and four recourse actions have been considered for this problem. The recourse actions impose the extra travel cost. For instance, H_i^k is the cost of recourse action type 1 and it should be multiplied by the relevant failure type which is A_i^k to compute the extra travel cost type 1. Also G_i^k should be multiplied by B_i^k and so on.

Finally, the total expected cost of recourse action in terms of distance can be computed as

$$E[\theta(R)] = \sum_{k=1}^{m} E[\theta(r_k)] \tag{4.9}$$

4.3 Formulation of TTRP with stochastic demand and time windows (TTRPSDTW)

TTRPSDTW is defined as an undirected graph $G = (V, E)$, where the set of vertices is $V = \{v_0, v_1, v_2, \ldots, v_n\}$ and $E = \{(v_i, v_j) : v_i, v_j \in V, i < j\}$ is the set of edges. The central depot is represented by 'v_0' and the other vertices in $V \setminus \{v_0\}$ correspond to customers. Each vertex v_i is associated with a stochastic and non-negative demand ξ_i. They can be split and are unknown until the vehicle arrives at the vertex. In addition, time window constraints have been considered for each customer and a service time is imposed when visiting a customer. A customer type t_i is available for all customers, where $t_i = 1$ shows that customer v_i is a truck customer (TC) and can be serviced only by a single truck. If $t_i = 0$, a customer i is a vehicle customer (VC) and it can be serviced by a single truck or a complete vehicle (truck pulling a trailer). $C = (c(v_i, v_j))$ is a symmetric travel cost, which is defined on E. It is assumed that all vehicles are the same and have a unit speed, so the travel cost is equal to the Euclidean distance between v_i and v_j. Say a fleet of m_k and m_r, trucks and trailers, respectively, is available. However, some trucks and trailers may not be used at any time in the TTRPSDTW solution. Without loss of generality, it is assumed that $m_k \geq m_r$, as in Chao (2002) and Scheuerer (2006) and Lin et al. (2009). All trucks have the same capacity Q_k, and all trailers also have the same capacity Q_r, where Q_k and Q_r are different. Three types of route are available in TTRPSDTW. These types of route are same as the routes in TTRPSD with same assumptions.

The TTRPSDTW consists of designing the first-stage routes, including the truck route, vehicle route and complete route, satisfying all constraints and if a failure occurs, a recourse action is applied. The purpose is to minimize the sum of the total distance of the first-stage routes and the expected recourse costs.

4.3.1 Mathematical estimation of the total expected cost

It should be considered that TTRPSDTW has three different types of route. Each route is planned in the first stage of the solution $R = (r_1, r_2, \dots, r_m)$, where $r_k = (v_0^k = v_0, v_1^k, \dots, v_{n_k}^k, v_{n_k+1}^k = v_0)$. The final objective function $T(R)$ is the sum of two costs: $\Phi(R)$ and $R_c(R)$, where $\Phi(R)$ is the total distance of the first-stage routes, and $R_c(R)$ is also the sum of two terms: $\theta(R)$ and $\psi(R)$. Here, $R_c(R)$ is the recourse cost, $\theta(R)$ is the expected recourse cost in the case of failure and $\psi(R)$ is the recourse cost in the case of customers whose time window is missed. So, the objective function is,

$$T(R) = \Phi(R) + R_c(R)$$

$$= \Phi(R) + \theta(R) + \psi(R) \tag{4.10}$$

The computation of $\Phi(R)$ is not difficult. To compute $\Phi(R)$, the cost of each route should be found and the costs (total distances) of all routes, which are planned in the first stage, should be computed (Lin et al., 2010). The estimations of $\theta(R)$ and $\psi(R)$ are complicated and these are shown in the next section. First, the probability of failure should be computed. ξ_i^k and X_i^k are the demand from customer v_i and the cumulative demand up to customer v_i in a route r_k.

The probability of the cumulative demand up to the customer v_i^k, on a route r_k, can be calculated by the following recursive equation (Lei et al., 2011), where $P_{\xi_0^k}(t)$ is a boundary condition for this equation and $P_{X_i^k}(t) = P\{X_i^k = t\}$.

$$P_{X_i^k}(t) = \sum_{d=0}^{t} P_{X_{i-1}^k}(t-d)\mathrm{P}_{\xi_i}(d) \tag{4.11}$$

If the failure occurred at vertex v_i^k on a route r_k as follows, then $X_{i-1}^k < Q_k$ and $X_i^k \geq Q_\mathrm{k}$, if failure occurred in a pure truck route or ST or $X_{i-1}^k < Q_k + Q_r$ and $X_i^k \geq \mathrm{Q_k} + Q_r$, if failure occurred in a pure vehicle route or a main tour. Then depending on the type of route, the probability P_i^k can be computed. The probability of route failure P_i^k at customer v_i^k on a route r_k can be computed (Lei et al., 2011) as

$$P_i^k = \begin{cases} \sum_{t=0}^{Q_k-1} P_{X_{i-1}^k}(\mathrm{t}) - \sum_{t=0}^{Q_k-1} P_{X_i^k}(t) & \text{if failure occurred in PTR or sub tour,} \\ \sum_{t=0}^{Q_k+Q_r-1} P_{X_{i-1}^k}(\mathrm{t}) - \sum_{t=0}^{Q_k+Q_r-1} P_{X_i^k}(t) & \text{if failure occurred in PVR, main tour,} \\ 0 & \textit{other wise.} \end{cases}$$

(4.12)

For example, if the failure occurs on the main tour of CVR the probability P_i^k can be computed as

$$\begin{aligned} P_i^k &= P\{\, X_{i-1}^k < Q_k + Q_r \text{ and } X_i^k \geq Q_k + Q_r \,\} \\ &= 1 - P\{X_{i-1}^k \geq Q_k + Q_r\} - P\{X_i^k < Q_k + Q_r\} \\ &= P\{X_{i-1}^k < Q_k + Q_r\} - P\{X_i^k < Q_k + Q_r\} \\ &= \sum_{t=0}^{Q_k+Q_r-1} P_{X_{i-1}^k}(\mathrm{t}) - \sum_{t=0}^{Q_k+Q_r-1} P_{X_i^k}(t)\,. \end{aligned}$$

4.3.2 The expected recourse cost

Failure can happen in different situations. First, failure may occur in the PTR, PVR or main-route on the CVR; second failure may occur in an ST on the CVR. The recourse cost can be computed according to four failure types as follows:

5- Type 1: $H_i^k = c(v_i^k, v_r^k) + c(v_r^k, v_{i+1}^k) - c(v_i^k, v_{i+1}^k)$, if $X_i^k + \xi_i^k = Q_k$, if failure occurred in the PTR or ST

6- Type 2: $G_i^k = 2c(v_i^k, v_r^k)$, if $X_i^k + \xi_i^k > Q_k$, if failure occurred in the PTR or ST

7- Type 3: $F_i^k = c(v_i^k, v_0^k) + c(v_0^k, v_{i+1}^k) - c(v_i^k, v_{i+1}^k)$, if $X_i^k + \xi_i^k = Q_k + Q_r$, if failure occurred in the PVR, main tour

8- Type 4: $E_i^k = 2c(v_i^k, v_0^k)$, if $X_i^k + \xi_i^k > Q_k + Q_r$, if failure occurred in the PVR, main tour

Let t_c^k be the arrival time at the customer v_c^k with a time window $[a_{v_c^k}, b_{v_c^k}]$ before applying recourse action when failure occurred at customer i. $₮_c^k(i)$ is the new arrival time after applying the recourse action. In addition, s_i^k is the service time for customer i. The value of $₮_c^k(i)$ can be computed as follows where $₮_1^k = c(v_0^k, v_1^k)$

$$₮_c^k(i) = \begin{cases} t_c^k, & c = 2, \dots, i, \\ Ł_c^k(i) & c = i+1, \\ ₦_c^k(i) & c = i+2, \dots, n_k, \end{cases} \tag{4.13}$$

where $t_c^k = \max\left\{a_{v_{c-1}^k}, t_{c-1}^k\right\} + s_i^k + c(v_{c-1}^k, v_c^k)$ and n_k is the number of customers in route r_k. Since recourse action has not occurred during service up to customer v_i^k, the new arrival time is the same as the arrival time before the recourse action.

The computing of $Ł_c^k(i)$ and $₦_c^k(i)$ is dependent on the failure types and time windows, and needs further discussion.

Type1:

$$Ł_c^k(i) = ₮_{c-1}^k(i) + s_{c-1}^k + H_{c-1}^k + c(v_{c-1}^k, v_c^k)$$

$$₦_c^k(i) = \begin{cases} \max\left\{a_{v_{c-1}^k}, ₮_{c-1}^k(i)\right\} + s_{c-1}^k + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) \le b_{v_c^k} \\ ₮_{c-1}^k(i) + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) > b_{v_c^k} \end{cases}$$

Type 2:

$$Ł_c^k(i) =$$

$$\begin{cases} \max\left\{a_{v_{c-1}^k}, ₮_{c-1}^k(i)\right\} + s_{c-1}^k + G_i^k + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) + s_{c-1}^k \le b_{v_c^k} \\ ₮_{c-1}^k(i) + G_i^k + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) + s_{c-1}^k > b_{v_c^k} \end{cases}$$

$$₦_c^k(i) = \begin{cases} \max\left\{a_{v_{c-1}^k}, ₮_{c-1}^k(i)\right\} + s_{c-1}^k + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) \le b_{v_c^k} \\ ₮_{c-1}^k(i) + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) > b_{v_c^k} \end{cases}$$

Type 3:

$$Ł_c^k(i) = ₮_{c-1}^k(i) + s_{c-1}^k + F_{c-1}^k + c(v_{c-1}^k, v_c^k)$$

$$₦_c^k(i) = \begin{cases} \max\left\{a_{v_{c-1}^k}, ₮_{c-1}^k(i)\right\} + s_{c-1}^k + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) \le b_{v_c^k} \\ ₮_{c-1}^k(i) + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) > b_{v_c^k} \end{cases}$$

Type 4:

$$Ł_c^k(i) =$$

$$\begin{cases} \max\left\{a_{v_{c-1}^k}, ₮_{c-1}^k(i)\right\} + s_{c-1}^k + E_i^k + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) + s_{c-1}^k \le b_{v_c^k} \\ ₮_{c-1}^k(i) + G_i^k + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) + s_{c-1}^k > b_{v_c^k} \end{cases}$$

$$₦_c^k(i) = \begin{cases} \max\left\{a_{v_{c-1}^k}, ₮_{c-1}^k(i)\right\} + s_{c-1}^k + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) \le b_{v_c^k} \\ ₮_{c-1}^k(i) + c\left(v_{c-1}^k, v_c^k\right) & if\ ₮_{c-1}^k(i) > b_{v_c^k} \end{cases}$$

The failure occurred at customer v_i^k then the arrival times were not affected by a failure up to this vertex. Therefore, $₮_c^k(i) = t_c^k$ $(c = 1, \dots, i)$. However, since failure occurred at vertex v_i^k, the failure actions are dependent on time windows and the failure type and they should be considered separately as follows.

For example, if the failure is of the first type, it means that after serving customer v_i^k, the vehicle has to return to the root of the route if the vehicle is in ST, otherwise it must return to the depot, then continue serving customers from the next vertex v_{i+1}^k. Therefore, the cost of $Ł_c^k(i)$ is equal to $Ł_c^k(i) = ₮_{c-1}^k(i) + s_{c-1}^k + H_{c-1}^k + c(v_{c-1}^k, v_c^k)$. In addition, $₦_c^k(i)$ equals $\max\left\{a_{v_{c-1}^k}, ₮_{c-1}^k(i)\right\}$, plus the service time at customer v_i^k and the travel time from v_i^k to v_{i+1}^k if this recourse action does not violate the time windows; however, the cost is equal to $₮_{c-1}^k(i) + c\left(v_{c-1}^k, v_c^k\right)$ if the vehicle violates the time windows because it skips vertex v_{c-1}^k. If the the second failure type occurs, after serving customer v_i^k, the single truck must return to the depot or to the root of its route and again proceed to vertex v_i^k. Therefore, $Ł_c^k(i)$ equals $\max\left\{a_{v_{c-1}^k}, ₮_{c-1}^k(i)\right\}$, plus the service time at vertex v_i^k, plus the second type of recourse action, plus travel time between vertex v_i^k to vertex v_{i+1}^k if this recourse action does not violate the time windows, $\text{Ŧ}_{c-1}^k(i) + s_{c-1}^k \leq b_{v_c^k}$. Also, $\text{Ł}_c^k(i)$ equals $\text{Ŧ}_{c-1}^k(i) + G_i^k + c\left(v_{c-1}^k, v_c^k\right)$ if $\text{Ŧ}_{c-1}^k(i) + s_{c-1}^k > b_{v_c^k}$ because the vehicle skips customer i and service time is not imposed. Other similar proofs can be used for failure types 3 and 4.

Hence, some customers, whose time windows are missed, should be considered separately in the model. Consequently, these are classified into four groups in terms of four failure types as follows.

1- $W_1(i,k) = \{v_c^k |\ \text{Ŧ}_c^k(i) > b_{v_c^k}\ and\ X_i^k + \xi_i^k = Q_k, c = i, \dots n_k\}$ for failure type 1 (single truck). (4.14)

2- $W_2(i,k) = \{v_c^k |\ \text{Ŧ}_c^k(i) > b_{v_c^k}\ and\ X_i^k + \xi_i^k > Q_k, c = i, \dots n_k\}$ for failure type 2 (single truck). (4.15)

3- $W_3(i,k) = \{v_c^k |\ \text{Ŧ}_c^k(i) > b_{v_c^k}\ and\ X_i^k + \xi_i^k = Q_k + Q_r\ , c = i, \dots n_k\}$ for failure type 3 (complete vehicle) (4.16)

4- $W_4(i,k) = \{v_c^k |\ \text{Ŧ}_c^k(i) > b_{v_c^k}\ and\ X_i^k + \xi_i^k > Q_k + Q_r\ , c = i, \dots n_k\}$ for failure type 3 (complete vehicle) (4.17)

Therefore, a separate single truck must be considered for each customer whose time window is missed for all types of route since the dispatcher cannot serve the customer after the lateness time. This issue imposes an additional cost equal to the distance between a customer and the depot multiplied by two.

The expected cost of recourse for route $r_k$can be computed as

$$E[\theta(r_k)] = \sum_{i=2}^{n_k}(A_i^k\left(H_i^k + \sum_{v\in W_1(i,k)}(c(v_r^k, v) + c(v, v_r^k))\right) + (B_i^k\left(G_i^k + \sum_{v\in W_2(i,k)}(c(v_r^k, v) + c(v, v_r^k))\right) + (C_i^k\left(F_i^k + \sum_{v\in W_3(i,k)}(c\left(v_0^k, v\right) + c\left(v, v_0^k\right))\right) + (D_i^k(E_i^k + \sum_{v\in W_4(i,k)}(c\left(v_0^k, v\right) + c\left(v, v_0^k\right)))) \quad (4.18)$$

where $A_i^k, B_i^k, C_i^k, D_i^k$ are the probabilities that the first, second, third and fourth failure types occur, respectively. Considering Eqs. 4.11 and 4.12, the four probabilities can be written as

$$A_i^k = \begin{cases} \sum_{d=1}^{Q_k} p_{\xi_i^k}(d) P_{X_{i-1}^k}(Q_k - d) & \text{if failure occurred in PTR or sub tour,} \\ 0 & \textit{other wise.} \end{cases}$$

(4.19)

$$B_i^k = \begin{cases} \sum_{t=1}^{Q_k-1} P_{X_{i-1}^k}(t) - \sum_{t=1}^{Q_k-1} P_{X_i^k}(t) - A_i^k & \text{if failure occurred in PTR or sub tour,} \\ 0 & \textit{other wise.} \end{cases}$$

(4.20)

$$C_i^k = \begin{cases} \sum_{d=1}^{Q_k+Q_r} p_{\xi_i^k}(d) P_{X_{i-1}^k}(Q_k + Q_r - d) & \text{if failure occurred in PVR, main tour}, \\ 0 & \textit{other wise.} \end{cases}$$

(4.21)

$$D_i^k = \begin{cases} \sum_{t=1}^{Q_k+Q_r-1} P_{X_{i-1}^k}(t) - \sum_{t=1}^{Q_k+Q_r-1} P_{X_i^k}(t) - C_i^k & \text{if failure occurred in PVR, main tour}, \\ 0 & \textit{other wise.} \end{cases}$$

(4.22)

To recognize the failure types and their probabilities, it should be mentioned that the expected costs of recourse comprise two parts: the first is the extra travel cost and the second is the cost of serving customers whose time windows are missed and need special services. Therefore, four failure types and four recourse actions have been considered for this problem. For instance, H_i^k is the cost of recourse action type 1 and should be multiplied by the relevant failure type which is A_i^k to compute the extra travel cost type 1. Also, G_i^k should be multiplied by B_i^k and so on. In addition, to compute the second part of the recourse cost, the cost is $\sum_{v \in W_1(i,k)}(c(v_r^k, v) + c(v, v_r^k))$ and should be multiplied by the corresponding failure type probability. Consequently, the total expected recourse cost is the sum of two failure parts in terms of four failure types. Hence, $P\{\xi_i \leq Q_k\} \cong 1(v_i \in V \backslash \{v_0\})$, then the total expected recourse cost can be computed as

$$E[R_c(R)] = \sum_{k=1}^{m} E[F(r_k)], \tag{4.23}$$

Subject to:

$$\sum_{j \in V} \sum_{k \in K}\left(X_{ijk} + Y_{ijk}\right) = 1 \qquad \forall i \in V \tag{4.24}$$

$$\sum_{j \in V}\left(X_{0jk} + Y_{0jk}\right) = 1 \qquad \forall k \in K \tag{4.25}$$

$$\sum_{i \in V}(X_{i0k} + Y_{i0k}) = 1 \qquad \forall k \in K \tag{4.26}$$

$$\sum_{i \in V} X_{ijk} - \sum_{i \in V} X_{jik} = 0 \qquad \forall j \in V,\ k \in K \tag{4.27}$$

$$\sum_{i \in V} Y_{ijk} - \sum_{i \in V} Y_{jik} = 0 \qquad \forall j \in V, k \in K \tag{4.28}$$

$$P\{\sum_{i \in v} \xi_i (\sum_{j \in v} X_{ijk} < 2(Q_k + Q_r)\} \cong 1 \quad \text{If } v_i \in \text{PVR or CVR} \tag{4.29}$$

$$P\{\sum_{i \in v} \xi_i (\sum_{j \in v} Y_{ijk} < 2(Q_k)\} \cong 1 \qquad \text{If } r_k \in \text{PTR or ST} \tag{4.30}$$

$$X_{ijk} \in \{0,1\},\ \ Y_{ijk} \in \{0,1\},\ \ \forall i,j \in V,\ \ k \in K \tag{4.31}$$

where, r_k is the *k-th* route and *m* is the number of routes including PTR, PVR and CVR. X_{ijk} is equal to 1 if customers *i* and *j* (edge $(i,j) \in E$) are serviced by a complete vehicle (the *k*-th truck with a trailer), and 0 otherwise. Y_{ijk} is equal to 1 if edge $(i,j) \in E$ is used by the *k*-th truck (without trailer). Eq. (4.24) gives information about each customer that must be serviced by a single truck or complete vehicle. Eq. (4.25) is concerned with starting each route from the depot and going to exactly one customer using vehicle *k*. Eq. (4.26) is similar to Eq. (4.25); however, it shows the route terminates by leaving one customer. Eqs. (4.27) and (4.28) indicate the flow on the route to be followed by vehicle *k*. Eqs. (4.29) and (4.30) are the capacity constraints for the vehicle route and the truck route, respectively, and ensure the feasibility of servicing customers, and q_i is the expected value of the stochastic customers' demands.

CHAPTER 5: FORMULATION ON TTRP WITH STOCHASTIC TRAVEL AND SERVICE TIME WITH TIME WINDOWS

5.1 Introduction

This Chapter presents a formulation and solution on truck and trailer routing problem(s) under stochastic travel and service time with time window (TTRPSTTW) constraints. For solving TTRPSTTW, it appears that its solution is computationally more difficult than VRP with stochastic travel and service times under certain time windows (VRPSTTW). Indeed, VRP with stochastic parameters itself is one of the most difficult combinatorial optimization problems. This type of problems is generally framed and solved by heuristics approaches (Baker & Ayechew, 2003; Chin et al., 1999; Cordone & Calvo, 2001; Eksioglu et al., 2009). To formulate and solve TTRPSTTW, one can make effort to reduce it to VRPSTTW. As VRPSTTW is also a complex type of combinatorial optimization problem, it can be solved by heuristics approaches (Tillman, 1969; Chao, 2002; Scheuerer, 2006; Derigs et al., 2013) which could be done in repetative manner under a dynamic situation. The purpose of TTRPSTTW is to design a set of routes to cover all customers and optimize the total costs that will satisfy all constraints.

In some real applications, special operational restrictions or requirements may exist such as customer's working period that some customers must be serviced during a specified time interval and there can be no delays in servicing those customers. These issues cause to be considered VRP with time windows. Correspondingly, time windows constraints can be seen in TTRP applications in the name of TTRP with time windows. In addition, due to traffic congestion, varied weather conditions, level of driver's skills or effect of distribution technology, often travel and service times are not really deterministic between two vertices but normally follow stochastic distributions. Therefore, taking notes on some limitations in VRP model mentioned earlier and the necessity of stochastic travel and service times in real-life issues, the truck and trailer routing problem with stochastic travel and service times with time windows need to be considered.

5.2 Formulation on TTRP with stochastic travel and service times with time windows

TTRPSTTW is an extension of the TTRP. It is defined as an undirected graph $G = (V, E)$, where $V = \{v_0, v_1, v_2, \ldots, v_n\}$ is a set of vertices, and $E = \{(v_i, v_j) : v_i, v_j \in V, i < j\}$ is the set of edges. The central depot is represented by v_0 and the other vertices in $V \setminus \{v_0\}$ correspond to customers. Each vertex v_i is associated with a deterministic and non-negative demand q_i that has to be met. In addition, time window constraints are considered for each customer and a stochastic service time is imposed when visiting a customer. Also the travel times between customers are considered stochastic. A customer type t_i is available for all customers. If $t_i = 1$, the customer *i* is a truck customer (TC) and can be serviced only by single truck. If $t_i = 0$, a customer *i* is a vehicle customer (VC) and it can be serviced by single truck or complete vehicle (truck pulling a trailer). $C = (c(v_i, v_j))$ is a stochastic travel cost (distance) defined on E.

