AN ABSTRACT OF THE DISSERTATION OF

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Title: Incorporating Uncertainty in Truckload Relay Network Design

Abstract approved:

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In a relay network for full truckload (TL) transportation, facilities known as relay points (RPs) serve as exchange points where truck drivers can exchange trailers. This would help carriers to assign more regular tours to drivers when compared to the excessively long tours that exist in the traditional Point-to-Point (PtP) method. More regular driver tours would help to alleviate the driver turnover problem that significantly affects the industry. However, modifying the current system and completely replacing it with relay networks would not be practical. Instead a hybrid configuration known as truckload relay network design with mixed fleet dispatching (TLRND-MD) would allow certain loads to be delivered via the relay network while others are still served via the traditional PtP method. The strategic design of these hybrid networks entails locating RPs, determining the appropriate dispatching method for truckloads, and the selection of the appropriate route for those truckloads that are dispatched over the relay network. Most of the existing literature on the strategic design of truckload relay networks assumes deterministic parameters in the formulation of mathematical programs used to find optimal solutions. However, the TL transportation environment

can be affected by uncertainty in terms of demands, travel times, transportation costs, disruptions, etc. Understanding the impacts of uncertainty on the design of relay networks for TL transportation is essential for making effective decisions. In this dissertation, we aim to explicitly incorporate demand uncertainty in the formulation of the TLRND-MD and the capacitated TLRND-MD problems.

First, a robust optimization approach with a controllable level of conservatism is used to develop the robust counterpart for an existing mathematical model for the TLRND-MD problem. Solutions that perform well under any possible realization of the demand satisfying an uncertainty set are obtained for different network instances to show how incorporating uncertainty affects the total facility installation and transportation costs as well as other characteristics of the resulting truckload relay networks such as the required number of RPs. Then, we develop a two-stage stochastic programming formulation to capture demand uncertainty when demand is considered as a random variable governed by a posited probability distribution. Therefore, this approach allows us to optimize the expected transportation costs over scenarios of demand realizations. A Monte-Carlo simulation-based sampling algorithm known as Sample Average Approximation (SAA) is used to approximate the objective function value. Computational results are analyzed and compared with solutions obtained for the deterministic scenario. Finally, we propose to integrate the robust optimization and stochastic optimization approaches to incorporate demand uncertainty when the variability parameter which controls the level of conservatism in the robust formulation is also uncertain. We assume that the variability parameter follows a probability distribution, and develop a corresponding two-stage stochastic program.

Based on the insights provided by the computational tests in this dissertation about the effect of uncertainty in the TLRND-MD and capacitated TLRND-MD problems, we conclude that robust optimization provides more conservative solutions compared to stochastic optimization, but it also provides a more tractable mathematical formulation. Considering the resulting network designs, robust optimization solutions show an increase in the transportation costs to move additional loads and more RPs needed when compared to deterministic solutions. On the other hand, as stochastic optimization does not deal with worst case values of demand, solutions obtained with this method tend to require fewer RPs compared to the deterministic solutions. However, stochastic programs seem to be computationally intractable for large size network instances and need to be coupled with efficient solution approaches to alleviate the computational burden.

Incorporating Uncertainty in Truckload Relay Network Design

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Zahra Mokhtari, Author

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INCORPORATING UNCERTAINTY IN TRUCKLOAD RELAY NETWORK DESIGN

1 Introduction

1.1 Background

Trucking is a key transportation mode for goods in the United States accounting for 73.1% of the total value and 71.3% of the total weight transported every year (Bureau of Transportation Statistics 2010). There are two types of trucking operations: less-than-truckload (LTL) and full truckload (Campbell 2005). LTL carriers have traditionally used hub-and-spoke (H&S) networks to dispatch smaller loads that do not use the full capacity of a trailer. In LTL, loads are sorted and consolidated at hubs to take advantage of economies of scale. On the other hand, TL carriers normally use a Point-to-Point (PtP) dispatching method where a single driver delivers a load that fills up a trailer all the way from origin to destination (Campbell 2005). The PtP dispatching method for TL transportation results from carriers attempting to minimize empty repositioning movements between consecutive load deliveries to improve vehicle utilization. Since it is difficult to find appropriate back-haul trips to get drivers back to their home domiciles under PtP dispatching, drivers are usually assigned to a series of new load pick-ups originating in the vicinity of previous drop-offs. The resulting tours keep drivers on the road for an average of two to three weeks at a time (Powell et al. 2002). As a consequence, the perception of low quality of life for drivers due to long driver tours motivates them to quit. The resulting high driver turnover and the lack of qualified drivers are major issues that historically have affected the TL industry (American Trucking Associations 2012). In contrast, LTL carriers have not experienced large driver turnover rates as their use of H&S networks allows them to assign shorter tours to drivers who are able to return to their home domiciles more frequently (Taylor and Whicker 2010).