In the fleet of m_k and m_r, respectively, the number of trucks and trailers are available at a point of time. However, some available trucks and trailers may not be used any time in TTRPSTTW solution.

Three types of route are available in TTRPSTTW as: 1) a pure travel route (PTR), which can be travelled by only single truck. 2) A pure vehicle route without any sub-tour (PVR). Only a complete vehicle can be travelled in this route. 3) Complete vehicle route (CVR). CVR consists of a main tour and at least one sub-tour. A sub-tour starts and finishes at the same vehicle customer (v_r) (trailer is parked in parking place which is known as the root) and it can be travelled only by a single truck; nonetheless, it should be serviced by complete vehicle in the main tour. The TTRPSTTW can be cast as a stochastic programming with recourse. In SPR optimization model, the set of tours and sub-tours are constructed in the first stage before considering the stochastic travel and service times. Recourse actions considering the random variables are then revealed in the next stage.

The TTRPSTTW consists of designing the first-stage routes such as truck route, vehicle route and complete route under the given conditions: (1) each route starts and finishes at the depot; (2) each vertex is visited only by one vehicle, (3) if the time taken is reached or exceeded at any vertex, a recourse action need to be applied, and (4) the objective function is a minimization function.

5.3 The stochastic programming model with recourse of TTRPSTTW

Since CCP model cannot consider recourse cost, e.g., when time window constraints are violated or the driver needs to work more than predetermined D hours. Therefore, in order to bring the model closer to the reality, recourse cost need to be considered in the model. The common recourse policy in TTRPSTTW is as follows: the set of tours and sub-tours is constructed in first stage. Recourse actions considering random variables are then revealed in the second stage. In this research, soft time windows constraint is considered for the model because this is more general than hard time window and it is closer to the reality than hard time window constraint (Li et al., 2010). In soft time window, the dispatcher does not have any permission to start serving a customer before its earliest time window and have to wait until this time comes. Therefore, additional waiting time on the route may be imposed.

It should be considered that TTRPSTTW has three different types of routes. Each route is planned in the first-stage of the solution. The final objective function $F(X,Y)$ is the sum of two costs: $T(X,Y)$ and $R(X,Y)$, where $T(X,Y)$ is the objective function value of the first stage routes, and $R(X,Y)$ is also the sum of two terms: B_k and P_k. Here $R(X,Y)$ is the recourse cost, B_k is the expected cost of recourse in case of driver remuneration and P_k is the recourse cost in case of customers whose time window is missed. So, the objective function is,

$$F(X,Y) = T(X,Y) + B_k + P_k \tag{5.1}$$

Assume the vertex v_j is the last vertex in the route k, the route k is feasible if the route is terminated before l_0. Then

$$A_{0k} = \{\max(A_{jk}, e_j) + t_{j0} + \gamma_j\} \leq l_0 \tag{5.2}$$

In addition, the arrival time of all customers can be calculated by the following recursive equation when $\gamma_0 = 0$. It should be mentioned that the equation 5.3 is an extension from (Li et al., 2010).

$$A_{ik} = \{\max(A_{i-1,k}, e_{i-1}) + t_{i-1,i} + \gamma_{i-1}\} \tag{5.3}$$

Since servicing customer i before the earlier time e_i is not possible and the vehicle has to wait until this time comes. Therefore, additional waiting time W_i on the route may be occurred, which is a random variable for e_i and A_{ik} are random variables.

$$W_i = \max(e_i - A_{ik}, 0) \tag{5.4}$$

Consequently, the total waiting time is computed as

$$W = E\sum_{i=1}^{n_k} W_i \tag{5.5}$$

Also the penalty cost is imposed to the objective function when the customer is serviced after deadline l_0. The total random variable penalty cost P_k can be computed as

$$P_k = \sum_{j=1}^{n_k} \delta_j . \max(A_{jk} - l_j, 0) \tag{5.6}$$

Where δ_j is the unit penalty cost in servicing customer *j* after the deadline.

The objective function value of the first stage routes can be computed by the following equation.

$$\mathrm{T(X,Y)} = \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} C_{ij} X_{ijk} + \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} C_{ij} Y_{ijk} \tag{5.7}$$

Where X_{ijk} is equal to 1 if customer i and j (edge $(i, j) \in E$) are serviced by a complete vehicle (the *k*-th truck with a trailer), and 0 otherwise. Y_{ijk} is equal to 1 if edge $(i, j) \in E$ is used by the *k*-th truck (without trailer).

The normal working hours for each driver is *D* hours. If the driver works more than *D* hours, he needs to get remuneration for each extra hour.

The total driving duration is T_k including travel, service and waiting times and the total driver remuneration B_k on the route *k* can be computed by the following equations.

$$T_k = \sum_{i \in V} \sum_{j \in V} t_{ij} \left(X_{ijk} + Y_{ijk} \right) + \sum_{i \in V} (\gamma_i + W_i) \sum_{j \in V} \left(X_{ijk} + Y_{ijk} \right) \tag{5.8}$$

$$B_k = \begin{cases} r_k . (T_k - D) & if\ T_k \geq D \\ 0 & O.W \end{cases} \tag{5.9}$$

Where r_k is the unit driver remuneration for each one hour extra work on the route *k*. The purpose is to minimize the objective function of SPR version of TTRPSTTW in two stages. Each route is planned in the first stage and recourse cost consists of T_k and B_k are considered in the second stage.

$$\min\ [F(X, Y)] \tag{5.10}$$

Subject to:

$$\sum_{j \in V} \sum_{k \in K} \left(X_{ijk} + Y_{ijk} \right) = 1 \qquad \forall i \in V \tag{5.11}$$

$$\sum_{j \in V} \left(X_{0jk} + Y_{0jk} \right) = 1 \qquad \forall k \in K \tag{5.12}$$

$$\sum_{i \in V} (X_{i0k} + Y_{i0k}) = 1 \qquad \forall k \in K \tag{5.13}$$

$$\sum_{i \in V} X_{ijk} - \sum_{i \in V} X_{jik} = 0 \qquad \forall j \in V,\ k \in K \tag{5.14}$$

$$\sum_{i \in V} Y_{ijk} - \sum_{i \in V} Y_{jik} = 0 \qquad \forall j \in V, k \in K \tag{5.15}$$

$$\sum_{i \in V} (q_i \sum_{j \in V} X_{ijk}) \leq Q_k + Q_r \qquad \forall k \in K \tag{5.16}$$

$$\sum_{i \in V} (q_i \sum_{j \in V} Y_{ijk}) \leq Q_k \qquad \forall k \in K \tag{5.17}$$

$$P_k = \sum_{j=1}^{n_k} \delta_j . \max(A_{jk} - l_j, 0) \tag{5.18}$$

$$T_k = \sum_{i \in V} \sum_{j \in V} t_{ij} \left(X_{ijk} + Y_{ijk} \right) + \sum_{i \in V} (\gamma_i + W_i) \sum_{j \in V} \left(X_{ijk} + Y_{ijk} \right) \tag{5.19}$$

$$B_k = \begin{cases} r_k . (T_k - D) & if\ T_k \geq D \\ 0 & O.W \end{cases} \tag{5.20}$$

$$X_{ijk} \in \{0,1\}, \quad Y_{ijk} \in \{0,1\}, \quad \forall i, j \in V, \quad k \in K \tag{5.21}$$

Eq. (5.11) gives information about each customer that must be serviced once by a single truck or complete vehicle. Eq. (5.12) is about starting each route from depot to exactly one customer place by vehicle k. Eq. (5.13) is similar to Eq. (5.12); however, it shows the route termination by leaving one customer. Eq. (5.14) and Eq. (5.15) indicate the flow on the route to be followed by vehicle k. Eq. (5.16) and Eq. (5.17) are capacity constraints for vehicle route and truck route, respectively which are to ensure the feasibility of servicing customers.

CHAPTER 6: ANALYSIS, RESULT AND DISCUSSION

6.1 Introduction

This chapter presents the relevant analysis accomplished for the fulfillment of the research objectives mentioned in Chapter 1. The purpose of this study is to expand the deterministic TTRP model by introducing stochastic parameters and time window constraints to bring the TTRP model closer to reality and solve the model in a reasonable timeframe by administering the meta-heuristic algorithms. Also, the performance validity of each proposed model is discussed in this chapter. In addition, the algorithms were coded by MATLAB 7.9.0 using a laptop with a 2.4 GHz dual processor and 4 G RAM.

6.2 Applicability of the proposed models and algorithms

Firstly, the applied algorithms should solve TTRP problem to confirm the efficiency and confidence of the algorithms. Since TTRP problem has been solved by other researchers, the results obtained by the algorithms and other researchers can be compared. For this purpose, TTRP benchmark instance problem which was generated by Chao (2002) has been chosen to solve. This TTRP has been solved using tabu search (Scheurer, 2006) and simulated annealing (Lin et al., 2009). In this study, different algorithms have been applied to solve the TTRP. However, the memetic algorithm, multi-point simulated annealing and tabu search were chosen for solving the proposed models due to their efficiency. Firstly, the procedure of each algorithm and generating the initial solutions need to be described.

6.2.1 Initial solutions

Generally, initial populations are randomly generated using logical concepts and methods. The algorithm uses this initial population to cover any area of search space. In this study, the particular method is used to produce an initial population for proposed TTRP with stochastic demand and proposed TTRP with stochastic travel and service time as well. The procedure of generating initial solution for TTRP with stochastic demand and TTRP with stochastic travel and service time are almost same; however, some differences need to be considered. This particular method is used to produce an initial solution for TTRP with stochastic demand considering the following assumptions.

$$P\{\sum_{v_i \in r_k} \xi_i < 2(Q_k + Q_r)\} \cong 1 \qquad \text{If } r_k \in \text{PVR and CVR}$$

$$P\{\sum_{v_i \in r_k} \xi_i < 2(Q_k)\} \cong 1 \qquad \text{If } r_k \in \text{PTR and ST}$$

All customers are classified as TCs and VCs. A string of numbers represents an initial solution, which is denoted by the set $\{1,2,\ldots,n\}$ and N dummy zeroes (see Figure 6.1). The parameter N is utilized to terminate the ST or the route. This parameter is only used to predict the number of routes or STs. If demand was deterministic and failure could not occur, this parameter could be $\lfloor \sum_i q_i / (Q_k) \rfloor$, where q_i is a customer's demand and Q_k is the truck capacity. However, since demand is stochastic and failure can occur a maximum of once, the parameter N can be computed by $\lfloor \sum_i q_i / (2Q_k) \rfloor$ where $\lfloor \bullet \rfloor$ denotes the largest integer, which is equal to or smaller than the enclosed number and q_i is the expected value of customers' demand. In the first $n + N$ positions, the *i*th non-zero number denotes the *i*th customer to be serviced. VC can be serviced either by a complete vehicle or a single truck and the service vehicle type can be of 1 or 0. Therefore, the vehicle type for VC is 1 if it is serviced by a single truck. Otherwise, its vehicle type is 0 and must be serviced by a complete vehicle. Hence, TCs must be serviced only by a single truck; therefore there is no need to mention it in the solution.

The presentation of the solution is explained more as follows. In this solution, the first number addresses the first customer that is to be served on the first route. A PTR is decided for the route, if a single truck is to service the first customer on a route. Without violating the following assumptions $P\{\sum_{v_i \in r_k} \xi_i < 2(Q_k + Q_r)\} \cong 1,$ if $r_k \in$ PVR and CVR or $P\{\sum_{v_i \in r_k} \xi_i < 2(Q_k)\} \cong 1,$ if $r_k \in$ PTR or ST to represent the servicing sequence, from left to right, one by one, other customers are added to the route. Note that if it is a complete vehicle on the CVR main tour or on a PVR, the vehicle capacity may be $(Q_k + Q_r)$ or on a CVR ST or on a PTR, if it is a single truck, it may be Q_k and it all depends on the vehicle type in use for the service. If, in the solution representation, the next customer to be served is zero, the vehicle will come back to the depot or the parking place. If it is on a CVR ST, the ST will be terminated, because the vehicle returns to the parking place. If not, it is on a CVR main tour, on a PVR or on a PTR. Consequently, the vehicle goes back to the depot and the route is terminated. It is worth mentioning that when recourse cost occurs, it should be considered and computed.

In the solution representation, generation of a new route will occur if termination of the previous route has taken place and there are still customers to be serviced. Therefore, the next customer will be selected for the new route. Figure 6.2 illustrates a simple individual representation of the initial solution. Initially, Customers 4, 5, 7 and 6 are serviced by a complete vehicle. Therefore, Customer 6 is the parking place (root) and the trailer has to be parked at this area while servicing Customers 3 and 2. Finally, Customer 1 is serviced and the route is finished by returning the complete vehicle to the depot. A TTRPSDTW (or TTRPSD) solution is given by this solution representation, without violating the foretold assumptions, and it can be verified. On the other hand, by using this solution representation, the number of the vehicles that are used might exceed the available vehicles. As a result, when the solution representation has generated the routes, in order to decrease the number of vehicles used, a procedure for route combination is considered necessary. Such a procedure checks the possibility of combining two existing routes. However, this combinatorial process must not violate the constraint of the capacity of the vehicle, and if there are routes that can be combined together without violation of this constraint they will be merged without any modification. This process goes on until the number of vehicles used does not exceed the number of vehicles available or stops if there are no more routes that can be combined without violating the assumptions. If the generated solution still persists in using more vehicles than available, for each additional trailer or truck that is used, a cost of P, as a penalty, is imposed on the objective function in order to make the solutions of this type undesirable.

The method to produce an initial solution for TTRPSTTW is almost same as TTRPSD. However, the parameter N is utilized to terminate sub-tour or route and can be calculated by $\lfloor \sum_i d_i / (Q_k) \rfloor$ since the demand is deterministic. In the solution representation, generation of a new route is almost same as the aforesaid one. This process goes on until the number of the used vehicles is not greater than the number of the vehicles available or it will stop if there are not any more routes that can be combined together without violating the constraints. If the outcome solution still persists on using more vehicles than are available, for each additional trailer or truck that is used, a cost of P_e, as a penalty, is added to the objective function in order to make the solutions of this type undesirable.

4	7	2	12	5	16	10	17	0	8	1	14	15	11	13	0	3	19	20	9	18	6	0
Route 1 CVR									Route 2 PTR							Route 3 PVR						

Figure 6. 1: A sample stochastic TTRP representation with 20 customers and 3 dummy zeros

4	5	7	6	3	2	1

Figure 6. 2: Representation of an individual solution

6.2.2 Multi-point simulated annealing to solve the models

Simulated annealing (SA) is one of the most famous local search heuristics. It can be applied to a wide variety of combinatorial optimization problems (Lin et al., 2009; Lin et al., 2011; Van Breedam, 1995). It was introduced by Metropolis et al. (1953). When using the local search methods, one should know that a standard SA thoroughly searches a solution space by moving from an existing solution to another likely solution in its neighborhood. However, due to increase the possibility of finding better solution, the standard SA needs to be modified. Therefore, a multi-point version of SA is considered for this study. At first, the number of predetermined initial solutions should be produced and it is known as best solutions. In each iteration, the algorithm produces some new solutions from the neighborhood of the current solutions and finds the best one between them and chooses this as a new solution. If a new solution appears to be better than the current solution, this new solution is termed as a best solution and the procedure is continued. In this process, the number of predetermined iterations is applied in each temperature level to improve the possibility of a set of appropriate solutions. However, sometimes the algorithm occurs in local optima. The procedure may escape from this issue by accepting worse solution with some conditions. This new solution with a worse objective function value can be accepted as the current solution with a small probability determined by the Boltzmann function, $exp(-\Delta/KT)$, where K is a predetermined constant and T is the current temperature in Boltzmann function (Lin et al., 2011).

6.2.2.1 Neighborhood

In a local search-based heuristic approach, it is important to define an appropriate method for finding the effective neighbors to improve an existing solution. A random neighborhood structure including swap, reversion, insertion, and change of service vehicle type of VCs is used for generating an appropriate neighborhood from a current solution. In each iteration, the algorithm generates new solution Y from the current solution X by using swap, reversion, insertion and change of service vehicle type randomly.

The swap is carried out by selecting two customers randomly and swapping them to generate a new solution from the current solution. The reversion is performed by selecting two numbers (customers) from the string of numbers representing the current solution then reversing the route from bigger number to smaller one. The insertion is performed by selecting two customers randomly and inserting the first customer immediately after the second one. The change of service vehicle type of VCs is fulfilled by selecting a vehicle customer randomly. If it is serviced by a single truck in the current solution, its service vehicle type will be changed to a complete vehicle and vice versa. It means that the vehicle service type of a selected VC will be changed from 1 to 0 or 0 to 1. For example, VC customer servicing in the main-tour by a complete vehicle will be serviced on a sub-tour by a single truck and vice versa.

The probability of selecting swap, reversion, insertion and change service vehicle type methods will be set to be 0.25 for each of them as it is assumed that each of these methods has an equal chance to improve the solution. In addition, failure may be occurred. Therefore, the failure should be diagnosed in the route and recourse action cost should be calculated for each failure.

6.2.2.2 Parameters

Multi-point Simulated annealing uses some parameters for improving the solutions, such as $T_0, T_f, I_{iter}, K, N_{non}, \alpha, P, n_{pop}, n_{move}, I_{iterpertemp}$, where T indicates the thermodynamic temperature, which is used to simulate the system at different temperatures , whereas T gradually cools down from an initial high temperature (T_0) to a final low temperature (T_f). It means that the procedure will be stopped when the temperature reaches lower than T_f. I_{iter} represents the number of iterations during the procedure. K is the Boltzmann constant which is used in the probability function. N_{non} denotes the maximum number of allowable iterations in temperature. The algorithm will be terminated if the number of reductions exceed the N_{non} without improving the best cost. α is the coefficient for controlling the cooling scheme. P is the penalty cost associated with the number of extra vehicles used. Hence it is not allowed to use more than the number of available vehicles in 21 benchmark instance problems that are used for TTRPSD, the penalty cost is assigned to be very large (e.g., $P = 10^5$ is considered for this model) to prevent from this issue. n_{pop} is the number of initial solution that should be considered for producing new solutions. n_{move} is the number of move from current solution to generate new solutions. It means that each current solution can produce n_{move} new solutions and then the best one should be chosen as new solution. $I_{iterpertemp}$ is the number of iterations in each temperature T.

6.2.2.3 The M-SA procedure

At first, the current temperature is set to be the initial temperature and the algorithm generates the initial solutions X_i randomly. In addition, the best solution $X_{i_{best}}$ and the best objective function considering recourse cost, if occurred, are set to be X_i and $obj(X_i, P)$, respectively. In each iteration, the algorithm generates new solutions Y_i from its neighborhood and evaluates its objective function value. Let Δ_i represents the differences between objective function values from X_i and Y_i. Therefore, $\Delta_{\mathrm{i}} = obj(Y_i, P) - obj(X_i, P)$. The probability of replacement of the current solution with the next solution is as follows.

$$\begin{cases} 1 & ,\Delta \le 0 \\ \exp\left(\frac{-\Delta_i}{KT}\right) & ,\Delta > 0 \end{cases}$$

If $\Delta_{\mathrm{i}} \le 0$, it means that the next solution is better than the current solution and should be replaced with the current solution. If $\Delta_{\mathrm{i}} > 0$, it means that the next solution is not appropriate. However, as it mentioned, since escaping from trapping in local search, these kinds of solutions will be accepted with $\exp\left(-\frac{\Delta_i}{KT}\right)$ probability by generating a random number r ∈[0,1] and replacing the solution X_i with Y_i if $r < \exp\left(-\frac{\Delta_i}{KT}\right)$.

After accomplishing the number of iterations, the current temperature will be decreased according to the formula $T = \alpha T$, where $0 < \alpha < 1$. As there are more chances to find a better solution, the algorithm uses a local search procedure which sequentially performs 2-Opt, swap, reversion, insertion and change of service vehicle types in every three temperature reductions (Lin et al., 2009).

If the current temperature T becomes lower than T_f or the number of reductions exceed the N_{non} without improving the best cost, the algorithm will be terminated.

6.2.3 Tabu search algorithm to solve the models

Similar to M-SA, TS also needs to start its procedure from an initial solution in the solution space. This initial solution can be infeasible. For this purpose, the initial solution method which is explained in previous section can be used for TS. TS algorithm tries to encourage the procedure to explore that part of the solution space which has not been visited yet. This purpose can be attained by preventing the reverse moves. The reversal of previous moves should become tabu for prohibiting a return to the previous solutions. Cycle avoidance can be obtained over the tabu tenure. At each iteration, the inverse modification is identified as a tabu and occurred in the tabu list. In this paper, four operators (swap, reversion, insertion, and change of service vehicle type of VCs) have been considered for finding new solutions. In addition, tabu tenure η is generated randomly with integer uniform distribution from $[r,\ s]$. Four tabu lists $TABU_i$ $(i = 1, 2, 3, 4)$ are considered to store the relevant inverse modifications for four operators. If the tabu status $TABU_i(j, k)$ is less or equal 0, it means that arc (j, k) is not tabu and vice versa.

Tabu moves can be overridden if the aspiration criterion is satisfied. If the tabu solution has less objective function value, it can be overridden.

The TS algorithm is explained as follows. At first, the relevant symbols are mentioned as follows:

- S: set of candidate solutions;
- t: iteration counter;
- t_{non}: current number of iteration without improvement;
- t_n: maximum number of allowable iterations;
- t_{max}: maximum number of iterations;
- n_c: current number of generated candidate solutions;
- n_{max}: maximum number of candidate moves;

- x^*: best-found solution for complete vehicle;
- y^*: best-found solution for single truck;
- $T(x, y)$: the objective value;
- $P(x, y)$: the penalized objective value.