Based on this observation, the use of relay networks for TL transportation has been studied as an alternative to PtP dispatching given their potential to produce more regular routes for the drivers and facilitate reducing tour lengths (Üster and Maheshwari 2007). In this alternative dispatching method, each load is transported by two types of drivers that exchange trailers at RPs. Local drivers move loads between non-RP nodes and RPs, while lane drivers move loads between RPs. Limitations on the distances that local and lane drivers are allowed to travel result in more regular routes for all drivers as compared to traditional PtP movements.

In this context, the Truckload Relay Network Design (TLRND) problem considers both strategic and tactical decisions while satisfying operational constraints in order to minimize installation and transportation costs. In the literature, a few studies have focused on developing mathematical models and solution approaches for this problem such as the work completed by Üster and Maheshwari (2007), Üster and Kewcharoenwong (2011), Vergara and Root (2012), and Melton and Ingalls (2013). Figure 1 shows an example of a TL Relay Network where a load is transported from node *i* to node *j* using three RPs.

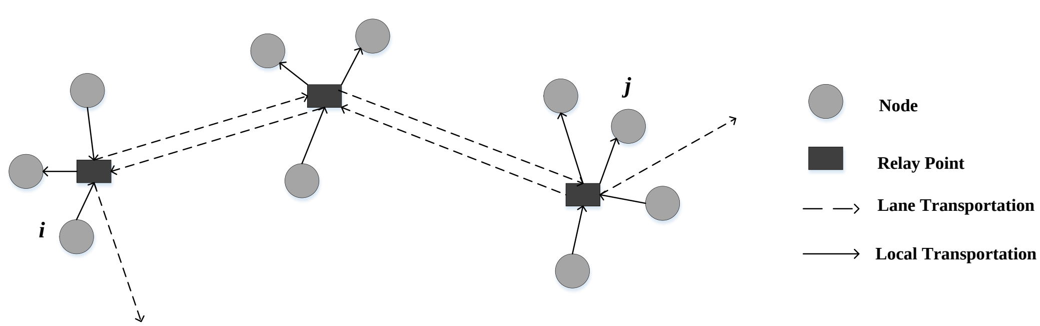

Figure 1: Example of a Relay Network for TL Transportation.

In a more complex configuration for TL transportation networks, a hybrid method of dispatching is allowed in which a freight load can be shipped either PtP or via the relay network. The design of this hybrid system is addressed by the TL relay network design with mixed fleet dispatching (TLRND-MD) problem studied by Vergara and Root (2013).

All of these previous studies that have developed mathematical programming formulations for the design of relay networks for TL transportation are limited to deterministic models that use the best estimates of the design parameters to determine the locations of RPs and routes for the freight loads in the system. However, in a realistic environment, several parameters such as transportation and installation costs, demand, and travel times that are related to the operations of TL carriers might be highly uncertain. Since the design of TL relay networks is classified as a strategic planning problem and not enough information about the input data exists for future periods in extended planning horizons, accounting for uncertainty becomes important in order to provide network designs that are more likely to capture future variability and are applicable in practice. To the best of our knowledge, no research studies exist in the literature related to the TLRND problem and its extensions that address the issue of uncertainty in the TL industry when formulating a mathematical model for this problem.

1.2 Research Objectives

The main objective of this dissertation is to develop mathematical formulations and efficient solution approaches for the strategic design of TL relay networks with mixed fleet dispatching that explicitly consider parameter uncertainty. A secondary objective is to use these formulations to understand the effect of uncertainty in the configuration of the resulting networks.

1.3 Research Questions

This dissertation answers the following research questions:

- What are the design parameters of the TLRND-MD problem that are affected the most by uncertainty?

- What methods could be used to incorporate parameter uncertainty based on an existing deterministic mathematical programming formulation of the TLRND-MD problem?
- How to find high quality solutions for realistic problems of the TLRND-MD problem under uncertainty in reasonable time?
- What is the effect of different levels of uncertainty in the design of TL relay networks with mixed fleet dispatching?

1.4 Research Tasks

The following tasks were completed as part of this dissertation:

- A comprehensive review of relevant literature in TL relay network design, as well as in modeling and solution approaches to explicitly incorporate uncertainty in deterministic models.
- Development of mathematical formulations for the TLRND-MD problem using two different modeling approaches that explicitly incorporate parameter uncertainty.
- Development of efficient solution methods to solve the mathematical models for the TLRND-MD problem under uncertainty and obtain high quality solutions in reasonable time.
- Comparison of the modeling challenges and performance of the two approaches for incorporating uncertainty in the TLRND-MD problem.
- Evaluation of the effect of uncertainty in the design of TL relay networks with mixed fleet dispatching.

1.5 Main Contributions

To address uncertainty in the TLRND-MD problem as introduced in Section 1.1, two uncertainty modeling approaches were utilized: (a) Robust optimization and (b) Stochastic optimization. Robust optimization assumes that precise knowledge about the distribution of the uncertain parameter is rarely available and models the uncertainty deterministically using uncertainty sets. In this dissertation, we use a robust optimization approach that optimizes against all worst case scenarios of the uncertain parameter satisfying the uncertainty set with a controllable level of conservatism. Stochastic optimization models the uncertainty probabilistically and treats the uncertain parameter as a random variable which makes it a powerful approach in modeling uncertainty. A popular avenue in stochastic optimization which is used in this dissertation is analyzing and optimizing the expected performance of the system with respect to the uncertain parameter.

We apply these techniques to incorporate uncertainty in the strategic design of the TLRND-MD problem and the capacitated TLRND-MD problem which is introduced in this research. Specifically,

(a) In Chapter 3, we present a comprehensive survey on research studying alternative dispatching methods for truckload trucking as a potential solution to the driver turnover problem. We address studies that have used operations research (OR) methods for their strategic design of the TL transportation network. The contributions in this area are classified into three main categories based on techniques used: simulation studies, mathematical programming and other OR modeling and solution techniques.

(b) In Chapter 4, we develop a robust counterpart for the TLRND-MD problem under demand uncertainty. We use the robust optimization approach introduced by Bertsimas and Sim (2003) that allows us to control the level of conservatism and protection using a variability parameter. We obtain solutions for deterministic and uncertain scenarios considering different levels of uncertainty and discuss how incorporating uncertainty affects the total cost of the system as well as the design of the network. We also take advantage of the tractability of the robust counterpart formulation for the TLRND-MD problem and obtain solutions for network instances of up to 100 nodes.

(c) In Chapter 5, first we extend the TLRND-MD formulation to incorporate a more realistic assumption restricting the capacity at the RPs, and then we develop a two-stage stochastic program for the capacitated TLRND-MD formulation. The idea behind the two-stage program is that strategic facility location as the first-stage decisions need to be made regardless and in advance to realizations of demand. While, transportation and routing as the second-stage decisions are closely dependent on the realizations of demand and should be made afterward. In Chapter 5, stochastic optimization allows us to observe a large number of scenarios of demand following a distribution and therefore generates considerable insights on the expected performance of the system under uncertain demand. To approximate and optimize the expected transportation cost, we use a sampling approach based on Monte Carlo simulation known as Sample Average Approximation (SAA) algorithm. Furthermore, since this algorithm deals with large size samples, we use an accelerated Benders decomposition algorithm to overcome the computational difficulties. We present computational results and discussion on the impact of demand uncertainty on the obtained solutions.

(d) In Chapter 6, we propose to bridge the robust optimization and stochastic optimization approaches to incorporate demand uncertainty and uncertainty in the variability parameter of the robust counterpart of the capacitated TLRND-MD formulation. The idea behind Chapter 6 is that capturing the choice of the variability parameter for the robust optimization approach is a major challenge. Therefore, we propose to treat this parameter as a random variable and examine a large number of scenarios of this parameter. In this study, similar to Chapter 4, we treat demand as an uncertain parameter fluctuating in a symmetric interval and develop a robust counterpart for the capacitated version of the TLRN-MD problem. Then, we assume that the variability parameter in the robust model that controls the size of the uncertainty sets and therefore the level of conservatism is also random and governed by a probability distribution. To account for its uncertainty, we use a two-stage stochastic program which allows us to analyze and optimize the *average worst case* behavior of the system. We use the SAA algorithm to find solutions for the two-stage program.