6.2.3.1 Tabu search procedure

1) Generate an initial solution.
2) Initialize the parameters: $A_1 = A_2 = 1$, $A_3 = A_4 = 1000$, $S = \emptyset$, $t = 0$, $n_c = 0$, $t_{non} = 0$, $\delta_i = 0$, n_{max}, t_{max}, t_n, r, s.
3) Update the data: $x \to x^*$, $y \to y^*$, $T(x, y)$ and $P(x, y)$.
4) If $n_c \geq n_{max}$, go to 3.
5) Generate random neighborhood $N(x, y)$ and moves from current solution to new solution.
6) Update $t + 1 \to t$, $n_c + 1 \to n_c$, $S = S \cup \{x_{n_c}\} \cup \{y_{n_c}\}$.
7) Evaluate all solutions in S by procedure 1 and set $i = 1$, $x_{best} = \emptyset$, $y_{best} = \emptyset$ and $P(x, y) = \infty$ and insert all non-tabu solutions in $N'(x, y)$.
8) If $i > n_c$, go to 10
9) If $(x_i, y_i) \in N'(x, y)$ and $P(x_i, y_i) < P(x_{best}, y_{best})$, $(x_{best}, y_{best}) = (x_i, y_i)$ and $P(x_{best}, y_{best}) = P(x_i, y_i)$; else if the solution is feasible, and $T(x_i, y_i) < T^*(x^*, y^*)$, some parameters should be updated as follows. $(x_{best}, y_{best}) = (x_i, y_i)$, $P(x_{best}, y_{best}) = P(x_i, y_i)$ and $i + 1 \to i$ and go to 8.
10) If $P(x_{best}, y_{best}) \geq P^*(x, y)$, set $t_{non} + 1 \to t_{non}$, else update: $(x_{best}, y_{best}) \to (x, y)$, $(x_{best}, y_{best}) \to P^*(x, y)$.

11) If (x_{best}, y_{best}) is feasible and $T(x_{best}, y_{best}) < T^*(x^*, y^*)$, then set $(x_{best}, y_{best}) \rightarrow (x^*, y^*)$. In addition, $T(x_{best}, y_{best}) \rightarrow T^*(x^*, y^*)$ and update the values of E_k, F_k, G_k, H_k and δ_i.

12) Set $TABU_i(j, k) - 1 \rightarrow TABU_i(j, k)$. It should be mentioned that the corresponding inverse modifications are tabooed for a tabu tenure η, which is generated randomly from $[r, s]$.

13) If $mod(t, 10) = 0$, then A_i should be updated. In addition, $\delta_i = 0$ and $t + 1 \rightarrow t$.

If $t \leq t_{max}$ and $t_{non} \leq t_n$, then go to 5; else the algorithm is terminated and the best solution found is (x^*, y^*).

6.2.4 Memetic algorithm to solve the models

MAs fit into the category of the evolutionary algorithms (EAs) where LS procedures are used to distribute the search area and enhance the search to refine the individual. In fact, MA is a hybrid algorithm which combines the population and LS procedures to improve the initial solutions. The inspiration for MA was realized from the adaptation of models in the natural systems (Ghaderi et al., 2012). These models combine the lifetime learning of an individual with the populations' evolutionary adaptation (Tavakkoli-Moghaddam et al., 2006). Besides, another inspiration of the MAs was obtained from the concept of meme from Dawkin. A cultural evolution unit is represented by this concept and it can indicate the local refinement (Norouzi et al., 2012; Tavakkoli-Moghaddam et al., 2006) and can be applied in solving TTRPs.

In applied MAs, the population P consists of a set of individuals generated randomly. Each individual is called a 'chromosome', which is simply a permutation of the set of n nodes (customers) $\{1, 2, \ldots, n\}$ and N dummy zeroes (artificial stores or the root of ST). This idea was initially proposed by Beasley (1983) as part of a route-first cluster-second heuristic, and was then used by Prins (2004). Recently, this method has been applied to other versions of the VRP, such as heterogeneous fleets (Prins, 2009), pickup and delivery vehicle routing problems (Velasco et al., 2009) and TTRP (Villegas et al., 2010).

The presentation of the solution for TTRPSDTW is explained more as follows. Initially, parents are selected based on tournament selection. Then, in each stage, offspring are randomly generated from the initial population. First, two chromosomes (parents) are randomly selected and two new chromosomes (offspring) are produced by crossover operation. The functional value is computed by the chromosomes. The new solutions are compared with the existing solutions. If a new solution is better than an existing solution, the algorithm replaces the existing solution with the new one. Then the new solution can be improved by mutations and LS procedures. This procedure is continued until the termination condition occurs.

6.2.4.1 Crossover operator

Partial-mapped crossover (PMX) and order crossover (OX) have been considered as permutation representations. PMX was first proposed by Goldberg and Lingle (1985). The PMX operator is an extension of the two-point crossover. Two-point crossover is used for a binary string and some infeasible solutions may occur using this operator. However, PMX uses some procedures to fix this illegitimacy (infeasible solutions) by repairing solutions caused by two-point crossover. First, two positions in the chromosome are randomly selected and the sub-chromosomes situated between these positions are substituted. Then the relations between two mapping sections are determined. Finally, the remaining customers are arranged randomly in the remaining positions according to the relations discovered (Tavakkoli-Moghaddam et al., 2006). This PMX operator is considered for the TTRPSDTW solution. The sample representation of a PMX is depicted in Figure 6.3. In this figure, two samples known as parent chromosomes are selected and two new offspring are produced according to PMX. First, shadow customers (sub-chromosomes) are selected. Then all customers in this sub-chromosome are replaced and finally the remaining customers are randomly allocated according to the relations developed.

Parent 1	2	6	4	7	11	17	15	3	8	9	12
Parent 2	3	9	4	8	6	2	15	12	7	11	17
Offspring 1	7	4	17	8	6	2	15	12	3	9	11
Offspring 2	12	6	8	7	11	17	15	3	9	4	2

Figure 6.3: Partial-mapped crossover

The OX operator uses different methods for repairing the procedure. This operator has been successfully applied for the TSP (Oliver et al., 1987) and VRP (Prins, 2004). First, a sub-chromosome from one parent is randomly selected. Then the new offspring is made by dropping the sub-chromosome into the same position. Finally, the remaining customers are arranged according to their positions in the other parent. A sample representation of an OX is illustrated in Figure 6.4.

Parent 1	2	6	4	7	11	17	15	3	8	9	12
Parent 2	3	9	4	8	6	2	15	12	7	11	17
Offspring 1	9	4	8	7	11	17	15	3	6	2	12

Figure 6.4: Order crossover

6.2.4.2 Mutation operator

Different types of mutations such as inversions, insertions, swaps, displacements and changes in service vehicle type for VCs have been applied in producing offspring by the MA. The displacement mutation is implemented by selecting the sub-chromosomes randomly and inserting them in a random situation. Swap is performed by choosing two customers at random and changing them to create new solutions from the existing solution. Reversion is carried out by selecting two customers of the chromosome and reversing the route from the larger number to the smaller. Insertion is achieved by choosing two customers at random and inserting the first one just after the second. The change in service vehicle type for VCs is fulfilled by selecting a VC at random. If it is serviced by a single truck in the current solution, its service vehicle type will be changed to a complete vehicle and vice versa. This means that the vehicle service type of the selected VC will be changed from 1 to 0 or 0 to 1. For example a VC serviced in the main tour by a complete vehicle will be serviced on an ST by a single truck and vice versa. Figures 6.5, 6.6, 6.7 and 6.8 illustrate different kinds of mutations that are used in MA.

Parent	2	6	4	7	11	17	15	3	8	9	12
Offspring	2	6	17	15	3	4	7	11	8	9	12

Figure 6.5 : Displacement mutation

Parent	2	6	4	7	11	17	15	3	8	9	12
Offspring	2	6	3	7	11	17	15	4	8	9	12

Figure 6.6: Swap mutation

Parent	2	6	4	7	11	17	15	3	8	9	12
Offspring	2	6	3	15	17	11	7	4	8	9	12

Figure 6.7: Reversion mutation

Parent	2	6	4	7	11	17	15	3	8	9	12
Offspring	2	6	7	11	17	15	3	4	8	9	12

Figure 6.8: Insertion mutation

6.2.4.3 Local search operator

After applying crossovers and mutation procedures, LS approaches are applied to improve the chromosomes in the pool of candidates. Four various LS procedures, one-point movement (OMP), two-point exchange (TPE), change ST root and two-opt are used in the MA. Each approach can be chosen randomly with equal probability. In OPM, a customer is moved from one route to another. If the cost is decreased by this movement, it can be accepted. Also one customer is considered at a time. In executing the movement, moving a TC customer to the main tour of the CVR or two PVRs is forbidden. First, the algorithm examines customers on the PTR and the main-tours, and then the ST customers are examined. In a TPE, two customers of two different routes should be replaced. However, moving a TC customer into the main tour in the CVR or into a PVR is banned. When customers are switched between two routes, all of the sub-route continues to be feasible taking into account truck capacity. In the case of the two aforesaid procedures, the root node never changes its position. This may happen as a result of an improved solution when some of the root nodes are replaced. In this stage, re-selecting roots or re-sequencing the customers are considered. The two-opt algorithm is a kind of *k*-opt algorithms (Chao, 2002). In *k*-opt, *k* edges are removed by the *k*-opt algorithm and then reconnected in any possible situation. In the same way, the two-opt algorithm removes two edges randomly and then re-inserts the edges in any possible situation (Chao, 2002). An example of two-opt is given in Figure 6.9. If the objective function is not deteriorated by these movements, the procedure is applied. This procedure is continued until the algorithm cannot find any other improvements.

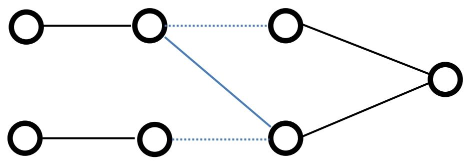

Figure 6. 9: *2-opt* illustration

6.3 TTRP benchmarks solutions using aforesaid algorithms

For solving TTRP, 21 TTRP benchmark problems which were generated by Chao (2002) have been considered. This benchmark is derived from Christofides et al (1979). To evaluate the performance of the solutions, the results are compared with Chao (2002), Scheuerer (2006) and Lin et al. (2010). Chao and Scheuerer used proposed tabu search while Lin et al., used proposed SA for solving TTRP. The results from Chao, Scheuerer, Lin et al., and proposed MA are presented in Table 2. Each instance has been run in 10 times and the best solutions from 10 run are located in the last column. Also the time taken for best solutions is presented in the next columns. In addition, Table 6.1 shows the number of customers and the capacity of each truck and trailer which are mentioned by Chao (2002).

Table 6.1: Dimensions of the TTRP benchmark problems proposed by Chao (2002)

Problem ID	Number of VC	Number of TC	Truck capacity	Trailer capacity	Ratio of demand to capacity
1	38	12	100	100	0.971
2	25	25	100	100	0.971
3	13	37	100	100	0.971
4	57	18	100	100	0.974
5	38	37	100	100	0.974
6	19	56	100	100	0.974
7	75	25	100	100	0.911
8	50	50	100	100	0.911
9	25	75	100	100	0.911

10	113	37	100	100	0.931
11	150	75	100	100	0.931
12	100	112	100	100	0.931
13	150	49	150	150	0.923
14	100	99	150	150	0.923
15	50	149	150	150	0.923
16	90	20	150	150	0.948
17	60	60	150	150	0.948
18	30	90	150	150	0.948
19	75	25	150	150	0.903
20	50	50	150	150	0.903
21	25	75	150	150	0.903

Table 6.1 continued

Table 6. 2: Results obtained using MA and other approaches

ID	Chao	Scheuerer	Lin	BKS	Best-Sol MA	Average Sol MA	Gap(%)	Time(min)
1	565.02	566.80	566.82	564.68	**561.62**	578.32	-2.88767	5.44
2	662.84	615.66	612.75	**611.53**	612.75	624.11	-1.82019	6.57
3	664.73	620.78	618.04	618.04	**618.04**	628.90	-1.72682	6.84
4	857.84	801.60	808.84	**798.53**	809.53	817.25	-0.94463	13.91
5	949.98	839.62	839.62	839.62	**839.62**	851.03	-1.34073	13.09
6	1084.82	936.01	934.11	930.64	**928.92**	940.77	-1.25961	11.78
7	837.80	830.48	830.48	830.48	**830.48**	843.86	-1.58557	22.87
8	906.16	878.87	875.76	872.56	**872.56**	886.26	-1.54582	22.94
9	1000.27	942.31	912.64	912.02	**909.60**	922.39	-1.38662	23.45
10	1076.88	1039.23	1053.90	**1036.20**	1042.73	1067.88	-2.35513	55.43
11	1170.17	1098.84	1093.57	1091.91	**1083.89**	1098.10	-1.29405	57.33
12	1217.01	1175.23	1155.44	**1149.41**	1157.43	1170.98	-1.15715	48.27
13	1364.50	1288.46	1320.21	**1284.71**	1296.22	1313.91	-1.34636	102.58
14	1464.20	1371.42	1351.54	**1333.66**	1342.99	1356.21	-0.97478	105.06
15	1544.21	1459.55	1436.78	**1416.51**	1427.82	1435.06	-0.50451	88.00
16	1064.89	1002.49	1004.47	**1000.84**	1002.49	1009.43	-0.68752	42.11
17	1104.67	1042.35	1026.88	1026.17	**1021.12**	1033.31	-1.1797	34.56
18	1202.00	1129.16	1099.09	1098.15	**1096.10**	1105.26	-0.82876	28.21
19	887.22	813.50	814.07	812.69	**811.72**	823.72	-1.45681	31.29
20	963.06	848.93	855.14	848.12	**848.12**	859.16	-1.28498	27.73
21	952.29	909.06	909.06	909.06	**909.06**	920.45	-1.23744	21.53
Avg	1025.74	962.40	958.06	951.69	953.50	966.02	-1.37	36.62

The solutions for TTRP benchmarks tested by Chao (2002) obtained using proposed MA and other approaches are compared in Table 6.2. Table 6.2 indicates that the proposed MA obtained 13 best solutions from 21 which are shown in boldface in this table. Furthermore, the average of Best-sol, the average of Avg-sol are computed and the results confirm that the difference is very small. So, the MA can generate the results. In addition, the average times taken for the solutions are presented, which are rounded to the nearest integer. Thus MA can solve the problems faster in comparison with SA and TS. Table 6.3 compared the results obtained from proposed MA with other approaches.

Table 6. 3: Comparison of MA with other approaches

Problem ID	Comparison of best solution between proposed MA and Chao's results (MA-TS)/TS (%)	Comparison of best solution between proposed MA and Scheuerer's results (MA-TS)/TS (%)	Comparison of best solution between proposed MA and Lin's results (MA-SA)/SA (%)	Comparison of best solution between proposed MA and BKS (MA-BKS)/BKS (%)
1	−0.60175	−0.9139	−0.9174	-0.00542
2	−7.55688	−0.47266	0	0.001995
3	−7.0239	−0.44138	0	0
4	−5.63159	0.989271	0.085307	0.013775
5	−11.6171	0	0	0
6	−14.371	−0.75747	−0.55561	-0.00185
7	−0.87372	0	0	0
8	−3.69802	−0.70773	−0.35512	0
9	−9.06455	−3.47126	−0.3331	-0.00265
10	−3.1712	0.336788	−1.05987	0.006302
11	−7.37329	−1.36053	−0.88517	-0.00734
12	−4.8956	−1.5146	0.172229	0.006977
13	−5.00403	0.602269	−1.81714	0.008959
14	−8.27824	−2.07303	−0.63261	0.006996
15	−7.53719	−2.17396	−0.62362	0.007984
16	−5.85976	0	−0.19712	0.001649
17	−7.56334	−2.03674	−0.56092	-0.00492
18	−8.81032	−2.92784	−0.27204	-0.00187
19	−8.50973	−0.21881	−0.28867	-0.00119
20	−11.8508	0	−0.7262	0
21	−4.53958	0	0	0
Average	−6.84912	−0.81627	−0.427	0.001

Table 6.3 indicates that the average results obtained using proposed MA were improved about 6.85 percent, 0.82 percent and 0.427 percent comparing with Chao's results, Scheuerer' results and Lin's results, respectively. Also, the average results obtained using MA is almost same as BKS. Consequently, the performance of proposed MA is better than SA and TS. Then the results can be accepted as the new solutions. Therefore, the results approved and indicate that the MA is efficient and effective in solving TTRP and can generate the results. Finally, the TTRP benchmarks results tested by Lin et al. (2010). Each instance has been run in 10 times and the best solutions (Best-

Sol) from 10 run, the average solutions (Avg-Sol) from the 10 runs and the gap between the Best-Sol and Avg-Sol are located in Table 6.4. Moreover, BKS is prepared for each solution to compare the results obtained using proposed MA and the others. Also the time taken for best solutions is presented in the last column.

Table 6.4: Results for TTRP benchmark by Lin et al., (2010) obtained using MA and other approaches

ID	Number of customers	BKS	Best-Sol MA	Average-Sol MA	Gap (%)	Time (min)
1	75	1640.53	1640.53	1645.90	-0.3262	3.41
2	75	1706.36	1708.22	1715.09	-0.4005	2.94
3	75	1774.14	1772.75	1780.36	-0.4274	4.01
4	75	1273.56	1273.56	1279.31	-0.4494	4.10
5	75	1292.60	1291.01	1298.26	-0.5584	4.20
6	75	1414.41	1416.47	1421.78	-0.3734	6.75
7	75	1205.57	1204.00	1210.30	-0.5205	4.30
8	75	1243.13	1243.13	1247.82	-0.3758	3.48
9	75	1314.78	1312.55	1319.63	-0.5365	3.19
10	75	1372.84	1374.51	1379.50	-0.3617	4.76
11	75	1414.84	1412.43	1420.71	-0.5828	4.69
12	75	1501.18	1501.18	1508.46	-0.4826	4.11
13	100	2047.53	2047.53	2052.01	-0.2183	4.01
14	100	2109.50	2109.50	2115.45	-0.2812	4.89
15	100	2245.80	2243.13	2248.39	-0.2339	4.40
16	100	1901.08	1901.08	1910.01	-0.4675	4.68
17	100	1957.70	1957.70	1961.43	-0.1901	3.66
18	100	2041.76	2040.11	2045.25	-0.2513	4.58
19	100	1274.92	1274.92	1280.49	-0.4349	5.20
20	100	1324.83	1326.10	1332.17	-0.4556	5.26
21	100	1460.88	1461.69	1467.38	-0.3877	4.29
22	100	1467.82	1466.24	1471.59	-0.3635	5.54
23	100	1536.95	1536.95	1539.42	-0.1604	4.92
24	100	1615.71	1617.30	1623.03	-0.3530	3.87
25	150	3224.64	3226.90	3233.40	-0.2010	14.74
26	150	3295.78	3292.01	3300.14	-0.2463	9.00
27	150	3429.69	3429.69	3432.67	-0.0868	23.94
28	150	2580.92	2579.13	2586.58	-0.2880	18.14
29	150	2653.12	2653.12	2658.43	-0.1997	19.36
30	150	2796.44	2797.38	2804.21	-0.2435	20.53
31	150	2027.70	2027.70	2031.79	-0.2013	13.64
32	150	2112.03	2111.31	2116.88	-0.2631	9.64
33	150	2374.85	2374.85	2378.50	-0.1534	8.50
34	150	2669.92	2671.02	2677.43	-0.2394	39.00
35	150	2727.15	2725.10	2731.28	-0.2262	41.37
36	150	2896.85	2896.85	2900.39	-0.1220	40.42
AVG	----	1970.21	1969.94	1975.71	-0.324	10.10

Table 6.4 indicates that the proposed MA obtained 27 best solutions from 36 which are bolded in this table. The Table 4 proofed that the differences between the results of Best-sols, Avg-sols and the BKS in each group are not considerable and the

results confirm that the differences is small. Therefore, as the algorithm generates 27 best solutions, the applied MA is efficient with confidence consistency of a reasonable time.

6.4 TTRPSD benchmarks solutions using aforesaid algorithms

This type of problem has not yet been considered and there is no scope to compare this solution with an existing one. To overcome this issue, the special 21 TTRPSD benchmark instances are modified which are derived from Chao (2002). First, the benchmarks were solved in order to increase the validity of the aforesaid algorithms and to show the consistency of the results. Then the case study problem was solved using MA, M-SA and TS. Further, the case study problem was checked by sensitivity analysis to confirm the results. The implementation of the benchmark was discussed in Chapter 3. Parameters used in the model may affect the quality of computational results. These parameters may be used for MA, M-SA or TS. In order to obtain better solutions, different values have been tested in initial experiments. These are:

$P = 10000$; $\alpha = 0.99, 0.975, 0.95$; $I_{iter} = 2000, 4000, 6000, 8000, 10000$; $I_{iterpertemp} = 2,4,6,8,10$; $K = 1, 0.9, 0.8, 0.7, 0.6, 0.5$; $n_{pop} = 1,3,5,7,9$; $n_{move} = 1,3,5,7,9$; $T_0 = 1000, T_F = 0.1$ or $T_0 = 10, T_F = 0.001$; $N_{non} = 100, 200$; $[r, s] = [5,10]$; $n_{max} = 150$; $t_{max} = 1000$; $t_n = 50, 100$; $P_c = 0.7, 0.75, 0.8$; $P_m = 0.2, 0.3, 0.4$; $P_l = 0.3, 0.4, 0.5$; $n = 50, 100$, where P_c, P_m, P_l and n are the probability of crossover, mutation, LS improvement and population size, respectively. Since it is not possible to use more than the predetermined number of vehicles, the penalty cost is considered too high. The parameters have been examined with different values and set to be $\alpha = 0.95, I_{iter} = 6000, K = 0.7, T_0 = 10$, $T_F = 0.001$, $n_{pop} = 5$, $n_{move} = 9$,

$I_{iterpertemp} = 6$ and $N_{non} = 200$, $t_n = 50$, $P_c = 0.7$, $P_m = 0.3$, $P_l = 0.5$ and $n = 100$. They seem to give the best results and will be used for further computation.

Table 6.5 illustrates the benchmark results. Each set has been run 10 times and the best solutions of MA, M-SA and TS from the 10 runs are shown.