The rest of this dissertation is organized as follows. Chapter 2 provides a discussion about the sources of uncertainty in the TLRND-MD problem and justifies the selection of the uncertain parameter considered in this study. Chapter 3 shows a comprehensive review of existing research applying OR techniques to evaluate alternative dispatching methods in TL transportation. In Chapter 4, the robust counterpart of the TLRND-MD problem and its solution approach are presented. The mathematical formulation for the capacitated TLRND-MD problem and its corresponding two-stage stochastic program are presented in Chapter 5. Furthermore, Chapter 5 shows the SAA and the accelerated Benders decomposition algorithm that were tested for solving the stochastic program. Chapter 6 presents the proposed framework to bridge the robust optimization and stochastic optimization approaches to incorporate demand and variability parameter uncertainty. Finally, Chapter 7 presents general conclusions about the research completed in this dissertation and future research directions.

2 Sources of Uncertainty in Truckload Transportation

As discussed in Section 1.1, the trucking environment can be highly uncertain. In most cases, it can be difficult to estimate current and future values of several parameters involved in truckload transportation. Gifford (2010) discusses a key difference between truckload transportation network operations and most other freight transportation modes (e.g. air, railroad, ocean, etc.) is that forecasting the expected value of the parameters in truckload transportation is less accurate. The reason is that other transportation modes maintain a static nature and in most cases the tactical level decisions have been made in advance. While in truckload transportation, carriers have to fulfill the expectations of a diverse set of customers with short lead times. Moreover, in this environment, the availability of the resources at a particular time and location cannot be anticipated in advance. Major elements that could be assumed to be sources of uncertainty or are affected by it in the trucking industry are presented below.

- Total freight between O-D pairs (demand): According to anecdotal information from carriers, the amount of demand, service time to fulfill the demands, the pattern that customers follow as they place demands, and demand location are the main aspects of this parameter that are subject to uncertainty. In particular, the carriers are mostly concerned with uncertainty in the amount of demands between the O-D pairs which usually should be fulfilled in short service times (Gorman et al. 2014, Van der Vorst and Beulens 2002).
- Transportation cost: One of the major challenges that carriers face is the estimation of per mile transportation costs that can be affected by inaccurate estimation of fuel prices, parking fees, transit fares, drivers' payment, maintenance costs, etc. (Litman 2009).
- Installation cost: In general, the estimation of the fixed cost for establishing facilities is affected by the changes in political, societal, and environmental contexts. Inaccurate estimations on the price of the land, land availability, facility construction (e.g. labor and material) costs, etc. add variations to the estimation of the installation cost (Zhao et al. 2004).

- Travel time, and loading/unloading time at RPs: According to (Gorman et al. 2014), travel time is an important factor in freight transportation that is affected by uncertainty. The estimation of these parameters is affected by the availability of drivers at the origin nodes as well as the RPs to exchange the trailers, road network congestions, etc.
- Network and facility disruptions: Random physical failures in the transportation network, facilities and trucks can impact the decision maker’s estimation about the operations in the network from a resource availability perspective. According to (Sumalee et al. 2006), the network is exposed to several sources of uncertainty such as weather conditions or natural/man-made disruptions that can lead in variable service state of the network. “Transport network reliability” is an emerging area studying the effects of network disruptions on the network operations (Sumalee et al. 2006).

Figure 2 summarizes potential sources of uncertainty that affect the planning and operation of TL carriers.

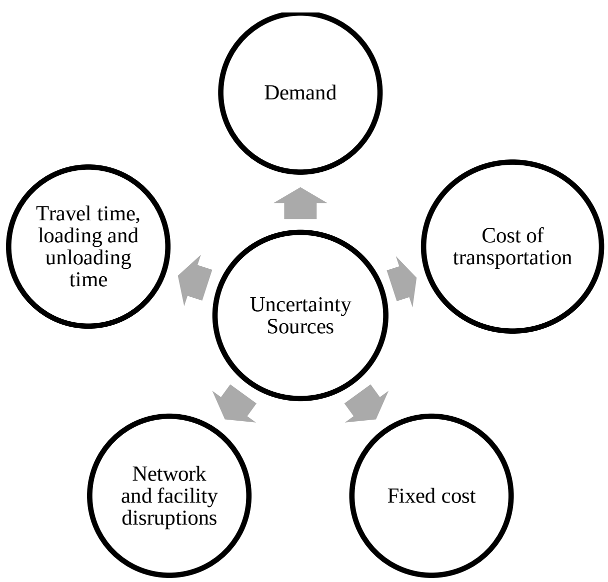

Figure 2: Sources of Uncertainty in the Trucking Environment.

Among the sources of uncertainty that were identified, demand was selected as the uncertain parameter that is considered in this dissertation. There are three reasons for selecting demand as the uncertain parameter. First, since the TLRND-MD problem is classified as a strategic planning problem that integrates tactical decisions and constraints, parameters such as demand corresponding to strategic and tactical level decisions need to be considered when modeling the network in the presence of uncertainty. Second, our literature review shows that demand has usually been considered as the only one or one of the main sources of uncertainty in studies addressing uncertainty in transportation network design problems. Considering that this work is the first study addressing uncertainty in the TLRND-MD problem, assuming demand as the uncertain parameter can provide useful insights about the impact of uncertainty on the design of this type of transportation network. Third, demand volume has been consistently mentioned as the most uncertain factor in the planning and operation of TL service based on anecdotal information provided some TL carriers.

3 Alternative dispatching methods for full truckload transportation: A review of operations research methods[1]

3.1 Abstract

Alternative dispatching methods for truckload trucking are a possible solution to the driver turnover problem, and operations research (OR) methods have been used for their strategic design. Although, several research studies have been completed over several years, there is no comprehensive review and categorization of the most important contributions in this area. We present a comprehensive survey in which contributions are classified into three main categories based on techniques used: simulation studies, mathematical programming and other OR modeling and solution techniques. Relevant research ideas related to alternative dispatching methods are also presented to motivate further research in this area.

Keywords: truckload transportation; dispatching; relay networks; optimization; simulation; algorithms

3.2 Introduction

Trucking is one of the most important modes of freight transportation in the United States accounting for 73.1% of the total value and 71.3% of the total weight transported in a year, according to the 2012 Commodity Flow Survey (Bureau of Transportation Statistics 2014). There are two major types of operation in trucking transportation: less than truckload (LTL) and full truckload (TL) trucking. LTL is generally used for relatively small freight loads that do not fill up a trailer. Normally, a hub and spoke configuration is used for LTL trucking and since regular trips are possible through the hub and spoke network, LTL drivers have more attractive jobs and more loyalty to carriers when compared to TL drivers (Campbell 2005). The TL driver turnover rate

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[1] This work has been submitted for publication to *Computers & Operations Research*.

is approximately 80% for small TL companies and around 100% for large TL companies per year, while the driver turnover rate in LTL trucking is significantly less than in TL trucking being around 13% per year (American Trucking Associations 2013).

Despite the large driver turnover rate in the industry, TL trucking is the main method used by manufacturers, suppliers and warehouses for freight transportation and it is appropriate for long haul travel movements (Campbell 2005). The most common method to dispatch loads in TL is using Point to Point (PtP) or direct dispatching. In this method, loads are picked up from their origins and directly sent to their destinations using a single driver. Drivers are assigned to several consecutive loads forming a single tour before they can return to their home domiciles. Figure 3 shows one complete tour for a single driver in a partial network in which PtP dispatching is used for transportation of truckloads between three different origin/destination (O-D) pairs.

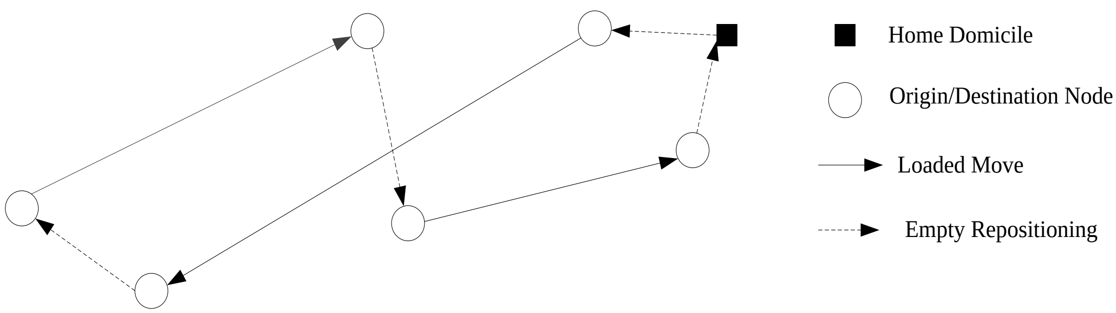

Figure 3: Partial Point to Point Truckload Transportation Network.