Table 6.5: The best solutions of TTRPSD benchmarks

Problem ID	Number of VC	Number of TC	Truck number	Truck capacity	Trailer number	Trailer capacity	MA results	M-SA results	TS results
1	38	12	5	60	3	60	635.45	639.38	643.30
2	25	25	5	60	3	60	671.84	659.77	666.56
3	13	37	5	60	3	60	677.44	683.76	686.42
4	57	18	9	60	5	60	929.11	931.63	942.32
5	38	37	9	60	5	60	921.01	919.10	924.55
6	19	56	9	60	5	60	971.90	991.28	1007.85
7	75	25	8	100	4	60	934.34	931.83	926.79
8	50	50	8	100	4	60	879.80	898.86	911.33
9	25	75	8	100	4	60	956.87	949.57	954.27
10	113	37	12	100	6	60	1117.32	1126.66	1133.38
11	75	75	12	100	6	60	1220.02	1198.94	1228.06
12	38	112	12	100	6	60	1221.29	1230.32	1243.02
13	150	49	17	100	9	60	1312.69	1309.84	1305.68
14	100	99	17	100	9	60	1374.32	1377.01	1381.58
15	50	149	17	100	9	60	1473.65	1475.00	1482.67
16	90	30	7	100	4	60	1092.37	1129.42	1113.86
17	60	60	7	100	4	60	1139.52	1114.28	1118.90
18	30	90	7	100	4	60	1118.93	1127.65	1120.05
19	75	25	10	100	5	60	843.46	843.46	852.14
20	50	50	10	100	5	60	853.72	867.77	876.15
21	25	75	10	100	5	60	867.62	965.24	948.41
Avg.							1010.13	1017.65	1022.25

Table 6.5 indicates that the average results generated by the MA are better than M-SA and TS. However, the differences between these results are insignificant and the results show that these algorithms are effective for solving related problems.

Table 6.6: Compared the results obtained from proposed MA with TS and M-SA

Problem ID	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%)	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%)
1	-1.22	-0.61
2	0.79	1.83
3	-1.31	-0.93
4	-1.40	-0.27
5	-0.39	0.21
6	-3.60	-1.96
7	0.81	0.27
8	-3.58	-2.12
9	0.27	0.76
10	-1.44	-0.84

11	-0.66	1.73
12	-1.78	-0.74
13	0.53	0.22
14	-0.53	-0.20
15	-0.61	-0.09
16	-1.93	-3.28
17	1.81	2.21
18	-0.10	-0.78
19	-1.02	0
20	-2.56	-1.62
21	-8.52	-10.11
Average	-1.27	-0.78

Table 6.6 indicates that the average results obtained by the proposed MA were improved about 1.27 and 0.78 percent comparing with tabu search and multi-point simulated annealing, respectively. Consequently, the performance of the proposed MA is found slightly better than SA and TS. As the differences between these results are insignificant, the results obtained by MA, M-SA and TS can be accepted as the new solutions. Therefore, the results indicate that the algorithms are efficient and effective in solving TTRP with stochastic demands.

6.5 TTRPSDTW benchmarks solutions using aforesaid algorithms

This is a new model of the TTRPSDTW. Hence, there is no scope to compare this solution with an existing one. In the first step, two experimental TTRPSDTW tests were carried out in order to increase the validity of the modified MA, M-SA and TS and to show the consistency of the results. In the case of the first test, all the customers are supposed to be TC. Therefore, all the capacities of the trucks have the same features as the vehicle in the original VRPSDTW (Lei et al., 2011). Consequently, the TTRPSDTW problem is converted to VRPSDTW since the TCs cannot be serviced by a CVR or PVR; therefore, the results should not be significantly different from the

VRPSDTW results. Three problem-instances, such as R103, C206 and RC204, are randomly selected and the results are reported in Table 6.7.

Table 6.7: The applied MA solutions with a comparison of results obtained by LNS

ID	Instance	$\Phi(R)$	$R(R)$	$T(R)$	LNS	Time (second) (MA)	Time (second) (LNS)
1	R101	647.241	28.974	**676.215**	683.529	421	445
2	R102	693.969	32.034	**726.003**	**726.003**	732	812
3	R103	441.260	49.104	490.364	**477.878**	1421	1607
4	C101	421.104	22.788	443.892	**439.468**	734	935
5	C102	433.700	29.395	**463.095**	473.793	894	1004
6	C103	367.581	11.206	378.787	**376.468**	583	627
7	RC101	627.563	2.995	**630.558**	639.631	1165	1417
8	RC102	957.847	1.256	**959.103**	959.373	1659	2172
9	RC103	466.715	3.113	469.828	**466.461**	2148	2666
Average	-----	-----	-----	**581.982**	582.178	1084	1298

Table 6.7 indicates that the results generated by the MA are slightly better than LNS except for R103. The differences between these results are insignificant and the results show that this MA is effective for solving both TTRPSDTW and VRPSDTW.

The second test is customized as follows. All customers are set to be VCs. The truck and trailer capacities are equal and half of the vehicle capacity is already in the original VRPSDTW. The difference between tests 1 and 2 is that VCs can be serviced by either a single truck or a complete vehicle; however, TCs have to be serviced only by a single truck. Therefore, in the second test all types of route can be produced. In addition, all failure types may occur in test 2 whereas only failure types 1 and 2 can happen in test 1. To compare the results in Tables 6.8 and 6.9, the same instances are chosen and solved in test 2. The results of test 2 can be seen in Table 6.7.

Table 6. 8: Results of the first experiment

ID	Instance	$\Phi(R)$	$R(R)$	$T(R)$	LNS
1	R103	441.260	49.104	490.364	**477.878**
2	C206	331.107	3.293	**334.400**	350.271
3	RC204	720.017	0	**720.017**	722.483
Average	-----	-----	-----	**514.927**	516.877

Table 6. 9: Results of the second experiment.

ID	Instance	$\Phi(R)$	$R(R)$	$T(R)$ (test 2)	Result in test 1	LNS
1	R103	442.128	50.005	492.133	490.364	**477.878**
2	C206	331.107	3.293	**334.400**	**334.400**	350.271
3	RC204	722.017	0.804	722.821	**720.017**	722.483
Average	-----	------	------	516.451	**514.927**	516.877

These results also reveal that the proposed MA approach is efficient and can confidently solve TTRPSDTW. In addition, the average time taken for the solutions is presented in the last column of each table, which is rounded to the nearest integer. Thus MA can solve the problems faster in comparison with LNS.

Further, to solve TTRPSDTW, the special 54-benchmark-instance problems are modified in three different classes, as derived from Lin (2011) for the TTRPSDTW. The numbers of customers are 50, 100 and 200 in the first, second and third classes, respectively. The implementation of the benchmark was discussed in Chapter 3. The parameters used in the model may affect the quality of the computational results and are the same as TTRPSD solutions.

Since it is not possible to use more than the predetermined number of vehicles, the penalty cost is considered to be too high. The parameters have been examined with different values are the same as the TTRPSD solutions and one-at-a-time sensitivity analysis has been used to solve the problems. To apply sensitivity analysis for every parameter, the algorithms were tuned sequentially, leaving the remaining parameters unchanged. For each of the benchmark problems, in total about 400 runs were undertaken during the sensitivity analysis (including running a parameter setting 10 times on the same benchmark problem).

The results from 50, 100 and 200 customers are presented in Tables 6.10–6.18, respectively. Each set has been run 10 times and the best solutions (Best-sol) and the average solutions (Avg-sol) from the 10 runs are shown. Also the time taken for the best solutions is presented in the last column. Hence, this problem has not yet been considered; the results cannot be compared with any comparative data or proposed heuristics considered previously by other researchers. However, the problems were solved by sensitivity analysis. Therefore, the results can be compared.

Table 6.10: Results for TTRPSDTW with 50 customers using M-SA

Problem ID	Original	Best-sol	Avg-sol	Sensitivity analysis	Time second
1	C101	429.12	442.28	426.10	816
2	C101	514.43	530.05	511.16	622
3	C101	519.66	526.50	518.56	862
4	C201	403.90	409.04	397.52	781
5	C201	404.56	408.00	400.64	650
6	C201	396.11	409.23	392.48	802
7	R101	968.23	976.64	963.15	995
8	R101	986.28	992.31	980.09	908
9	R101	1018.42	1031.62	1014.98	871
10	R201	842.62	867.74	842.62	864
11	R201	848.27	861.40	842.62	843
12	R201	842.62	852.21	842.62	941
13	RC101	984.61	993.05	983.92	891
14	RC101	1004.44	1010.71	998.28	882
15	RC101	1010.71	1021.25	1008.65	843
16	RC201	723.73	731.21	722.83	757
17	RC201	723.73	729.77	721.47	877
18	RC201	725.08	729.39	721.47	808
Average	-----	741.47	751.24	738.29	834

Table 6.11: Results for TTRPSDTW with 50 customers using MA algorithm

Problem ID	Original	Best-sol	Avg-sol	Sensitivity analysis	Time second
1	C101	427.74	436.60	424.65	693
2	C101	511.02	523.43	510.09	531
3	C101	521.89	524.32	517.11	724
4	C201	399.64	404.91	394.21	701
5	C201	401.23	405.46	397.77	672
6	C201	390.99	401.58	385.05	762
7	R101	963.57	967.82	959.94	901
8	R101	982.09	990.51	977.72	829
9	R101	1011.42	1023.33	1009.28	721
10	R201	842.62	854.47	842.62	839
11	R201	842.62	848.08	842.62	790
12	R201	842.62	849.39	842.62	892
13	RC101	987.23	989.98	982.22	852
14	RC101	1001.19	1007.80	996.58	782
15	RC101	1010.71	1015.00	1007.05	812
16	RC201	723.73	726.81	721.47	718
17	RC201	723.73	723.38	721.47	832
18	RC201	723.73	725.36	721.47	785
Average	-----	739.32	745.46	736.33	769

Table 6.12: Results for TTRPSDTW with 50 customers using TS

Problem ID	Original	Best-sol	Avg-sol	Sensitivity analysis	Time second
1	C101	433.89	452.22	429.23	896
2	C101	518.84	528.48	514.07	742
3	C101	519.66	532.27	519.66	922
4	C201	410.27	421.74	403.75	901

5	C201	406.07	418.23	403.58	728
6	C201	396.11	412.58	395.67	833
7	R101	964.66	973.00	963.15	952
8	R101	983.16	995.07	980.47	893
9	R101	1021.17	1039.43	1018.55	855
10	R201	842.62	869.05	842.62	898
11	R201	844.49	856.32	843.34	868
12	R201	842.62	858.89	842.62	1003
13	RC101	984.61	989.97	984.10	828
14	RC101	1009.95	1021.45	1006.62	924
15	RC101	1008.78	1016.89	1008.78	890
16	RC201	723.73	738.78	723.73	799
17	RC201	725.73	731.77	722.69	778
18	RC201	724.57	732.35	722.64	837
Average	-----	742.27	754.92	740.29	864

Table 6.13: Results for TTRPSDTW with 100 customers using M-SA

Problem ID	Original	Best-sol	Avg-sol	Sensitivity analysis	Time (second)
1	C101	931.37	940.64	928.85	2809
2	C101	1009.68	1020.02	1007.92	3101
3	C101	1027.64	1030.05	1021.48	2812
4	C201	799.64	809.21	799.64	1920
5	C201	806.69	811.40	799.54	2021
6	C201	890.99	908.91	887.00	1925
7	R101	1467.83	1481.51	1463.18	2881
8	R101	1578.51	1586.09	1575.72	2750
9	R101	1414.42	1430.65	1411.21	3121
10	R201	1240.09	1247.86	1240.09	1960
11	R201	1287.62	1312.25	1282.01	1821
12	R201	1189.16	1215.26	1187.65	2124
13	RC101	1893.83	1905.52	1890.38	2902
14	RC101	1798.69	1810.47	1797.33	2832
15	RC101	1915.54	1923.23	1909.87	3009
16	RC201	1223.42	1231.71	1223.42	2402
17	RC201	1263.52	1286.38	1260.82	2210
18	RC201	1270.12	1286.48	1270.12	2546
Average	-----	1278.26	1290.98	1275.35	2508

Table 6.14: Results for TTRPSDTW with 100 customers using MA

Problem ID	Original	Best-sol	Avg-sol	Sensitivity analysis	Time (second)
1	C101	927.74	936.60	925.43	2693
2	C101	1011.02	1023.43	1007.92	2931
3	C101	1021.89	1024.32	1017.03	2724
4	C201	799.64	804.91	797.82	1801
5	C201	801.23	805.46	795.74	1972
6	C201	890.99	901.58	886.63	1862
7	R101	1463.57	1477.82	1460.83	2801
8	R101	1582.09	1590.51	1580.11	2629
9	R101	1411.42	1423.33	1408.49	3021
10	R201	1242.22	1254.47	1240.07	1839
11	R201	1284.38	1308.08	1282.01	1790
12	R201	1189.16	1209.39	1183.82	2092
13	RC101	1887.23	1889.98	1884.36	2852
14	RC101	1801.19	1807.80	1797.33	2782
15	RC101	1910.71	1915.00	1903.93	2912
16	RC201	1223.42	1227.81	1223.42	2218
17	RC201	1263.52	1273.37	1260.82	2132
18	RC201	1271.81	1280.33	1270.67	2485
Average	-----	1276.85	1286.34	1273.69	2419

Table 6. 15: Results for TTRPSDTW with 100 customers using TS

Problem ID	Original	Best-sol	Avg-sol	Sensitivity analysis	Time (second)
1	C101	933.45	947.05	929.90	3023
2	C101	1007.53	1016.61	1006.42	3241
3	C101	1032.89	1040.24	1028.85	2905
4	C201	802.02	808.87	799.64	1965
5	C201	807.74	815.38	802.00	2066
6	C201	888.85	911.33	887.00	1987
7	R101	1469.68	1479.81	1465.43	2909
8	R101	1577.14	1589.01	1576.73	2798
9	R101	1413.59	1425.11	1410.26	3100
10	R201	1241.33	1248.60	1240.09	2013
11	R201	1287.62	1307.54	1283.34	1877
12	R201	1188.80	1205.44	1187.65	2099
13	RC101	1891.26	1900.07	1890.38	2919
14	RC101	1801.19	1814.06	1799.19	2901
15	RC101	1917.46	1927.73	1913.00	2958
16	RC201	1223.42	1241.35	1223.42	2381
17	RC201	1268.58	1289.98	1264.62	2258
18	RC201	1273.32	1289.49	1271.24	2505
Average	-----	1279.22	1292.09	1276.62	2550

Table 6. 16: Results for TTRPSDTW with 200 customers using M-SA

Problem ID	Original	Best-sol	Avg-sol	Sensitivity analysis	Time (second)
1	C101	3331.49	3365.73	3326.56	12805
2	C101	3414.42	3450.77	3408.58	14090
3	C101	3741.89	3775.85	3739.86	11875
4	C201	2401.81	2410.00	2397.61	10951
5	C201	2401.23	2418.95	2399.18	11035
6	C201	2394.89	2407.05	2390.33	11978
7	R101	5960.60	5988.85	5957.24	9961
8	R101	5982.09	5994.34	5979.18	9852
9	R101	6013.65	6047.94	6008.56	10143
10	R201	3731.83	3767.98	3730.73	12933
11	R201	3827.22	3856.67	3824.74	13956
12	R201	3690.40	3721.30	3688.86	12234
13	RC101	3987.23	4005.07	3985.67	14990
14	RC101	3601.19	3637.89	3600.43	13909
15	RC101	3813.46	3845.87	3809.74	14360
16	RC201	3025.01	3036.19	3021.55	12727
17	RC201	3149.04	3174.00	3147.21	13361
18	RC201	3099.95	3137.78	3095.23	12633
Average	-----	3753.74	3780.12	3750.63	12433

Table 6. 17: Results for TTRPSDTW with 200 customers using MA

Problem ID	Original	Best-sol	Avg-sol	Sensitivity analysis	Time (second)
1	C101	3327.74	3356.60	3320.83	12693
2	C101	3411.02	3463.43	3404.90	13931
3	C101	3741.89	3774.32	3737.02	11724
4	C201	2399.64	2412.91	2394.29	10801
5	C201	2401.23	2411.46	2393.03	10972
6	C201	2390.99	2401.58	2386.39	11862
7	R101	5963.57	5977.82	5955.46	9801
8	R101	5982.09	5996.51	5976.52	9629
9	R101	6011.42	6053.33	6002.88	10021
10	R201	3734.17	3804.47	3730.73	12837
11	R201	3825.80	3848.08	3822.62	13792
12	R201	3692.02	3739.39	3685.63	12092
13	RC101	3987.23	3999.98	3984.04	14852
14	RC101	3601.19	3647.80	3600.43	13782
15	RC101	3810.71	3845.00	3804.52	14212
16	RC201	3023.38	3026.81	3021.55	12518
17	RC201	3151.82	3183.10	3147.21	13132
18	RC201	3095.22	3125.42	3091.86	12485
Average	-----	3752.84	3781.56	3747.77	12286

Table 6. 18: Results for TTRPSDTW with 200 customers using TS

Problem ID	Original	Best-sol	Avg-sol	Sensitivity analysis	Time (second)
1	C101	3331.49	3357.42	3329.63	12942
2	C101	3417.31	3442.36	3411.90	14220
3	C101	3738.42	3777.75	3738.42	11202
4	C201	2402.70	2427.08	2399.75	11051
5	C201	2401.23	2423.69	2401.23	11130
6	C201	2398.70	2416.11	2395.24	12043
7	R101	5958.48	5979.58	5956.98	10032
8	R101	5986.77	6003.13	5982.89	9910
9	R101	6016.00	6035.65	6011.39	10219
10	R201	3731.83	3754.03	3730.73	12019
11	R201	3829.89	3869.69	3826.54	13291
12	R201	3687.77	3701.08	3687.77	12271
13	RC101	3985.25	4015.12	3983.34	14060
14	RC101	3601.19	3636.32	3600.43	13853
15	RC101	3817.68	3833.11	3813.70	14680
16	RC201	3026.67	3053.80	3024.33	12327
17	RC201	3149.04	3167.08	3147.21	13901
18	RC201	3097.74	3122.80	3092.29	12493
Average	-----	3754.34	3778.66	3751.88	12314

Tables 6.10–6.18 indicate that the differences between the results of Best-sols, Avg-sols and sensitivity analysis in each group are not considerable. In addition, the average of Best-sol, the average of Avg-sol and the average of the results obtained by sensitivity analysis are computed and the results confirm that the difference is very small. Therefore, the applied algorithms are efficient with confidence consistency of a reasonable time.

Table 6.19: Compared the TTRPSDTW results with 50 customers obtained from proposed MA with TS and M-SA

Problem ID	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%)	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%)
1	-1.42	-0.32
2	-1.51	-0.66
3	0.43	0.43
4	-2.59	-1.06
5	-1.19	-0.82
6	-1.29	-1.29
7	-0.11	-0.48
8	-0.11	-0.43
9	-0.96	-0.69
10	0	0
11	-0.22	-0.67
12	0	0

Table 6.19, continued: Compared the TTRPSDTW results with 50 customers obtained from proposed MA with TS and M-SA

Problem ID	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%)	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%)
13	0.27	0.27
14	-0.87	-0.32
15	0.19	0
16	0	0
17	-0.28	0
18	-0.12	-0.19
19	-1.42	-0.32159
20	-1.51	-0.66287
21	0.43	0.429127
Average	−0.54	−0.35

Table 6. 20: Compared the TTRPSDTW results with 100 customers obtained from proposed MA with TS and M-SA

Problem ID	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%)	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%)
1	-0.61	-0.39
2	0.35	0.13
3	-1.07	-0.56
4	-0.30	0
5	-0.81	-0.68
6	0.24	0
7	-0.42	-0.29
8	0.31	0.23
9	-0.15	-0.21
10	0.07	0.17
11	-0.25	-0.25
12	0.03	0
13	-0.21	-0.35
14	0	0.14

Table 6.20, continued: Compared the TTRPSDTW results with 100 customers obtained from proposed MA with TS and M-SA

Problem ID	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%)	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%)
15	-0.35	-0.25
16	0	0
17	-0.39	0
18	-0.12	0.13
19	-0.61	-0.39
20	0.35	0.13
21	-1.07	-0.56
Average	−0.21	−0.12

Table 6. 21: Compared the TTRPSDTW results with 200 customers obtained from proposed MA with TS and M-SA

Problem ID	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%)	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%)
1	-0.11	-0.11
2	-0.18	-0.10
3	0.09	0
4	-0.13	-0.09
5	0	0
6	-0.32	-0.16
7	0.09	0.05
8	-0.08	0
9	-0.08	-0.04
10	0.06	0.06
11	-0.11	-0.04
12	0.12	0.04
13	0.05	0
14	0	0
15	-0.19	-0.07
16	-0.11	-0.05
17	0.09	0.088
18	-0.08	-0.15
19	-0.11	-0.11
20	-0.18	-0.10
21	0.09	0
Average	−0.05	−0.03

Tables 6.19, 6.20 and 6.21 indicate that the average results obtained by the proposed MA were improved about 0.54 and 0.35 percent comparing with tabu search and multi-point simulated annealing for TTRPSDTW with 50 customers, respectively. These improvement are 0.21 and 0.12 percent for TTRPSDTW with 100 customers and 0.05 and 0.03 percent for TTRPSDTW with 200 customers, respectively. Consequently, the performance of the proposed MA is found slightly better than SA and TS. As the differences between these results are insignificant, the results obtained by MA, M-SA and TS can be accepted as the new solutions. Therefore, the results indicate that the algorithms are efficient and effective in solving TTRP with stochastic demands and time windows.

6.6 TTRPSTTW benchmark solutions using aforesaid algorithms

The performance of the M-SA, MA and TS are evaluated for solving SPR versions of TTRPSTTW. Parameters used in the model might have some shake on the quality of computational results and they are same as TTRPSD solutions. In order to obtain better solutions, different values have been tested during initial experiments.

Since it is not possible to use more than the predetermined number of vehicles, the penalty cost is considered too high. The parameters have been examined with different values and set to be $\alpha = 0.975, I_{iter} = 80000, K = 0.7, T_0 = 10,\quad T_F = 0.001$, $n_{pop} = 5$, $n_{move} = 7$, $I_{iterpertemp} = 6$ and $N_{non} = 50$. They seem to give best results and will be used for further computational study. Firstly the algorithm is applied for solving CCP version of the problem. The problems have been tested with different significance and confidence levels α and β. However, the algorithm cannot find any feasible solution for these problems when both confident levels of α and β are active simultaneously since the CCP model is completely depended on the confidence level and sometimes makes the solutions infeasible. Therefore, the results indicate that although CCP model is easily understood, it is not appropriate for modelling TTRPSTTW. In real applications, these method may only use for a few important customers. The aforesaid algorithms are then applied for solving SPR version of TTRPSTTW. Each set has been run for 10 times and the best one ($F(X,Y)$) and the average results of each problem are located in Tables 6.22-6.27. In addition, the problems have been solved by sensitivity parameter analysis to understand the impact of parameters and data elements.

Table 6. 22: Results for TTRPSTTW with 50 customers and R1 scheduling horizons

ID	Best solution M-SA	Average solution M-SA	Sensitivity parameter analysis M-SA	Best solution MA	Average solution MA	Sensitivity parameter analysis MA	Best solution TS	Average solution TS	Sensitivity parameter analysis TS
1	5047.45	5073.63	5036.90	5042.46	5065.49	5039.03	5049.43	5070.34	5041.21
2	4960.84	5024.88	4947.71	4958.92	4967.58	4951.10	4961.01	4979.90	4955.32
3	5194.44	5217.31	5189.65	5195.84	5206.94	5190.02	5196.42	5213.28	5188.82
4	4529.11	4542.56	4517.05	4528.29	4539.03	4519.27	4532.94	4540.86	4522.13
5	3487.01	3503.11	3479.73	3486.98	3501.12	3480.37	3489.73	3507.33	3480.81
6	3801.90	3821.86	3792.31	3801.90	3817.85	3794.42	3803.55	3820.75	3795.72
7	2812.34	2819.09	2807.52	2810.48	2820.11	2805.43	2814.81	2829.73	2807.76
8	2833.20	2845.23	2828.86	2830.93	2845.31	2838.92	2835.89	2850.03	2830.37
9	2878.87	2890.76	2871.33	2878.87	2889.02	2880.96	2881.91	2898.66	2872.22
10	2607.32	2615.12	2599.29	2607.32	2619.92	2599.29	2609.42	2618.82	2601.27
11	2720.02	2732.60	2719.03	2718.26	2729.77	2715.32	2720.02	2732.83	2717.92
12	2891.29	2908.34	2887.74	2890.11	2904.48	2883.04	2890.11	2910.91	2886.62
13	5232.69	5241.77	5226.37	5228.20	5239.59	5225.37	5231.43	5243.57	5226.40
14	5300.32	5308.56	5289.65	5298.24	5309.32	5287.22	5303.44	5320.21	5294.50
15	5392.65	5401.53	5378.12	5392.65	5406.62	5380.29	5394.27	5407.32	5390.12
16	3592.37	3610.09	3588.73	3594.02	3602.92	3589.92	3596.29	3610.39	3591.23
17	3359.52	3367.73	3352.68	3355.38	3364.41	3353.19	3357.03	3370.53	3354.85
18	3478.93	3485.82	3468.38	3478.93	3489.23	3472.29	3484.35	3493.35	3475.11
19	3769.00	3777.83	3756.00	3770.22	3779.18	3761.12	3769.00	3779.39	3760.24
20	3783.72	3790.70	3778.93	3779.99	3788.33	3775.32	3782.29	3790.34	3775.32
21	3844.62	3853.52	3835.59	3839.02	3846.94	3834.82	3841.92	3857.62	3838.31
22	2932.74	2941.94	2926.48	2929.25	2938.00	2922.02	2932.74	2939.32	2924.43
23	2777.93	2790.45	2769.75	2773.83	2784.55	2770.23	2780.38	2792.40	2775.01
24	2894.23	2910.11	2889.53	2894.23	2905.52	2887.47	2895.42	2914.95	2888.39
Avg	3755.11	3769.77	3747.39	3753.51	3765.05	3748.19	3756.41	3770.54	3749.53

Table 6. 23: Results for TTRPSTTW with 50 customers and R2 scheduling horizons

ID	Best solution M-SA	Average solution M-SA	Sensitivity analysis M-SA	Best solution MA	Averag e solution MA	Sensitiv ity anal ysis MA	Best solution TS	Averag e solution TS	Sensitivit y analys is TS
1	4584.96	4601.43	4577.75	4584.96	4595.59	4578.43	4587.49	4606.69	4584.30
2	4621.35	4642.24	4611.56	4617.28	4638.53	4613.61	4623.99	4641.29	4616.29
3	4441.93	4456.23	4436.98	4438.30	4449.04	4434.01	4442.56	4458.83	4436.04
4	5101.11	5112.86	5093.17	5103.43	5114.82	5091.84	5107.73	5119.05	5095.66
5	5009.47	5120.55	4997.85	5009.47	5016.83	5002.78	5011.38	5021.14	5007.56
6	5222.54	5231.54	5218.09	5220.92	5232.20	5217.36	5224.69	5243.93	5219.72
7	2724.47	2731.84	2717.68	2727.53	2743.90	2720.20	2729.79	2740.12	2722.15
8	2841.43	2850.73	2833.11	2838.33	2845.84	2830.62	2835.92	2848.11	2830.62
9	2821.63	2834.56	2816.60	2821.63	2834.49	2817.12	2825.26	2832.15	2819.05
10	2562.53	2572.88	2557.30	2559.30	2570.24	2554.38	2563.29	2571.44	2556.22
11	2611.21	2630.42	2603.62	2607.47	2623.31	2601.11	2610.10	2626.92	2607.27
12	2579.09	2583.86	2564.42	2579.09	2587.62	2570.55	2586.75	2597.09	2579.21
13	4023.37	4035.54	4011.56	4018.63	4032.16	4010.07	4018.63	4029.61	4012.49
14	4165.54	4173.03	4156.99	4161.13	4176.95	4155.90	4167.81	4180.50	4159.20
15	4089.90	4101.86	4086.42	4089.90	4100.10	4084.84	4091.01	4102.24	4087.42
16	3835.71	3849.09	3827.58	3830.29	3843.39	3824.04	3837.49	3845.53	3829.03
17	3495.47	3511.81	3487.92	3495.47	3503.44	3485.52	3499.24	3520.10	3489.93
18	3684.76	3699.22	3676.01	3680.48	3690.08	3675.67	3678.90	3687.69	3677.27
19	2947.48	2958.73	2941.91	2945.59	2951.15	2939.03	2949.94	2960.12	2942.20
20	3163.52	3181.85	3153.40	3163.52	3172.22	3155.42	3166.33	3178.82	3159.95
21	3215.96	3242.95	3210.76	3218.91	3230.91	3209.10	3217.02	3220.15	3211.46
22	2932.28	2950.01	2930.23	2930.32	2943.03	2928.43	2929.01	2940.84	2926.02
23	3010.83	3025.53	2999.02	3005.66	3014.48	3000.47	3012.39	3029.35	2999.02
24	3454.48	3479.88	3448.35	3452.20	3465.00	3444.92	3454.48	3461.39	3445.29
Avg	3630.89	3649.10	3623.26	3629.16	3640.64	3622.73	3632.13	3644.30	3625.56

Table 6. 24: Results for TTRPSTTW with 50 customers and R3 scheduling horizons

ID	Best solution M-SA	Averag e solution SA	Sensitivi ty analy sis SA	Best solution MA	Average solution MA	Sensitivity analysis MA	Best solution TS	Average solution TS	Sensitivity analysis TS
1	2968.75	2983.83	2959.73	2964.39	2972.20	2960.91	2970.02	2982.14	2963.81
2	3060.14	3084.74	3052.00	3060.14	3070.32	3053.58	3060.14	3076.01	3055.37
3	3194.60	3217.90	3186.86	3189.93	3199.94	3182.87	3191.04	3204.67	3189.09
4	2522.15	2542.56	2518.49	2526.95	2535.55	2517.02	2520.77	2534.36	2517.15
5	2407.71	2423.41	2394.72	2404.83	2413.59	2395.24	2411.63	2425.78	2399.74
6	2081.75	2101.96	2077.69	2084.77	2095.31	2079.48	2086.29	2102.26	2080.13
7	2112.34	2119.19	2109.37	2109.37	2118.15	2107.74	2111.59	2121.73	2108.77
8	2133.20	2145.23	2124.62	2130.93	2143.03	2125.00	2135.23	2148.66	2127.70
9	2474.67	2490.36	2468.38	2471.18	2486.82	2466.79	2470.02	2483.45	2467.44
10	2527.82	2535.17	2523.47	2524.96	2533.85	2520.92	2528.98	2545.42	2524.70
11	2633.82	2652.43	2627.47	2633.82	2646.55	2626.83	2632.12	2650.61	2628.19
12	2991.54	3008.54	2984.02	2987.97	2995.84	2985.77	2989.83	2997.30	2986.12
13	4232.39	4251.37	4226.48	4229.66	4237.05	4225.27	4234.52	4242.63	4227.88
14	4324.21	4340.67	4321.15	4327.51	4337.39	4319.13	4330.05	4344.39	4321.17
15	4412.45	4431.13	4400.03	4409.35	4423.38	4401.12	4414.28	4436.49	4403.42
16	2743.17	2760.02	2737.31	2742.95	2753.89	2735.99	2745.86	2759.75	2737.95
17	2384.92	2407.23	2377.62	2384.92	2398.77	2378.93	2384.92	2401.60	2379.88
18	2975.33	3005.05	2968.21	2974.26	2986.03	2967.62	2974.26	2983.99	2970.29
19	3024.37	3037.81	3018.92	3021.87	3033.38	3017.42	3024.37	3038.00	3019.80
20	3283.28	3299.70	3278.54	3281.57	3289.90	3277.52	3285.36	3294.76	3279.67
21	3731.85	3753.02	3727.11	3729.20	3738.95	3726.80	3731.85	3750.99	3728.63
22	3072.54	3101.94	3068.53	3072.54	3089.39	3067.25	3070.54	3083.29	3068.31
23	2977.73	2990.95	2968.27	2976.29	2989.21	2967.67	2979.08	2993.35	2969.40
24	3194.13	3210.11	3180.37	3193.34	3207.64	3181.32	3193.34	3209.04	3186.46
Av	2977.70	2995.60	2970.81	2976.36	2987.34	2970.34	2978.17	2992.11	2972.55

Table 6. 25: Results for TTRPSTTW with 100 customers and R1 scheduling horizons

ID	Best solution M-SA	Average solution M-SA	Sensitivit y analys is M-SA	Best solution MA	Average solution MA	Sensitivit y analys is MA	Best solution TS	Average solution TS	Sensitivit y analys is TS
1	8963.53	9003.63	8957.07	8958.39	8972.09	8953.39	8966.63	8996.82	8957.67
2	6599.54	6634.35	6589.52	6595.73	6627.50	6687.11	6601.21	6629.62	6590.00
3	7294.43	7317.30	7285.72	7294.43	7308.60	7286.38	7298.00	7315.19	7290.22
4	10562.8	10642.56	10552.98	10555.59	10600.27	10551.29	10563.09	10625.92	10554.39
5	9407.71	9443.41	9399.32	9410.18	9439.39	9397.38	9409.60	9430.73	9402.24
6	8081.42	8101.56	8077.22	8078.69	8094.92	8076.58	8078.69	8097.38	8077.52
7	6115.42	6129.59	6115.42	6116.03	6122.29	6115.42	6118.83	6131.34	6116.53
8	5432.04	5445.93	5424.58	5428.77	5439.32	5420.76	5431.41	5448.07	5424.82
9	6271.78	6310.06	6265.05	6268.29	6282.02	6264.21	6272.29	6308.39	6266.32
10	4527.42	4552.26	4519.85	4525.03	4543.30	4520.23	4530.20	4550.33	4522.31
11	4682.03	4698.43	4674.94	4682.56	4690.01	4675.88	4686.82	4707.59	4677.84
12	5011.54	5018.27	5002.24	5007.47	5017.74	5003.63	5012.25	5021.15	5006.32
13	6032.99	6051.11	6021.31	6030.48	6046.49	6025.31	6036.64	6052.25	6023.28
14	5324.43	5344.32	5319.90	5320.75	5338.70	5317.69	5325.58	5346.68	5319.73
15	5712.46	5731.17	5705.18	5715.70	5730.61	5707.05	5714.71	5735.74	5709.00
16	8753.66	8770.82	8746.66	8755.40	8764.93	8747.12	8756.75	8772.31	8750.90
17	8374.72	8400.23	8363.60	8369.34	8379.99	8362.02	8372.96	8397.62	8367.08
18	9275.23	9288.62	9265.41	9275.23	9286.58	9266.81	9279.06	9307.76	9267.50
19	7024.69	7041.81	7016.79	7020.30	7033.14	7015.53	7022.20	7037.61	7019.07
20	6783.78	6799.74	6775.04	6784.25	6798.86	6773.09	6786.00	6796.41	6777.48
21	5991.95	6053.04	5988.56	5989.05	6021.46	5987.41	5993.20	6038.29	5988.48
22	4672.54	4701.24	4666.83	4675.22	4698.31	4668.02	4677.47	4695.66	4668.02
23	4957.43	4990.44	4950.97	4955.95	4970.70	4951.23	4957.43	4981.14	4953.09
24	4094.14	4110.72	4090.14	4093.86	4105.00	4087.38	4093.86	4112.82	4091.70
Av	6664.49	6690.86	6657.26	6662.80	6679.68	6660.87	6666.04	6689.03	6659.23

Table 6. 26: Results for TTRPSTTW with 100 customers and R2 scheduling horizons

ID	Best solution M-SA	Average solution MA	Sensitivit y analys is TS	Best solution MA	Average solution MA	Sensitivit y analys is MA	Best solution TS	Average solution TS	Sensitivit y analys is TS
1	11528.1	11563.8	11522.26	11524.65	11558.90	11520.12	11528.15	11560.89	11523.02
2	10960.6	11004.0	10954.72	10963.28	10989.01	10957.80	10963.28	11008.18	10959.64
3	10074.9	10117.4	10067.76	10070.91	10102.21	10066.92	10080.35	10126.42	10068.93
4	9572.45	9602.56	9561.55	9568.38	9589.42	9559.00	9575.55	9604.74	9565.50
5	8727.71	8743.21	8720.21	8725.01	8750.61	8721.14	8724.59	8742.71	8722.58
6	8081.93	8101.32	8074.78	8078.22	8098.34	8075.53	8080.25	8107.68	8077.67
7	6102.34	6119.59	6091.16	6104.29	6122.25	6094.30	6104.69	6125.93	6098.44
8	6734.27	6765.43	6722.54	6727.61	6749.90	6721.83	6735.10	6769.32	6725.69
9	6474.32	6490.66	6465.80	6474.32	6496.38	6466.34	6478.28	6502.45	6467.24
10	5323.94	5355.37	5314.57	5318.58	5360.39	5313.30	5320.15	5349.76	5315.03
11	5661.12	5682.43	5656.38	5658.94	5678.37	5656.38	5660.40	5680.31	5657.66
12	5291.34	5308.04	5283.46	5287.02	5299.24	5284.20	5287.02	5310.83	5285.55
13	8282.69	8301.37	8276.24	8279.19	8296.43	8274.05	8285.68	8313.32	8276.10
14	8994.51	9040.67	8988.56	8996.76	9042.03	8987.14	8994.51	9048.70	8989.08
15	8012.05	8063.13	7999.31	8009.92	8041.10	8001.37	8008.21	8038.63	8006.28
16	10743.1	10810.0	10736.04	10738.30	10789.53	10734.67	10746.49	10808.00	10737.00
17	9374.93	9407.23	9363.85	9370.39	9398.46	9364.30	9376.22	9410.01	9366.49
18	9975.53	10005.0	9971.92	9975.53	9998.03	9970.65	9979.90	10009.11	9973.35
19	7424.38	7437.41	7417.69	7420.31	7436.02	7418.71	7423.27	7447.40	7419.58
20	6887.68	6909.30	6879.73	6885.72	6915.56	6877.90	6890.66	6920.84	6880.35
21	7031.85	7053.02	7025.92	7026.00	7047.47	7023.38	7034.26	7060.99	7026.17
22	6076.74	6101.04	6066.54	6071.91	6090.21	6067.30	6074.04	6111.82	6068.06
23	5977.73	5990.95	5969.60	5980.61	6001.33	5973.26	5982.69	6011.15	5972.01
24	5197.13	5213.91	5192.27	5195.83	5210.90	5188.16	5200.72	5231.10	5191.02
Av	7854.65	7882.80	7846.79	7852.15	7877.59	7846.57	7855.60	7887.51	7848.85

Table 6. 27: Results for TTRPSTTW with 100 customers and R3 scheduling horizons

ID	Best solution M-SA	Average solution MA	Sensitivity para meter analysis TS	Best solution MA	Average solution MA	Sensitivity parameter analysis MA	Best solution TS	Average solution TS	Sensitivity para meter analysis TS
1	9568.35	9583.22	9559.43	9565.67	9580.71	9560.42	9569.66	9590.09	9562.90
2	9065.13	9074.34	9057.13	9060.33	9069.12	9056.10	9063.80	9074.14	9059.84
3	9194.60	9207.90	9190.92	9197.37	9210.42	9191.62	9200.06	9213.90	9192.57
4	8532.15	8544.36	8525.04	8529.59	8537.89	8526.61	8534.00	8546.93	8528.92
5	8807.71	8813.41	8798.63	8807.71	8814.03	8800.01	8809.12	8818.20	8801.29
6	8081.65	8094.06	8076.57	8081.65	8098.21	8076.57	8083.22	8101.10	8078.29
7	7612.14	7629.13	7603.85	7609.19	7620.38	7605.49	7615.05	7628.81	7608.00
8	7103.25	7115.03	7100.88	7101.34	7116.91	7100.88	7105.20	7117.01	7102.24
9	7436.17	7450.26	7427.54	7440.03	7457.66	7429.10	7442.36	7451.37	7430.54
10	6517.82	6528.87	6514.01	6515.95	6522.17	6512.53	6520.31	6529.45	6514.40
11	6634.22	6645.93	6629.36	6634.22	6641.76	6628.10	6632.75	6650.32	6630.00
12	7091.54	7108.54	7088.54	7093.32	7100.51	7088.54	7097.84	7106.42	7090.80
13	8272.42	8281.39	8266.22	8272.42	8279.20	8268.40	8269.38	8276.48	8266.22
14	8358.23	8370.27	8351.46	8360.39	8370.13	8355.00	8356.67	8365.19	8355.00
15	8415.35	8420.19	8410.14	8413.23	8424.03	8411.10	8418.10	8423.29	8413.38
16	9703.17	9714.42	9689.42	9700.35	9711.38	9690.24	9705.21	9720.58	9693.80
17	8704.92	8717.34	8701.82	8707.30	8720.58	8702.39	8709.28	8718.65	8702.20
18	8975.33	8990.05	8968.57	8970.28	8983.50	8966.04	8977.40	8995.43	8969.31
19	6724.75	6747.85	6716.67	6724.75	6736.64	6718.46	6721.69	6731.10	6717.20
20	7083.26	7100.70	7078.74	7079.57	7090.13	7078.74	7083.26	7098.04	7080.71
21	6931.53	6943.02	6926.89	6931.53	6940.92	6928.00	6935.83	6945.87	6930.11
22	6072.43	6080.98	6068.82	6070.40	6077.21	6068.82	6072.43	6089.05	6069.60
23	6977.73	6994.95	6972.49	6974.04	6989.49	6970.09	6971.80	6989.64	6970.09
24	6194.13	6207.11	6187.34	6190.37	6200.18	6187.34	6193.01	6210.33	6188.49
Avg	7835.75	7848.47	7829.60	7834.63	7845.55	7830.02	7836.98	7849.64	7831.50

Tables 6.22-6.27 present the detailed solutions information from 50 and 100 customers in three scheduling horizons, respectively and confirm that the differences between best results, average results and the results obtained by sensitivity analysis are very small. Since these differences are insignificant, the aforesaid algorithms are efficient that provides with consistency in a reasonable time and the results are useful. To confirm these differences please refer to Table 6.28 and 6.29.