The common mechanism used by TL carriers for assigning drivers to truckloads attempts to reduce empty miles driven by matching drivers with truckloads according to the distance from their domicile to the first truckload pick up point. From there, drivers are subsequently assigned to the truckload with the nearest pick up point with respect to the previous delivery point until returning to the vicinity of the driver's home domicile, thus forming a tour. As a result, there is no guarantee that a subsequent movement will immediately direct the driver back to his or her domicile after a drop off. Given the uncertainty about the location and timing of truckload demands, this dispatching method leads to very long periods of time being away from home for truckload drivers of about two to three weeks (Taylor and Whicker 2010). The resulting perception of low quality of life for drivers who spend a long time on the road is one of the main reasons for the significant driver turnover in the TL industry. When TL drivers quit, carriers are faced with extremely high driver turnover costs that are likely to exceed $2.8 billion annually (Rodriguez et al. 2000).

As a result, the problem of assigning drivers to truckloads in such a way that they are able to return to their domiciles more frequently has received some attention by carriers and researchers. Several research studies concentrate on alleviating this problem by exploring the strategic design of alternative dispatching methods using operations research (OR) methods and tools. The difference in driver turnover rates between LTL and TL industries has motivated researchers and carriers to think about the implementation of alternative transportation network configurations similar to hub and spoke in the TL trucking industry and restricting driving areas for a subset of TL drivers, so that the high driver turnover rates observed with the traditional dispatching method can be reduced. Other examples of transportation network configurations that have been developed with the goal of maintaining drivers near their home domiciles or at least provide more regular tours for the drivers include relay networks, zone and multi zone models, regional fleets, and lane and pipelines models.

According to the existing literature, the most common objectives considered in the design and optimization of TL trucking dispatching methods (either traditional or alternative) are the minimization of total transportation costs (Üster and Maheshwari 2007), maximization of total revenue (Powell 1996), and getting drivers home more frequently (Simão et al. 2009). Some of the major challenges associated with the satisfaction of these objectives for alternative dispatching methods are mainly related to keeping drivers' trips bounded by distances that do not exceed a specified amount of additional distance as compared to the case of PtP dispatching, and maintaining equipment balance at nodes in the network to limit empty movements to reposition the equipment (Üster and Maheshwari 2007, Üster and Kewcharoenwong 2011). Additionally, other relevant constraints considered are related to the number of stops or transshipments that can be made on a trip (Vergara and Root 2012), the required volume of load traffic at hubs or relay points (RPs), and limitations on the proportion of loads that can be dispatched directly PtP in hybrid dispatching models (Vergara and Root 2013).

Various alternative TL dispatching methods have been developed based on different perspectives on the problem that are related to specific levels of decision making. The decision making levels in TL transportation dispatching are categorized based on their role on the TL trucking system performance and time horizon over which they have an effect. The decision making levels in TL transportation are:

- *Strategic level*: Decisions at this level are made by the highest level of management over long time horizons. These decisions are mainly about the number, location and size of facilities and resources, and often require a significant capital investment and effort. Also, main rules and policies are defined at this level of decision making (Hendriks 2009).
- *Tactical level*: At this level, intermediate term decisions are made about the service network design using the facilities and resources determined at the strategic level. Decisions include determining the topology of the network (i.e., how to connect the established nodes) and the detailed layout of the terminals at the nodes with facilities (Hendriks 2009).
- *Operational level*: Short term decisions are made by local management at this level. Examples of operational decisions are determining detailed routes for truckloads, scheduling of drivers, and resource allocation to loads with respect to day to day demands (Crainic and Laporte 1997).

As more alternative TL dispatching methods and approaches for their design and optimization using OR methodologies are proposed, it is necessary to complete a comprehensive literature review in this area. The purpose of this review is to synthesize multiple contributions made in the literature to facilitate the understanding of different OR approaches and solution methods applied to TL transportation dispatching. Also, it will serve both TL carriers and academic researchers to understand existing challenges and enable them to conduct future research studies in this area.