Table 6. 28: Compared the TTRPSTTW results with 50 customers obtained from proposed MA with TS and M-SA

Problem ID	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%) and R1	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%) and R1	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%) and R2	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%) and R2	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%) and R3	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%) and R3
1	-0.13804	-0.09886	-0.05515	0	-0.18956	-0.14686
2	-0.04213	-0.0387	-0.14511	-0.08807	0	0
3	-0.01116	0.026952	-0.09589	-0.08172	-0.03478	-0.14618
4	-0.10258	-0.01811	-0.08419	0.04548	0.245163	0.190314
5	-0.0788	-0.00086	-0.03811	0	-0.28197	-0.11962
6	-0.04338	0	-0.07216	-0.03102	-0.07286	0.14507
7	-0.15383	-0.06614	-0.08279	0.112315	-0.10513	-0.1406
8	-0.1749	-0.08012	0.084981	-0.1091	-0.20138	-0.10641
9	-0.10549	0	-0.12848	0	0.046963	-0.14103
10	-0.08048	0	-0.15566	-0.12605	-0.15896	-0.11314
11	-0.06471	-0.06471	-0.10076	-0.14323	0.064587	0
12	0	-0.04081	-0.29612	0	-0.06221	-0.11934
13	-0.06174	-0.08581	0	-0.11781	-0.11477	-0.0645
14	-0.09805	-0.03924	-0.16028	-0.10587	-0.05866	0.076315
15	-0.03003	0	-0.02713	0	-0.11168	-0.07026
16	-0.06312	0.045931	-0.18762	-0.1413	-0.10598	-0.00802
17	-0.04915	-0.12323	-0.10774	0	0	0
18	-0.15555	0	0.042948	-0.11615	0	-0.03596
19	0.032369	0.032369	-0.14746	-0.06412	-0.08266	-0.08266
20	-0.06081	-0.09858	-0.08875	0	-0.11536	-0.05208
21	-0.07548	-0.14566	0.05875	0.09173	-0.07101	-0.07101
22	-0.119	-0.119	0.044725	-0.06684	0.065135	0
23	-0.23558	-0.14759	-0.22341	-0.17171	-0.09365	-0.04836
24	-0.0411	0	-0.066	-0.066	0	-0.02473
Average	-0.08136	-0.04426	-0.08464	-0.04914	-0.05995	-0.04496

Table 6. 29: Compared the TTRPSTTW results with 100 customers obtained from proposed MA with TS and M-SA

Problem ID	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%) and R1	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%) and R1	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%) and R2	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%) and R2	Comparison of best solution between proposed MA and TS results (MA-TS)/TS (%) and R3	Comparison of best solution between proposed MA and M-SA results (MA-SA)/SA (%) and R3
1	-0.0919	-0.05734	-0.03036	-0.03036	-0.04169	-0.02801
2	-0.08302	-0.05773	0	0.023812	-0.03828	-0.05295
3	-0.04892	0	-0.09365	-0.0396	-0.02924	0.030126
4	-0.071	-0.06826	-0.07488	-0.04252	-0.05168	-0.03
5	0.006164	0.026255	0.004814	-0.03094	-0.01601	0
6	0	-0.03378	-0.02512	-0.0459	-0.01942	0
7	-0.04576	0.009975	-0.00655	0.031955	-0.07695	-0.03875
8	-0.04861	-0.0602	-0.11121	-0.0989	-0.05433	-0.02689
9	-0.06377	-0.05565	-0.06113	0	-0.03131	0.051908
10	-0.11412	-0.05279	-0.02951	-0.10068	-0.06687	-0.02869
11	-0.09089	0.01132	-0.02579	-0.03851	0.022163	0
12	-0.09537	-0.08121	0	-0.08164	-0.06368	0.0251
13	-0.10204	-0.0416	-0.07833	-0.04226	0.036762	0
14	-0.09069	-0.06912	0.025015	0.025015	0.044515	0.025843
15	0.017324	0.056718	0.021353	-0.02658	-0.05785	-0.02519
16	-0.01542	0.019877	-0.07621	-0.04533	-0.05008	-0.02906
17	-0.04323	-0.06424	-0.06218	-0.04843	-0.02273	0.027341
18	-0.04128	0	-0.04379	0	-0.07931	-0.05627
19	-0.02706	-0.06249	-0.03987	-0.05482	0.045524	0
20	-0.02579	0.006928	-0.07169	-0.02846	-0.05209	-0.05209
21	-0.06925	-0.0484	-0.11743	-0.08319	-0.062	0
22	-0.0481	0.057356	-0.03507	-0.07948	-0.03343	-0.03343
23	-0.02985	-0.02985	-0.03477	0.048179	0.032129	-0.05288
24	0	-0.00684	-0.09403	-0.02501	-0.04263	-0.0607
Average	-0.05094	-0.02504	-0.04418	-0.0339	-0.02952	-0.01477

Tables 6.28 and 6.29 indicate that the average results obtained by the proposed MA were improved about 0.08 and 0.04 percent comparing with tabu search and multi-point simulated annealing for TTRPSTTW with 50 customers and R1, respectively. These improvements are 0.08 and 0.05 percent for TTRPSTTW with 50 customers and R2, 0.06 and 0.04 percent for TTRPSTTW with 50 customers and R3, respectively. Furthermore, these improvements are 0.05 and 0.02 percent for TTRPSTTW with 100

customers and R1, 0.04 and 0.03 percent for TTRPSTTW with 100 customers and R2, respectively. Also, the average results obtained by the proposed MA were improved about 0.03 and 0.01 percent comparing with tabu search and multi-point simulated annealing for TTRPSTTW with 100 customers and R3 as well.

Consequently, the performance of the proposed MA is found slightly better than SA and TS. As the differences between these results are insignificant, the results obtained by MA, M-SA and TS can be accepted as the new solutions. Therefore, the results indicate that the algorithms are efficient and effective in solving TTRP with stochastic travel and service time with time windows.

6.7 Case study

In this section, a real case study from an Iranian dairy company is provided. This study has been carried out with the aid of Pegah Co, a large dairy distribution company in Iran, whose products are distributed to more than 50,000 retailers (customers) in Iran and some other countries. Iran Dairy Industries Co. (IDIC) is the largest dairy producer in Iran with "PEGAH" brand. This factory produces some dairy products such as Pasteurized and UHT milk, flavored milk, pasteurized and UHT cream, a variety of cheese (process, slice, pizza, UF), different kinds of yoghurt, probiotic products (such as yoghurt, cheese, ice cream), and drinking yoghurt. The method of collecting data has been explained in Chapter 3.

6.7.1 Computational results for real case study

Same as the previous sections, these problems has been solved using M-SA, MA and TS. The parameters may be used for MA, M-SA or TS are same as previous sections as well. In order to obtain better solutions, different values have been tested in initial experiments. These are:

$P = 10000$; $\alpha = 0.99, 0.975, 0.95$; $I_{iter} = 2000, 4000, 6000, 8000, 10000$; $I_{iterpertemp} = 2,4,6,8,10$; $K = 1, 0.9, 0.8, 0.7, 0.6, 0.5$; $n_{pop} = 1,3,5,7,9$; $n_{move} = 1,3,5,7,9$;$T_0 = 1000, T_F = 0.1$ or $T_0 = 10, T_F = 0.001$; $N_{non} = 100, 200$; $[r,s] = [5,10]$; $n_{max} = 150$; $t_{max} = 1000$; $t_n = 50, 100$; $P_c = 0.7, 0.75, 0.8$; $P_m = 0.2, 0.3, 0.4$; $P_l = 0.3, 0.4, 0.5$; $n = 50, 100$, where P_c, P_m, P_l and n are the probability of crossover, mutation, LS improvement and population size, respectively. Since it is not possible to use more than the predetermined number of vehicles, the penalty cost is considered too high. The parameters have been examined with different values and set to be $\alpha = 0.95, I_{iter} = 2000, K = 0.7, T_0 = 10$, $T_F = 0.001$, $n_{pop} = 5$, $n_{move} = 9$, $I_{iterpertemp} = 6$ and $N_{non} = 200$, $t_n = 50$, $P_c = 0.7$, $P_m = 0.3$, $P_l = 0.5$ and $n = 100$. They seem to give the best results and will be used for further computation. The results in kilometers for three models (TTRPSD, TTRPSDTW and TTRPSTTW) which are obtained using MA, M-SA and TS are presented in Tables 6.30–6.33, respectively. Each set has been run 10 times and the best (Best-sol), the worst (worst-sol) and the average solutions (Avg-sol) from the 10 runs are shown. Also, the time taken for the best solutions is presented in the last column. As this type of problem was not solved earlier, the results cannot be compared with any data or earlier heuristic solutions. However, the problems were checked by sensitivity analysis. Now, the results can be compared.

Table 6. 30: The TTRPSD results

Algorithm	Best-sol	Worst-sol	Avg-sol	Sensitivity analysis	Time (second)
MA	164.484	175.498	169.389	163.673	947
M-SA	166.230	177.827	169.027	164.004	1010
TS	167.015	174.984	170.582	164.004	959

Table 6. 31: The TTRPSDTW results

Algorithm	Best-sol	Worst-sol	Avg-sol	Sensitivity analysis	Time (second)
MA	170.490	180.593	176.900	169.380	1049
M-SA	171.000	179.432	175.781	169.753	1099
TS	177.421	183.690	180.290	169.910	1180

Table 6. 32: The TTRPSTTW results

Algorithm	Best-sol	Worst-sol	Avg-sol	Sensitivity analysis	Time (second)
MA	190.889	197.003	194.502	189.381	1111
M-SA	191.392	196.012	193.452	189.381	1179
TS	192.889	198.346	195.367	189.381	1292

Tables 6.30 to 6.32 show the best solutions for TTRPSD obtained using MA, M-SA and TS are 164.484, 166.230 and 167.015, respectively. Moreover, these results are 170.490, 171.000 and 177.421 for TTRPSDTW and 190.889, 191.392 and 192.889 for TTRPSTTW, respectively. In addition, the comparison between the obtained results and the sensitivity analysis results confirm a very slight difference. Furthermore, the Best solution, worst solution and the average solution for each set from 10 run have been mentioned in Tables 6.30-6.32. As the differences between all these results are insignificant, the applied MA, M-SA and TS are efficient with confidence consistency of a reasonable time.

To indicate the convergence of the proposed approach, trends are shown in Figures 6.10 to 6.12. This study has presented the relation between the number of iteration and the obtained objective function value. As it can be noted from the figures, the improvement rate of the solution reduces as the number of the iteration increases and after a particular number of iteration, the achieved solution converges. Therefore, the quality of the solution may not be enhanced by a greater number of iteration.

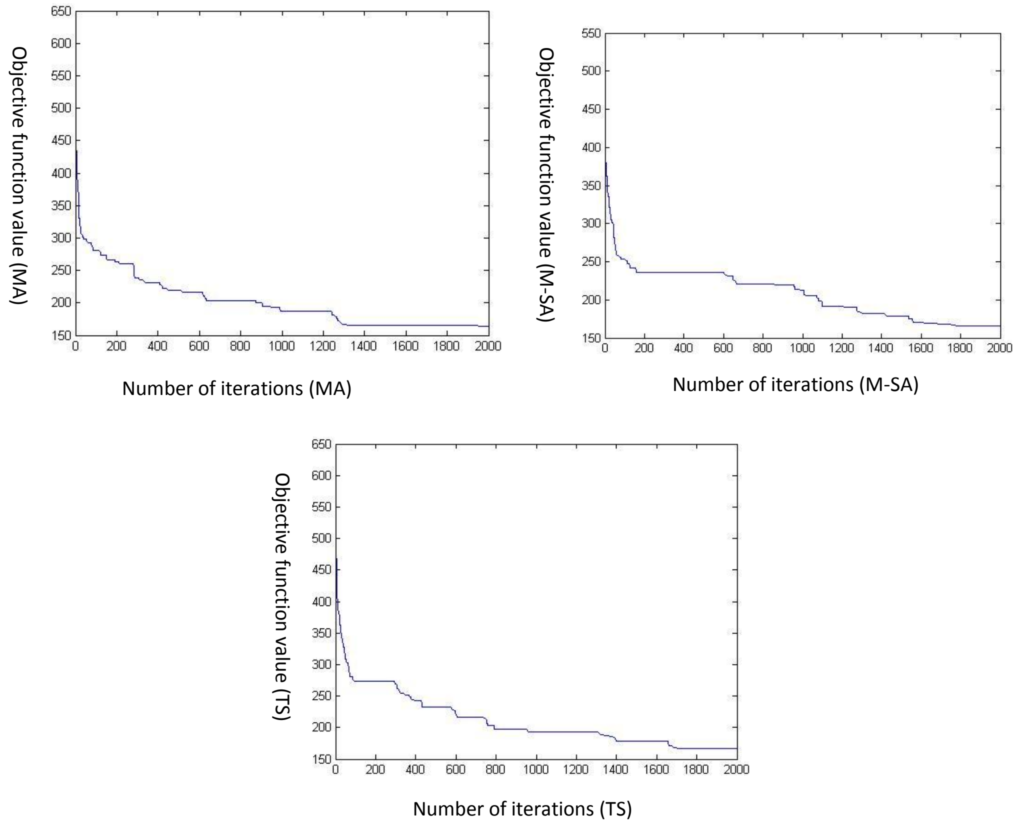

Figure 6. 10: Convergence trend for the algorithms' TTRPSD solutions

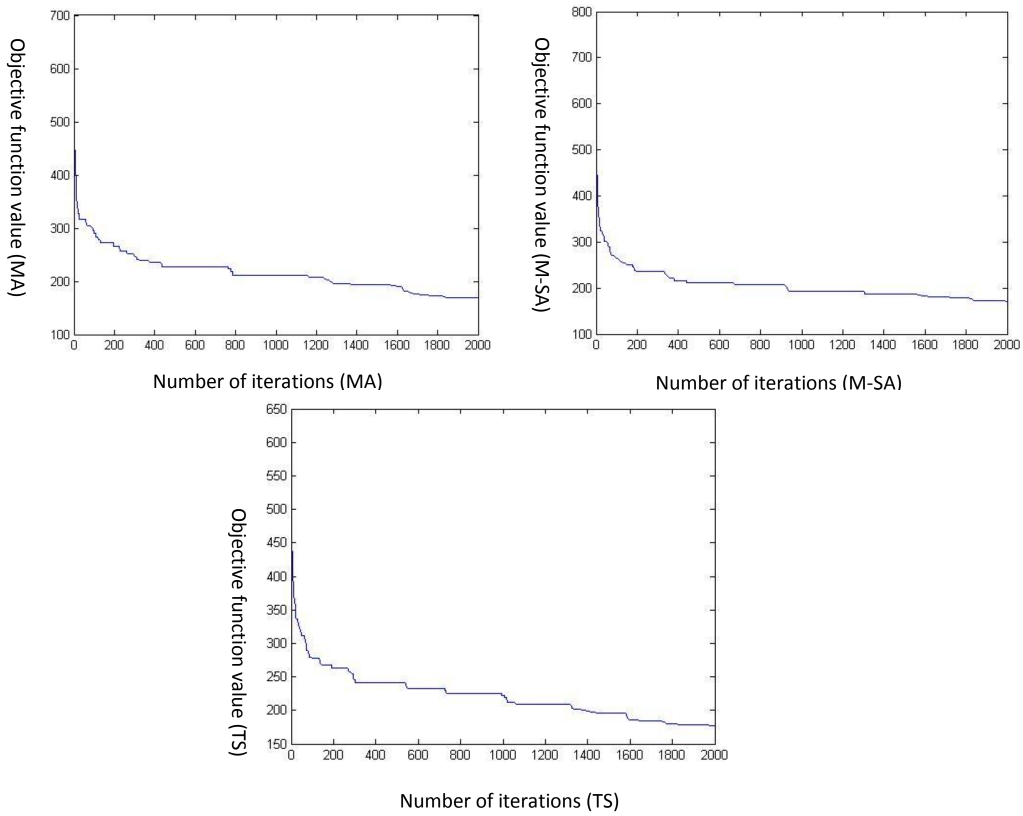

Figure 6. 11: Convergence trend for the algorithms' TTRPSDTW solutions

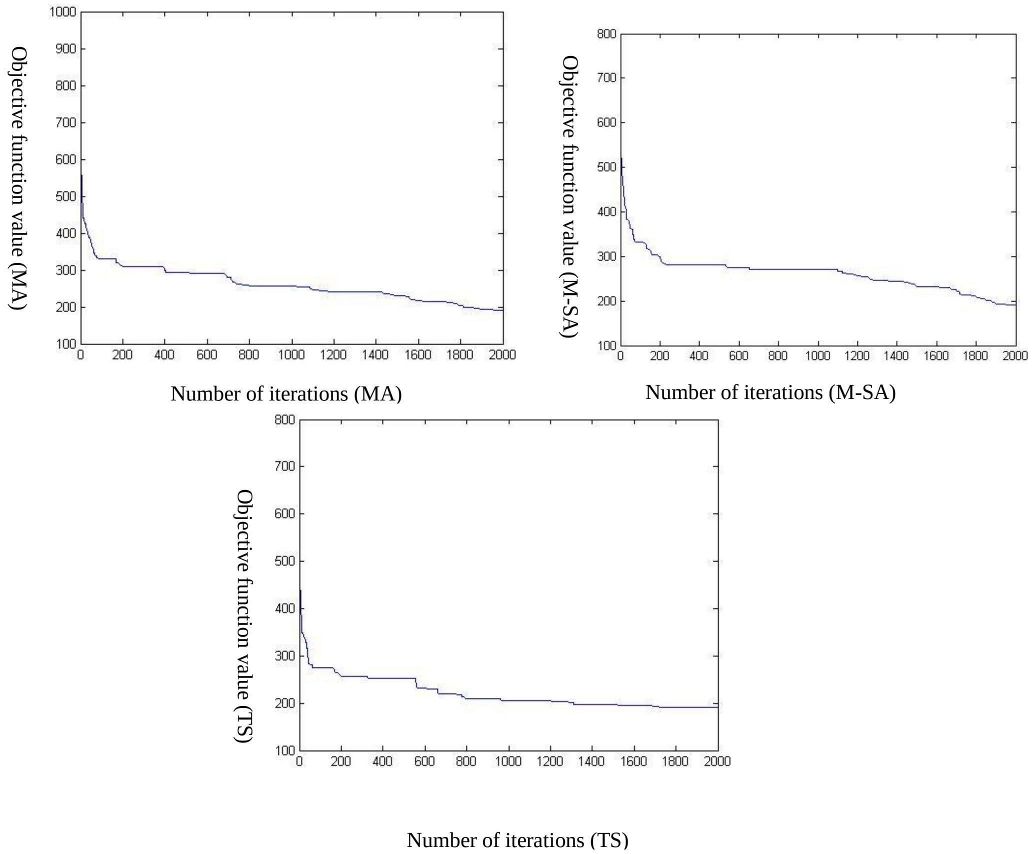

Figure 6. 12: Convergence trend for the algorithms’ TTRPSTTW solutions

In breif, the analyses show that all of the methods of TS, M-SA, and MA are greatly efficient and their efficiency is almost equal, however, its seems that MA indicates slightly more efficiency than the others.

CHAPTER 7: CONCLUSION AND RECOMMENDATION

Discussion on various issues and the main findings have been placed in the past chapters. Stochastic truck and trailer routing problems under different uncertainties were formulated and the proposed methods of solution were located. Results of analyses and the necessary recommendations were made. The main findings of the research have been summarized in this Chapter.

7.1 Summary of the work

Overall, the objectives of this research are achieved. Uncertainty in parameters such as demands, travel and service times are found to have critical importance in TTRP. In this research, the stochastic TTRP was introduced, modelled and solved. Most researchers have undertaken work on TTRP with deterministic parameters. However, to meet the real-life needs, stochastic parameters such as varying or stochastic demands, stochastic travel and service time should be taken into account and the deterministic TTRP should be expanded for stochastic parameters. In addition, the time window constraint occurs in many practical situations. Therefore, TTRP is extended in three parts by considering stochastic demands, stochastic demands and time windows, and stochastic travel and service time with time windows. Different meta-heuristic algorithms such as multi-point simulated annealing (M-SA), memetic algorithm (MA) and tabu search (TS) have been applied to solve these problems. For memetic algorithm, different kinds of crossover, such as PMX and OX, and different kinds of mutations, such as inversion, insertion, displacement, swap and change of service vehicle type of vehicle customers (VCs) were applied. In addition, various types of LS approaches were used to improve the chromosomes in the pool of candidates to find better solutions. For tabu search and multi-point simulated annealing, random neighborhood structure uses four different types of moves such as swap, reversion, insertion and the change of service vehicle type of VCs were considered to find the new solution. Besides, 2-Opt local search was used to augment the algorithm for improving the solution.

7.2 Conclusions

The main conclusions of this research are as follows:

i. Researchers have, thus far, observed that the deterministic truck and trailer routing problem (TTRP) cannot address the prevailing parameter uncertainties and/or other complexities. The purpose of this study is to expand the deterministic TTRP model by introducing stochastic parameters to bring the TTRP model closer to reality. Three new models have been considered to bring the TTRP model to that end. Stochastic demands and stochastic travel and service time have practical significance. In addition, the time window constraint occurs in many practical situations. Therefore, these new models are truck and trailer routing problems with stochastic demands (TTRPSD), truck and trailer routing problem with stochastic demands and time windows (TTRPSDTW). Finally, truck and trailer routing problem with stochastic travel and service time with time windows (TTRPSTTW).

ii. All these issues have been addressed in formulation of the problems within the framework of a stochastic program with recourse action. Since uncertainty is occurred in some parameters such as demands, travel and service time, the failure might occur in the models. Thus, the models must be considered with recourse cost.

iii. Different meta-heuristic algorithms such as multi-point simulated annealing (M-SA), memetic algorithm (MA) and tabu search (TS) have been successfully applied to solve variants of TTRP and stochastic TTRP.

iv. The proposed MA has been applied to solve TTRP. Different kinds of crossover, such as PMX and OX, and different kinds of mutations, such as inversion, insertion, displacement, swap and change of service vehicle type of VCs, are applied for this algorithm. In addition, various types of LS approaches have been used to improve the chromosome in the pool of candidates to find better solutions.The results have been compared with existing approaches to show the validity of the solutions. The results approved it and indicated that the MA is efficient and effective in solving TTRP. The proposed MA obtained 13 best solutions from 21 including 7 new best solutions and 6 best solutions, which were previously reported by applying other approaches for TTRP benchmark tested by Chao (2002). Also obtained 27 best solutions from 36 including 12 new best solutions and 15 best solutions which were previously reported for TTRP benchmarks tested by Lin et al. (2010).

v. Twenty-one TTRPSD benchmarked problems, 54 TTRPSDTW benchmarked problems in three equal sets and One hundred and forty four TTRPSTTW benchmarked problems in six equal sets have been generated and modified for these models to validate the models. Each of these benchmarks has been solved using the aforesaid meta-heuristic algorithms. Each set has been run 10 times and the best and average results are compared. In addition, since no results are available for comparing these solutions at this point in time, the problems are tested by sensitive-parameter analysis to realize the impact of the parameters. As the differences between the best and corresponding average solutions are insignificant, the algorithms are capable of producing the variant of stochastic TTRP solutions consistently and the results are useful.

vi. Three different models (TTRPSD, TTRPSDTW and TTRPSTTW) have been applied for three case study problems. Data collections including customers' information for a dairy factory product have been done and the analysis for these three models have been made using three aforesaid meta-heuristic algorithms. Each set of three case studies problem has been run for 10 times and the best, worst and average results have been compared. Furthermore, the problems have been tested by sensitive parameter analysis to realize the impact of the parameters. As the differences between the best, worst and corresponding average solutions are insignificant, the algorithm is found capable of producing TTRPSD solutions consistently and the results are useful.

vii. The research expanded the knowledge in the truck and trailer routing problem area and come up with the publications in Tier-1, Tier-2 ISI, non-ISI and conference papers (Appendix-B).

7.3 Further research direction

The research reported in this thesis is not necessarily exhaustive for the area in question but is a step ahead to the works done by quite a few other researchers. The main contribution of this research is to expand the deterministic TTRP model by introducing stochastic parameters such as stochastic demand, stochastic travel and service time to bring the TTRP model closer to reality and solve the models in a reasonable timeframe by administering the meta-heuristic algorithms. This research can be extended into the following areas/directions.

i. Results of the proposed models may be improved using other algorithms. It is appreciated if a new algorithm is applied to check this conceivability.

ii. Researchers may attempt to expand each of the aforesaid models by introducing more practical or real-world conditions, such as multiple time windows, time dependent travel times and multi-depots.

iii. Future work may be devoted to study a multi-objective version of the stochastic TTRP as the problem can be defined for more than one objective simultaneously.

iv. For any extension in stochastic TTRP mentioned above, new relevant TTRP benchmark instance problems need to be modified to validate the results.

v. To define the objective function value by considering monetary cost and time instead of distance. Then it would be interesting to see how flexible the different approaches can be modified, and to study their computational behaviour on these scenarios.

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Appendix A: Confirmation of implementation of the case study

شماره : ۱۴۵۹۱
تاریخ : ۱۳۹۳/۲/۶
پیوست : ندارد

شرکت صنایع شیر ایران
شرکت بازار گستر پگاه منطقه چهار (سهامی خاص)

شرکت بازار گستر پگاه منطقه چهار (سهامی خاص)

26 April 2014

To
Department of Mechanical Engineering, University Malaya

Re: Confirmation of implementation of case study

This is to inform that Mr. Seyedmehdi Mirmohammadsadeghi (Iranian Passport No. K21855450) under Associate Prof. Dr. Shamsuddin Ahmed supervision has received the data about more than 120 customers to minimize the transportation costs for his research. The project number in Malaysia is RG139-12AET. He is now analyzing the data to build more elaborated transportation system in order to increase profitability which can help the company in the future.

Yours sincerely
Koorosh Moosavi
ECO and a member of Directors Board
Bazar Gostar Pegah Region 4 CO.

اصفهان ، خانه اصفهان ، میدان گلها ، جنب بانک پارسیان ، ساختمان روناک ، طبقه ۵
تلفن : ۸-۰۳۱۱-۴۴۱۶۶۳۵ فکس : ۰۳۱۱-۴۴۱۶۶۲۴ info.bgm4@irandairy.ir

Appendix B: The name and demand of the customers

کد انبار : [۱] انبار محصول رفاه سازان اصفهان
گروه مشتري : همه موارد
مشتري : همه موارد
تاریخ : ۹۲,۱۲,۰۱
کد محصول : همه موارد
نوع : همه موارد
وضعیت : [۰] برگشتي کسر شده

شرکت:اصفهان خیابان هشت بهشت تلفن :۶۰۷۰۰
رفاه سازان اصفهان کداقتصادي۴۱۱۱۷۶۶۷۸۹۱۸
گزارش سرجمع فروش به مشتری

تاریخ چاپ : یک شنبه ۲۴ فروردین ماه ۱۳۹۳ ساعت ۰۹:۴۱
صفحه 1 از 1

Code — Name — Demand weight — Price — Perc

ردیف	کد مشتري	نام مشتري	وزن به کیلو	قیمت کل	رصد از کل قیمت:
1	030494	عشقي	210.00	14,250,000	8.80
2	040307	(مرتضي قادري(کوثر ۵	247.00	13,530,000	8.36
3	030001	رسول کوچکیان	128.00	10,083,200	6.23
4	050509	وایک طرسیان	50.70	6,255,592	3.86
5	060030	ایهامي	76.80	6,009,600	3.71
6	030550	مهدي کوچکیان	90.60	4,554,000	2.81
7	060299	(تعاوني جهاد کشاورزي (عمراني	57.60	4,507,200	2.78
8	030172	محمد کاظمي	111.60	3,605,712	2.23
9	060590	علي تهراني	27.00	3,132,000	1.93
10	030182	فراست	57.00	3,060,000	1.89
11	030289	حسین پاکدل	36.80	2,947,040	1.82
12	030065	محمد مهدي یکدانه	88.00	2,710,000	1.67
13	040528	حسن حیدري	40.20	2,553,000	1.58
14	030153	اصغر اميني	79.20	2,342,400	1.45
15	030372	تعاوني نهاد هاي انقلاب اسلامي	58.00	2,320,000	1.43
16	050022	محمدرضا وحیدي نژاد	42.00	2,262,132	1.40
17	050025	محسن اله دادیان	28.80	2,253,600	1.39
18	040540	علي اصغر حدادي	62.00	2,225,000	1.37
19	050141	تعاوني دانشگاه اصفهان	18.30	2,131,200	1.32
20	050508	محسن ترابي	49.30	2,074,936	1.28
21	060589	محمد مستاجران	57.60	2,011,200	1.24
22	030062	عباس نوروزي	18.80	1,908,320	1.18
23	030453	اکبر مویدي	67.00	1,870,800	1.16
24	050308	تعاوني ۴ دانشگاه جلال نکویي	37.30	1,701,196	1.05
25	040469	(ناظمي(شرکت تعاوني مخابرات	120.00	1,680,000	1.04
26	050024	محمود سخایي	46.00	1,675,360	1.03
27	040153	حجت قاسمي	23.60	1,651,200	1.02
28	040365	احمد خلیلي	61.20	1,631,400	1.01
29	040468	نمازي	16.40	1,627,520	1.01
30	050100	محمد سعید آخوندي	20.30	1,601,840	0.99
31	030181	حمید دستجردي	69.60	1,591,200	0.98
32	100849	جبار زارع	95.40	1,572,000	0.97
33	050565	حسین شاکري	35.60	1,477,952	0.91
34	080312	باغبان	14.00	1,472,000	0.91
35	030407	محمد حلبي ساز اصفهاني	66.40	1,467,160	0.91
36	030470	مهدي منصوري	31.00	1,465,360	0.91
37	060114	محسن شعباني	16.00	1,404,160	0.87
38	030544	سعید جعفري	29.40	1,397,520	0.86
39	030159	حسن ابوطالبي	64.80	1,276,320	0.79

شرکت:اصفهان خیابان هشت بهشت تلفن :۰۶۰۷
رفاه سازان اصفهان کداقتصادي۴۱۱۱۷۶۶۷۸۹۱۸
گزارش سرجمع فروش به مشتري

کد انبار : [۱] انبار محصول رفاه سازان اصفهان
گروه مشتري : همه موارد
مشتري : همه موارد
تاریخ : ۹۲,۱۲,۰۱
کد محصول : همه موارد
نوع : همه موارد
وضعیت : [۰] برگشتي کسر شده

تاریخ چاپ : یک شنبه ۲۴ فروردین ماه ۱۳۹۳ ساعت ۰۹:۴۱

ردیف	کد مشتري	نام مشتري	وزن به کیلو	قیمت کل	رصد از کل قیمت
40	030501	علاف چیان	64.80	1,276,320	0.79
41	040555	حسن ابولحسني	18.80	1,275,600	0.79
42	040507	بهرمند	90.00	1,260,000	0.78
43	030070	حسین وزمان	39.60	1,171,200	0.72
44	030340	رسول ابوطالبي	39.60	1,171,200	0.72
45	050023	اکبر قدمیان	37.20	1,145,160	0.71
46	030306	عباس بزرگزاد	75.00	1,050,000	0.65
47	050536	مصطفي عابدي	16.00	1,050,000	0.65
48	100607	مجید یوسفي	75.00	1,050,000	0.65
49	990001	جواد حبیب الهي	75.00	1,050,000	0.65
50	050563	علیرضا کریمي	23.05	965,005	0.60
51	030451	علیزاده	14.00	950,000	0.59
52	100647	سید فرهاد هاشمي	14.00	950,000	0.59
53	100853	احمدرضا دهخدایي	14.00	950,000	0.59
54	060521	(تعاوني دانشگاه مهاجر۳ (ترخاني	28.00	937,240	0.58
55	100280	محمد موذني	14.00	900,000	0.56
56	100570	محمد علي شفیعي	14.00	900,000	0.56
57	030548	کمال کارداني	9.60	872,640	0.54
58	040271	تعاوني هجرت سپاه	60.00	840,000	0.52
59	030328	مهدي تمیزي فر	8.00	778,800	0.48
60	030053	حسن بهرامي	9.60	751,200	0.46
61	030292	علیرضا بهرامي	9.60	751,200	0.46
62	040274	مرتضي احمدي	9.60	751,200	0.46
63	040472	روستازاده	9.60	751,200	0.46
64	050495	محسن نصر	9.60	751,200	0.46
65	040065	حمیدرضا شادور	45.00	630,000	0.39
66	040256	اکبر امیني	45.00	630,000	0.39
67	040474	ربیعي	45.00	630,000	0.39
68	060110	احمد حاجیان	45.00	630,000	0.39
69	050184	فضل اله محمدیان	7.90	586,360	0.36
70	050648	مجتبي رضایي	6.00	585,600	0.36
71	100785	حسین فشارکي	16.50	545,000	0.34
72	100210	مهدي باغبان	4.80	524,400	0.32
73	100366	خسرو دهقاني	6.40	504,160	0.31
74	050483	مهدي واعظي	21.90	501,072	0.31
75	030285	احمد رضا زارع	4.80	436,320	0.27
76	030354	حمید ترابي	30.00	420,000	0.26
77	040029	عبدالحسین ابراهیمي	30.00	420,000	0.26
78	040222	علیرضا کریمي	30.00	420,000	0.26

شرکت:اصفهان خیابان هشت بهشت تلفن :۶۰۷.
رفاه سازان اصفهان کداقتصادي۴۱۱۱۷۶۶۷۸۹۱۸
گزارش سرجمع فروش به مشتري

کد انبار : [۱] انبار محصول رفاه سازان اصفهان
گروه مشتري : همه موارد
مشتري : همه موارد
تاريخ : ۹۲,۱۲,۰۱
کد محصول : همه موارد
نوع : همه موارد
وضعيت : [۰] برگشتي کسر شده

تاريخ چاپ : يک شنبه ۲۴ فروردين ماه ۱۳۹۳ ساعت ۰۹:۴۱

رديف	کد مشتري	نام مشتري	وزن به کيلو	قيمت کل	درصد از کل قيمت
79	050128	علي رضا زمين پرواز	30.00	420,000	0.26
80	080816	حميد رئيسي	30.00	420,000	0.26
81	100300	محمد خاني	30.00	420,000	0.26
82	100322	حميد طالبي	30.00	420,000	0.26
83	100758	مهدي حق شناس	30.00	420,000	0.26
84	040242	رضا محمودي	20.40	418,872	0.26
85	100668	حسن واعظي	10.80	417,744	0.26
86	100854	علي موذني	15.00	358,800	0.22
87	100624	رسول مهدوي	3.20	310,400	0.19
88	040323	سعيد ربيعي	21	297,600	0.18
89	030543	حميد فلاح	15.00	210,000	0.13
90	040170	عليرضا خوانساري	15.00	210,000	0.13
91	040344	اخوان نصف جهان	15.00	210,000	0.13
92	040447	عبداله نجفي	15.00	210,000	0.13
93	040527	رضا رفيعي	15.00	210,000	0.13
94	040564	مهدي کريمي	15.00	210,000	0.13
95	040603	حميد ملکي	15.00	210,000	0.13
96	060513	شاهرخ بهرامي	15.00	210,000	0.13
97	100417	عليرضا خشوئي	15.00	210,000	0.13
98	100642	حسن خودسياني	15.00	210,000	0.13
99	100768	حسن مهدوي	15.00	210,000	0.13
100	100850	مسائلي	15.00	210,000	0.13
101	100842	احمد روخشاد	5.40	208,872	0.13
102	060334	حميدرضا شمس	5.40	189,000	0.12
		جمع	3,955	161,872,485	100

Appendix C: The name and location of the customers

منطقه	خیابان اصلی	نام فروشگاه	نام مسئول فروشگاه	شماره تماس ثابت	شماره همراه	مالکیت	پتانسیل	فروش
1	مسجد سید-جنب قنادی خشایار	راهویی	محمد راهویی	3351915	.	1	A+	B
1	مسجد سید-روبروی هتل ۴۰ستون	سلامت	رضا ماست بند زاده	.	9130118895	1	A+	A
1	میرداماد-اول میرداماد	کلبه	حبیب مکاریان	2351956	9132156929	1	A+	A
1	مسجد سید	کره شکلی	جواد ابراهیمیان	3369225	.	1	A+	غ ف
1	مسجد سید	تورجی	احمد تورجی زاده	.	9132332277	1	A+	غ ف
1	مسجد سید	.	کریم سلطانی	3362562	.	1	A+	B
1	مسجد سید	شرکت تعاونی پلی اکریل	شرکت فردوس	.	9137501216	1	A+	B
1	مسجد سید	.	آفرین	2361028	.	1	A+	B
2	خ خرم	شقایق	سعید باقری	3376259	.	1	A+	A+
2	شهیدان غربی جنب مدرسه شهدای ملک	تعاونی فرنگیان ناحیه ۵	تعاونی فرهنگیان	.	.	1	A+	غ ف
3	خ استانداری	.	محمد فلاح	2229871	.	1	A+	غ ف
3	احمداباد ۴راه گلستان	پاکدل	مجتبی پاکدل	2281294	.	1	A+	E
3	گلزار	1001	عباس صدری	2651465	.	1	A+	C
3	احمدابادبعدازبیمارستان امیرالمومنین	گلبهار	عباس سرانیان	2258011	.	1	A+	F
3	احمداباد	سی پل	احمدعطایی	2724262	.	1	A+	A
3	احمداباد	فتوت	مصطفی فتوت	2286664	.	1	A+	B
3	احمداباد	سارا	محمدرضا ادهمی	2258273	9132147226	1	A+	E
3	احمداباد	رحمتی	حمید رحمتی	2288479	9139266762	1	A+	A
3	بزرگمهر	دریا	روح ا... بهمن پور	.	9139088498	1	A+	A
3	بزرگمهر	مهدی	جعفر مهدیان	2640854	9133116291	1	A+	C
3	خ نشاط ابتدای خ نشاط از شکر شکن	پیوندی	فضل اله پیوندی	2254161	.	1	A+	A
3	خ ۴باغ خواجو	باران	گلشیرازی	2209458	.	1	A+	غ ف
3	4باغ خواجو	پارسیان	احسان طباطبایی	2208972	.	1	A+	غ ف
3	خ استانداری	فدک	بزرگزاد	2226727	.	1	A+	A+
3	خ استانداری	مهدی	مظلوم	2229134	.	1	A+	A+
3	بلوار هشت بهشت	حقیقت	احمد حقیقت	2217206	.	1	A+	E
3	4باغ پایین	پروتیین	.	2211716	.	1	A+	F
3	شریف واقفی	تجلی	مهدی پور زنگنه	2644711	.	1	A+	A+
3	شریف واقفی	وحدت	رحمت ا... عشقی	2656624	9132695413	1	A+	غ ف
3	شریف واقفی	اسپادانا	علی عباسی	2677793	9131949929	1	A+	A
4	بزرگمهر	کریمی	علیرضا کریمی	2680140	9131009205	1	A+	A
4	خ مشتاق دوم	مهرآباد	حمیدرضا وحدت	2604645	.	1	A+	A
4	خ مشتاق دوم	زیتون	اکبر ترک زاده	2605150	.	1	A+	B
4	خ همدانیان	باران	سعیدی	.	9136915091	1	A+	B
4	.	ماه	مهدی شعبانی	.	9334902380	1	A+	
4	.	تعاونی مصرف فرهنگیان	تعاونی مصرف فرهنگیان ناحیه ۲	2603323	.	1	A+	
5	محتشم کاشانی-ابتدای کوچه شهید رحیمی	شانديز	ابراهیم مرتضوی	6254472	.	1	A+	B
5	وحید-۴راه رودکی	صحت	رسول قاسمی	6256031	.	1	A+	A+
5	خاقانی-ابتدای خاقانی ازوحید	.	رجب یزدانی	6247563	.	1	A+	غ ف
5	خاقانی-روبروی مسجد امام موسی بن جعفر	پردیس	اصغر آقا داوود مارنانی	6252102	9133059261	1	A+	B
5	خاقانی-نرسیده به خواجه پتروس	میرداماد	واهان کشیشیان	6247572	.	1	A+	C
5	خاقانی-جنب فروشگاه رفاه	شانديز	حمید پاکبین	6245155	.	1	A+	غ ف

6	اپادانا اول-بعدازکوچه باغ توت-سمت چپ	یلدا	سید هادی عقیلی	6625795	9131159591	1	A+	A
6	4باغ بالا	.	محسن اله دادیان	6622198	9131143449	1	A+	غ ف
6	اپادانا دوم روبروی تعاونی	اویسی	مهدی اویسی	6414545	.	1	A+	F
6	اپادانا دوم نبش کوچه لاله	شهر	حسن نجفی پور	6413010	9139119070	1	A+	A
6	خ شهید خلیلی	آفتاب	مجید نصیری	6601853	9135921060	1	A+	A+
6	روبروی بیمارستان صدوقی	.	ملک شریف زارع	2642866	.	1	A+	A+
6	جنب پاساز قائم فلکه مرداویج	.	اکبر اسماعیلی	6687290	9131033205	1	A+	غ ف
7	زینبیه جنوبی	.	مصطفی مهری	4614739	9132047245	1	A+	A+
7	بعثت	دیرمجال	رحمان قربانی	4590356	.	1	A+	B
7	خ بنایی	نجفی	رضا نجفی	4610883	9132252308	1	A+	A+
7	.	بختیاری	مرادی	456585	9132077728	1	A+	
8	رباط دوم	نسیم	آیت مرتاضی	4401400	9138301410	1	A+	A+
8	خانه اصفهان	دام ودوشان	محسن بهمن پور	4205268	.	1	A+	A
8	کاوه	اتشی	عباس اتشی	4403602	9131273261	1	A+	B
8	کاوه	ترکان	رسول ترکان	4381256	9133095421	1	A+	A
8	باهنر	تک	رضا اسفندیاری	3383431	9131668196	1	A+	A
8	رباط اول	بهار	محمد زارع	4406180	9133252630	1	A+	B
8	جابر انصاری	نایت	محسن دوامی	4442202	9132241056	1	A+	A
8	بهارستان غربی	.	رسول حقیقی زاده	3201664	9133160651	1	A+	D
8	خ امام خمینی	دی تو دی	مسعود خراسانی	3318769	9133292571	1	A+	غ ف
8	باهنرساختمان مهتاب	مهتاب	زفره ای	3386757	.	1	A+	A
8	فروغی	هایپر مارکت	ایزدی	3376446	9131003028	1	A+	A
8	نبش خ قدرسی روبروی قنادی فاطمیه	.	صفری	4209158	9139090056	1	A+	
9	بلوار اشرفی اصفهانی	عمده فروش برادران	عارف منش	7385955	.	1	A+	غ ف
10	عسگریه-روبروی بیمارستان عسگریه	شادپسران	حسین رستمی	2254121	9133867613	1	A+	F
10	پروین	اسلامی	علی اکبر باقری	2259370	9132263110	1	A+	A
10	پروین	سپاهان	غلامحسین حمیدفر	2294275	.	1	A+	B
10	خ جی	ارکیده	بابایی	2313561	9139153286	1	A+	A+
10	خ معراج	مروارید	قنبری	5802087	.	1	A+	B
10	خ معراج	تمدن	اصغر عبدی نیان	5801219	.	1	A+	غ ف
10	میثم ابتدای خ میثم	میثم	محمود دهخدایی	.	9138152612	1	A+	غ ف
10	خ هفتون	.	احمد سلیمانی	5556437	9133071008	1	A+	A
10	زرین کوب	فروشگاه صاحب الزمان	محمود حیدری	5551871	.	1	A+	غ ف
10	اوحدی	نقش جهان	محمود اکبری	.	9131887679	1	A+	C
10	جی خواجه عمید	خواجه عمید	حسین احمدی	2302322	9137864120	1	A+	A+
10	معراج	.	حمید فخرایی	5549885	.	1	A+	A+
10	.	.	امیر حسین روناسی	2292143	9133009599	1	A+	D
10	جی	.	دوزنده	5210716	9133681573	1	A+	A
11	رهنان	ارزانی انصاری	انصاری	.	9133103290	1	A+	غ ف
11	خ شریف شرقی	.	جلال اعتصامی	.	9136003140	1	A+	غ ف
12	مطهری	سعید	سعیدقندهاری	4395777	9131669398	1	A+	غ ف
12	مطهری	نقش جهان	مهرداد مصاح	4436195	9132693633	1	A+	A+
12	17شهریور	پانیذ	علیرضا فرهادیان	4429360	9133170130	1	A+	C
12	شهرک قدس بازارچه سوپر کیان	کیان	مختار کاکایی	3241303	9132056756	1	A+	B

5	خاقانی-روبروی بانک تجارت	جلفا	فولادی(حسین ترکی)	6276734	.	1	A+	A
5	نظر غربی-روبروی بانک تجارت	سپاهیان	سپاهیان(غریبیان)	6244157	.	1	A+	C
5	نظرغربی نبش ک نماز خانه استیفن	زیتون	فرشید پیروزفر	6251597	.	1	A+	B
5	خ محتشم کاشانی	کریمی	علی کریمی	628143	.	1	A+	B
5	خ شمس	صدف	حسین علی کریمی	7757692	.	1	A+	B
5	خ رودکی ابتدای خ رودکی از سیمین	شهروند	محمدکریمی	7789032	.	1	A+	C
5	خ رودکی جنب داروخانه و جنب بانک سپه	ابگون	احسان ابگون	7753588	.	1	A+	A+
5	خ رودکی	کیان	مهدی کیانی	7758717	.	1	A+	غ ف
5	باغ دریاچه اخرکوچه ۷۰	صبا	علی لبنانی/دریایی	7862671	.	1	A+	B
5	باغ دریاچه نبش بن بست ۶۱	ونک	اصغررمضانی	7868601	.	1	A+	C
5	رودکی نبش چهارراه رودکی	اریا	غلامعلی قاسمی	7864418	.	1	A+	C
5	باغ دریاچه	باغ برج	محسن نوری	7867917	.	1	A+	A
5	3راه صمدیه جنب تالار قصر طلایی	طلایی	مسعود طلایی	2334011	.	1	A+	A+
5	خ وحید	یکتا	عبدالعلی مقدم	7756885	.	1	A+	A+
5	خ وحید	اسماعیلی	حسین اسماعیلی	7758882	.	1	A+	D
5	بلوار کشاورز-جنب ایران خودرو	تعاونی پرشیا فلز	سلطانی	7771617	.	1	A+	D
5	اواسط خ خاقانی	خاقانی	داریوش رحمانی	6274617	.	1	A+	A
5	خ دانشگاه-مقابل درب دانشگاه	118	کاظمی	6273705	.	1	A+	B
5	خ دانشگاه	شکلات	باقی پور	6282033	.	1	A+	غ ف
5	خاقانی	جانثاری	جانثاری	6278957	.	1	A+	غ ف
5	خ سوارکاران	آرامش	آرامش	7776065	.	1	A+	C
5	خ رودکی	محسنیه	حسین رضایی	7866594	.	1	A+	غ ف
5	حکیم نظامی	.	حسن نیلی	6258214	.	1	A+	A+
5	نظر شرقی	.	حسین علی بیک	6279088	9133082712	1	A+	A+
5	توحید میانی	اردیبهشت	ابراهیم عشقی پور	6282287	9131096576	1	A+	C
5	توحید میانی	.	غلامحسین بناکار	6249541	9133148726	1	A+	غ ف
5	هزارجریب	زیتون	شجاعی	6735908	.	1	A+	A
5	هزارجریب	.	جلال نکویی	6685734	.	1	A+	A+
5	حکیم نظامی	.	لرموندست آقایان	6244550	.	1	A+	C
5	نظر شرقی	.	حسین صالحی	6241524	9133185381	1	A+	C
5	حسین آباد	.	غلامرضا رمضانی	6271529	9133289282	1	A+	A
5	خ ارتش	.	علی صادقیان	6246573	9130090780	1	A+	A
5	خ ارتش	.	نادر کاظمی	6271993	9132120700	1	A+	D
5	4راه پلیس	.	سید اخوندی	6274610	9133688878	1	A+	غ ف
5	صمدیه	.	مسعود طلایی	2333979	9131172337	1	A+	غ ف
5	ارتش	.	رامین عبدالهی	6263694	.	1	A+	B
5	ارتش	.	اسماعیل خان محمدی	6275946	9132082747	1	A+	C
5	شریعتی	.	رحیمی	6241844	.	1	A+	F
5	شهید یار محمدی روبروی نانوایی	نیمه شعبان	محمود رضا حبیبی	7778127	9138275322	1	A+	
6	شیخ صدوق جنوبی	ممتاز	مهدی علی محمدی	6687220	9132300023	1	A+	غ ف
6	شیخ صدوق جنوبی	راتا	امیر علی شبستری	6695130	9133138904	1	A+	C
6	شیخ صدوق جنوبی	برج	عبدا.. درکشان	6692204	9133162398	1	A+	A
6	فلکه فیض-ابتدای خ فیض-سمت راست	پاتریس	رضا یوسفیان	6628728	9133151633	1	A+	A+
6	آپادانا اول-نرسیده به فلکه فیض-سمت راست	بهشت	مهران رجایی	6628180	9131173687	1	A+	A

12	خ نکارستان نبش فرعی چهارم	چشمک	داوود فرخنده	4336061	.	1	A+	غ ف
13	استاد مهیار	مهیار	منوچهر اسماعیلی	7787415	9131111140	1	A+	B
13	بلوار شفق	.	تعاونی نیروگاه	7882300	.	1	A+	B
13	بلوار کشاورز	کیانی	محمدجواد کیانی	7808030	.	1	A+	C
13	بلوار غدیر	هما	موسی جهاندار	6512085	.	1	A+	C
13	بلوار غدیر	فارسی مارکت	نوید پویدار	6506246	.	1	A+	A+
13	بلوارتوحید	امیر	امیر صادقیان	6511838	.	1	A+	A+
13	بلوار شاهد	پردیس	محسن اسماعیلی	6502038	.	1	A+	A+
13	.	عطر یاس	عارف رحیمی	6511412	9139715904	1	A+	
14	زینبیه شمالی	توسکا	رضا هادی عابدینی	5543719	9133668420	1	A+	A
14	بعثت	تعاون	حسین محمدی	5569284	9133297054	1	A+	A
14	حصه	مرادی	ناصرمرادی	5583028	9132275363	1	A+	غ ف
14	شهرک امام خمینی	ابوالفضل	مجید مرادی	5517475	9136478493	1	A+	C
14	خ آیت اله غفاری	بیات	عزیزاله بیات	5513373	.	1	A+	C
14	خ بعثت	مهدی	مهدی روان بخش	4581668	9133163606	1	A+	غ ف
14	زینبیه شمالی لاله	نعیم	علیدادی	5676001	.	1	A+	A
14	اتوبان چمران خ بهشت روبروی اداره برق	ارزانی دل ارا	افشین علی مردانی	5570253	9137127295	1	A+	
.	بلوار کشاورز	سوپر رفاه کشاورزی	اکبر مرادی	7773951	9131867331	1	A+	E
بهارستان	اردیبهشت شرقی	آپادانا	آرش دوستی	6825893	9139114176	1	A+	A
بهارستان	فرشته جنوبی	دلفین	شارقی	6811467	9132289150	1	A+	C
بهارستان	الفت ۴راه ایثار بریانی فانوس	.	خدادادی	6820297	.	1	A+	E
بهارستان	.	110	سعید جعفری	6818018	9131145155	1	A+	A
خوراسگان	شریعتی	.	مجید عابدینی	5225188	9132284550	1	A+	A
خوراسگان	جنب قرض الحسنه مهر	.	محمد کریمیان	5214791	.	1	A+	A
خوراسگان	شریعتی	تعاونی توحید	علی مشهدی	5215203	.	1	A+	B
خوراسگان	کیلومتر ۸جاده نایین	تعاونی کارکنان قند	ملکوتی	.	9131144706	1	A+	A
خوراسگان	ابتدای بلوار ارغوانیه	توحید	صبوری	5217100	.	1	A+	A+
خوراسگان	جی	فرهادی	احمد فرهادیه	5280252	.	1	A+	B
خوراسگان	.	مجید	عباس عابدینی	5230019	9133268979	1	A+	A
خوراسگان	.	.	برهانی	.	9132008731	1	A+	غ ف
خوراسگان	جی مقابل بانک سپه ابر	پگاه	حسین یزدی فروش	5210462	.	1	A+	A+
خوراسگان	.	.	حمید زمانی	.	9133109536	1	A+	غ ف
خوراسگان	بالاتر از ابر مقابل بانک سپه	.	حسین یزدی فروش	5210462	.	1	A+	A+
خوراسگان	الله اکبر ۴راه الله اکبر	.	احمد فرهادی	5280252	9133079804	1	A+	B
خوراسگان	جی شیر خ سروستان انتهای بوستان	هاپیر باران	نبوی	2630601/2630636	9138102462	1	A+	A
خوراسگان	جیلان اباد بلوار شهید بهشتی	گلچین	روح اله امینی	.	9133171077	1	A+	
سپاهان شهر	بلوار شاهد	پردیس	محسن اسماعیلی	6508220	.	1	A+	B
سپاهان شهر	بلوار توحید	امیر	امیر صادقیان	6511838	.	1	A+	B
شاهین شهر	سعدی جنوبی	قائم	علی محمدی	5279063	9131053463	1	A+	E
شاهین شهر	رازی	آراد	افشین مردانی	5248251	9134127917	1	A+	C
شاهین شهر	رازی	کسری	رضا الماسی	5274505	9133862692	1	A+	C
شاهین شهر	فردوسی	ستاره	عباس علیدادی	5245388	9313101788	1	A+	D
شاهین شهر	فردوسی	وحدت	شاه نظری	5240323	9133127889	1	A+	A
شاهین شهر	فردوسی	شهروند	ابراهیم بختیاری	5212499	9131075517	1	A+	B

Appendix D: Publications from this research

Published Journal Papers

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed, "Memetic heuristic approach for solving truck and trailer routing problems with stochastic demands and time windows", Networks and Spatial Economics,1-23. **ISI-Cited Publication-Q1**, Publisher: Springer.

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed" Meta-heuristic approaches for solving truck and trailer routing problems with stochastic demands: A case study from dairy industry", Mathematical Problems in Engineering, ISI cited, Publisher: Hindawi Publishing Corporation, **ISI-Cited Publication-Q2**,

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed, Shima Rezaei., A Simulated Annealing Heuristic for Truck and Trailer Routing Problem with Stochastic Travel Times and Time Windows. J. Appl. Sci. & Agric., 9(18): 55-60, 2014, **ISI-Cited** Publication.

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed, Shima Rezaei, Application of Memetic Algorithm to Solve Truck and Trailer Routing Problems. J. Appl. Sci. & Agric., 9(18): 72-78, 2014, **ISI-Cited** Publication.

Submitted Journal Papers

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed "Stochastic Vehicle Routing Problem (SVRP) variants and solution approaches: a review and research directions", International Journal of Production Research, **ISI-cited Publication-Q2**, Publisher: Taylor & Francis, Status: Submitted.

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed, Ardeshir Bahreininejad "A multi-point simulated annealing heuristic for truck and trailer routing problem with stochastic demands", Engineering Applications of Artificial Intelligence, **ISI-cited Publication-Q2**, Publisher: Elsevier, Status: Submitted.

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed "Heuristic approaches for truck and trailer routing problem with stochastic travel times and depot deadline", ANNALS OF OPERATIONS RESEARCH, **ISI cited Publication-Q2**, Status: Submitted,

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed "Memetic heuristic approach for solving truck and trailer routing problems with stochastic travel and service time under time windows" European Journal of Operational Research, **ISI-cited Publication-Q1**, Publisher: Elsevier, Status: Submitted.

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed, “memetic algorithm to solve truck and trailer routing problems” International Journal of Production Research, **ISI-cited Publication-Q2**, Publisher: Taylor & Francis, Status: Submitted.

Presented in Conferences

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed, Eida Nadirah Roslin "Meta-heuristics to solve truck and trailer routing problems, Proceedings of the 2014 International Conference on Industrial Engineering and Operations Management, Bali, Indonasia, January 7-9, 2014.

Eida Nadirah Roslin, Shamsuddin Ahmed, SEYEDMEHDI MIRMOHAMMADSADEGHI, Siti Zawiah Md Dawal "A Conceptual Model for Full-Blown Implementation of Lean Manufacturing System in Malaysian Automotive Industry" , Proceedings of the 2014 International Conference on Industrial Engineering and Operations Management, Bali, Indonasia, January 7-9, 2014.

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed, Shima Rezaei., A Simulated Annealing Heuristic for Truck and Trailer Routing Problem with Stochastic Travel Times and Time Windows. . International Postgraduate Conference on Engineering and Technology Research 2014 (IPCETR 2014) at The Langkawi, Sea view Hotel, Langkawi on 17-18th October 2014.

Seyedmehdi Mirmohammadsadeghi, Shamsuddin Ahmed, Shima Rezaei, Memetic Algorithm to Solve Truck and Trailer Routing Problems. International Postgraduate Conference on Engineering and Technology Research 2014 (IPCETR 2014) at The Langkawi, Sea view Hotel, Langkawi on 17-18th October 2014.

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Memetic Heuristic Approach for Solving Truck and Trailer Routing Problems with Stochastic Demands and Time Windows

Seyedmehdi Mirmohammadsadeghi · Shamsuddin Ahmed

Abstract Manufacturers and service providers often encounter stochastic demand scenarios. Researchers have, thus far, considered that the deterministic truck and trailer routing problem (TTRP) cannot address the prevailing demand uncertainties and/or other complexities. The purpose of this study is to expand the deterministic TTRP model by introducing stochastic demand and time window constraints to bring the TTRP model closer to reality and solve the model in a reasonable timeframe by administering the memetic algorithm (MA). This paper presents a model that can be applied in stochastic demand conditions. To employ the MA, various crossovers, mutations and local search approaches were applied. First, two experimental tests were carried out to show the validity and consistency of the MA for solving stochastic TTRPs. The results can be compared with the VRPSDTW (vehicle routing problem with stochastic demands (VRSPD) with time windows) solution obtained using large neighbourhood search (LNS) of earlier research. The average results from Tests 1 and 2 achieved by MA are 514.927 and 516.451. However, the average result obtained by LNS is 516.877. Therefore, the MA can generate results. Thus, MA is found to be suitable for solving truck and trailer routing problem(s) under stochastic demand with a time window (TTRPSDTW). Moreover, 54 benchmark instances were modified for this case and the initial feasible solutions were generated for this purpose. The solutions were significantly improved by the MA. Also, the problems were tested using sensitivity analysis to understand the effects of the parameters and to make a comparison between the best results obtained by MA and sensitivity analysis. Since the differences between the results are small, the MA was found to be appropriate and better for solving TTRPSDTW. The paper also gives some suggestions for further research.

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Research Article

Metaheuristic Approaches for Solving Truck and Trailer Routing Problems with Stochastic Demands: A Case Study in Dairy Industry

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Manufacturers and service providers often encounter stochastic demand scenarios. Researchers have, thus far, considered the deterministic truck and trailer routing problem (TTRP) that cannot address ubiquitous demand uncertainties and/or other complexities. The purpose of this study is to model the TTRP with stochastic demand (TTRPSD) constraints to bring the TTRP model closer to a reality. The model is solved in a reasonable timeframe using data from a large dairy service by administering the multipoint simulated annealing (M-SA), memetic algorithm (MA), and tabu search (TS). A sizeable number of customers whose demands follow the Poisson probability distribution are considered to model and solve the problem. To make the solutions relevant, first, 21 special TTRPSD benchmark instances are modified for this case and then these benchmarks are used in order to increase the validity and efficiency of the aforementioned algorithms and to show the consistency of the results. Also, the solutions have been tested using sensitivity analysis to understand the effects of the parameters and to make a comparison between the best results obtained by three algorithms and sensitivity analysis. Since the differences between the results are insignificant, the algorithms are found to be appropriate and relevant for solving real-world TTRPSD problem.

1. Introduction

These days, complex customer demands are required to be satisfied by many companies. Therefore, a large number of companies are trying to achieve a high level of reliability, flexibility, and agility for different demands. As a result, supply chain management (SCM) has become a thought-provoking subject for various companies, seeking for a way out of efficiently improving their customer satisfaction. In a way, according to the position and role, supply chain is categorized into three classes; the outbound, intracompany, and inbound supply chain. As the network of supplies begins at the inbound supply chain, the role of this group is transporting the semifinished products or the raw materials to the site of manufacturing. The main concern of the intracompany supply chain, as the intermediary part, is with the flow of material in the site of manufacturing. Finally, the outbound supply chain is concerned with the delivery of final products to the customers [1]. The inventory allocation and transportation are strongly considered in the outbound supply chain for minimizing the cost and satisfying the customers' demands. One significant part of the supply chain management is providing the services or/and goods from a supply point to different destinations, which are geographically distributed with significant implications of economics. Aside from the cost of purchasing the goods, on the average and compared to the other relative activities, a higher percentage of the costs of logistics are absorbed by transportation. Therefore, efficiency improvement through the maximum usage of the necessities of transportation and decreasing the costs of transportation along with the improvement of services for customers are the frequent and significant decision analysis problems [2].

Customers, warehouses, manufacturers, and suppliers are the main elements of a supply chain (SC), carrying the goods

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A Simulated Annealing Heuristic for Truck and Trailer Routing Problem with Stochastic Travel Times and Time Windows

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ABSTRACT

Manufacturers and services providers often encounter stochastic parametric scenarios in transportation. Researchers have, thus far, considered deterministic truck and trailer routing problem (TTRP) that cannot address the prevailing travel time uncertainties and/or other complexities. Therefore, truck and trailer routing problem with stochastic travel times and time windows (TTRPSTTW) has practical significance. The purpose of this study is to expand the deterministic TTRP model by introducing stochastic travel times with time window constraints to bring the TTRP model closer to reality and solve the model in a reasonable timeframe by administering the simulated annealing (SA). Eighteen benchmark-instance problems have been modified for this case and solved by using these algorithms. Also the problems are tested by sensitivity analysis to understand the effects of parameters and to make a comparison between the best results obtained by SA and sensitivity analysis.

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INTRODUCTION

This paper presents the truck and trailer routing problem with stochastic travel time and time windows (TTRPSTTW). It is an extension of truck and trailer routing problem (TTRP) is discussed. The truck and trailer routing problem is a variant of the vehicle routing problem (VRP). In TTRP, sometimes a truck pulls a trailer to serve the known customers (which is a feature that usually is ignored in the VRP). However, because of some limitations which are encountered in real-life situations, such as government regulations, limited space to manoeuver at customer site, and road conditions, only a truck may serve some of the customers. These constraints can be found in many practical situations (Lin *et al.*, 2009). Several researchers have been working on this field. Gerdessen worked on Vehicle Routing Problem with trailer (Gerdessen, 1996). He demonstrated two real applications which are relevant to TTRP. The first one is the distribution of dairy products in which many customers were located in cities with heavy traffic. Because of maneuvering a complete vehicle is found so difficult in these cities, therefore the trailer often parked in designated parking places and the truck serviced the customers. The second application is to distribute compound animal feed to farmers. Because most of the villages have narrow roads or small bridges, different kinds of vehicles are required to deliver the feed to farmers. One kind of vehicles called *double bottom*. It consists of a truck and a trailer. While the truck serves customers by making sub-tours, the trailer is remaining parked at the parking area.

In many real-life issues which are relevant to TTRP some constraints and limitations such as time windows are imposed to make the model more realistic. In addition, in practical situations travel time between customers are stochastic. Therefore, it is important to consider TTRP with stochastic travel time and time windows. This problem is an extension of VRP with stochastic travel time and time windows (VRPSTTW).

1. Formulation of the truck and trailer routing problem with stochastic travel times and time windows:

The TTRPSTTW is an extension of the TTRP. TTRP was first proposed by Chao (Chao, 2002). The TTRPSTTW is defined as an undirected graph $G = (V, E)$, where $V = \{v_0, v_1, v_2, \dots, v_n\}$ is the set of vertices and $E = \{(v_i, v_j) : v_i, v_j \in V, i < j\}$ is the set of edges. The central depot is represented by v_0 and the other vertices in $V \setminus \{v_0\}$correspond to customers. Each vertex v_i is associated with a deterministic and non-negative demand $q_i$to be met. Also each customer should be serviced in service timeγ_i. A customer typet_i is available for all customers. If $t_i = 1$, the customer i is a truckcustomer (TC) and can be serviced only by single truck.

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Application of Memetic Algorithm to Solve Truck and Trailer Routing Problems

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ABSTRACT

Application of memetic algorithm (MA) is considered in this work to solve the truck and trailer routing problem (TTRP). In TTRP, some customers can be designated as vehicle customers and can be serviced either by a complete vehicle (a trailer pulling by truck) or a single truck. However, some customers are known as truck customers and have to be serviced by a single truck. To employ this algorithm, Partial-mapped crossover (PMX), various mutations and local search approaches have been applied and a truck and trailer routing problem has been solved. The results compared with the findings available in the literature. The MA used for this purpose obtained 13 best solutions out of 21, including 10 new solutions. The results obtained from the application of MA are better than other algorithms such as tabu search and simulated annealing. Therefore, application of MA is useful for solving TTRP.

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INTRODUCTION

Truck and trailer routing problems (TTRP) are related to transporting manufacturing goods within a plant or factory floors or delivering products to markets or customers. TTRP is a variant of the vehicle routing problem (VRP). Indeed, VRP has been known as one of the most studied combinatorial optimization problem in the past few decades since it covered certain areas in practice and considered complexities to a reasonable extent (Golden and Assad, 1988, Laporte *et al.*, 2000). VRP concept has been extended since 1959. In 1959, Ramser and Dantzing introduced this terminology (Dantzig and Ramser, 1959). They defined it as a generalized solution on Travelling Salesman Problem (TSP). After that many researchers have extended this concept to make it useful in diverse areas. During the last twodecades, some constraints were added to the VRP such as time window, travel and service time. However, because of some obstacles which come out in real life time, such as government regulations, limited space to maneuver at customer site and road conditions, maneuvering a complete vehicle (truck pulling a trailer) is very difficult and only a truck may serve some of the customers. These constraints can be found in many practical situations (Lin *et al.*, 2009). Consequently, as VRP cannot consider these issues and they should be considered in TTRP model.

In the TTRP, sometimes trucks pull a trailer to serve the customers that is when the usage of trailers is considered (which is a feature that usually is ignored in the VRP). Some researchers have been working in this field. Gerdessen worked on The Vehicle Routing Problem with trailer (Gerdessen, 1996). He demonstrated two actual applications which are relevant to TTRP. The first one is the distribution of dairy products in which many customers were located in cities where heavy traffic is the reality. Because of maneuvering a complete vehicle was so difficult in this area, therefore the trailer often parked in parking places and the truck serviced customers. The second application is to distribute component animal feed to farmers. Because most of villages have narrow roads or small bridges, different kinds of vehicles are required to deliver the feed to farmers. One kind of vehicles called double bottom. It consists of a truck and a trailer. While the truck is making sub-tours (some parts of tour) the trailer parks at parking area. Another application which is relevant to TTRP is introduced by Semet and Taillard (Semet and Taillard, 1993). The application occurred in a major chain food market with 45 groceries. They located in Swiss state. The markets were serviced by a fleet of 21 trucks and 7 trailers. This scheduling for servicing customers with a combinational truck and trailer is interested for researchers.

TTRP model was first proposed by Chao (2002).Then Scheuerer applied an 0-1 integer programming formulation for solving TTRP. TTRP was a formulation in integer programming by Scheuerer (2006) for the first time. Chao (2002) and Scheuerer (2006) used a 2-phase approach for solving TTRP. They used heuristics to construct the initial TTRP solution in the first phase. In the second phase, they used Tabu search algorithm to

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