The rest of this chapter is organized as follows. In Section 3.3, we present a survey of the state of the art in the application of OR to problems associated with traditional TL dispatching. Section 3.4 is classified into three fundamental modeling and solution approaches for the design of alternative dispatching methods in TL transportation: simulation studies, mathematical programming, and other modeling and solution techniques. Finally, concluding remarks and future challenges are presented in Section 3.5.

3.3 Traditional Dispatching in TL Transportation

The most common approach for TL dispatching is the Point to Point (PtP) method. In this method, each loaded trailer carries the demand of one customer from origin to destination, so it is reasonable to assume that carriers will dedicate a single driver to transport one truckload from the customer's pick up location to the customer's desired destination (Liu et al. 2003). Although the direct shipment approach results in fast fulfillment of demands due to the fact that the transport time is primarily dependent on the driving distance between origin and destination, it also produces empty equipment repositioning miles and associated costs due to the difficulty in finding appropriate back haul movements. The driving tours that result from this dispatching approach are usually long and keep drivers away from their home domiciles for weeks at a time. Being away from home for long periods of time gradually affects the perception of quality of life for the drivers and motivates them to quit. The very high driver turnover rate for the TL industry that usually exceeds 100% for large carriers represents excessive costs and results in a driver shortage problem that has been consistently ranked in the top five major concerns for the industry (American Trucking Associations 2012).

In TL trucking, different from the relatively static nature of most of the other transportation systems, a large part of the demand comes from customers with very short notice and must be met in a short period of time (Gifford 2010). This fact determines that the system is subject to an uncertain environment. Moreover, the assignment of a driver to a specific truckload at a particular point in time and the unavailability of the same driver for future upcoming demands can directly affect the status of the system (i.e., the resources) and have an effect on subsequent decisions (i.e., movements for the drivers). Different series of decisions lead to different costs over time, and cost is one of the most important factors for TL carriers that wish to remain competitive in an industry with relatively low margins per truckload. As a result of this and because TL shipments are typically routed directly from origin to destination, there is no need to use OR tools to address a network design problem for traditional TL dispatching, however OR becomes essential when dealing with the allocation and management of drivers and equipment at both tactical and operational levels.

The allocation of drivers to loads is commonly referred to as the load matching problem and attempts to minimize the empty miles driven by drivers. Although the real nature of TL trucking involves dynamic operations, this important aspect has been neglected when allocating drivers to loads until recent years. Simão et al. (2009) emphasize that it is impossible to take into account the dynamic nature of the traditional TL dispatching problem with traditional mathematical programming assignment approaches that focus on optimizing operations of the system for a specific single period of time. Traditionally, the problem of assigning a set of drivers to a set of truckloads was mostly addressed as a simple assignment problem (Raff 1983; Desrosiers et al. 1995; Crainic and Laporte 1997 ; Gendreau et al. 1999; Toth and Vigo 2001). However, this approach does not recognize the dynamic nature of the TL dispatching problem. Simão et al. (2009) explicitly considered the uncertainty and dynamic nature discussed above and developed a model using approximate dynamic programming (ADP) (Powell 2007) to solve a dynamic driver assignment problem combined with a fleet management problem. The first part of their model attempts to assign drivers to loads that should be picked up in the current time period. The second part of the model considers forecasted demands as well as known loads to be picked up in the future and evaluates the effects of changes in the future availability of drivers on the system from a cost perspective. This approach was applied at Schneider National, one of the largest TL motor carriers in the United States. The authors used a complex simulator that can both consider the large number of drivers (over 6,000 drivers) and the extreme dynamic nature of the operations of the company. The authors compared the effect of the decisions made by the developed model to historical data provided by the company to see if the output obtained with the model matched the historical performance and validate the usability of the tool for the company. The authors also explicitly incorporated in their model business policies of the company determined by regulations of the U.S. Department of Transportation regarding hours of service (HOS) and returning drivers home, and operational restrictions on the use of particular driver types. In this way, the carrier was able to determine the effect of changing the rules over time on the improvement of the operations and the operating costs. The objective function defined in this model considered the contribution that results from applying different decisions to different drivers (i.e., resources). The contribution was considered to be either "hard dollars" which are tangible costs and revenues or "soft dollars" which are bonuses and penalty type costs and revenues. The mechanism used for updating the value function in the objective function of their model allowed the researchers and the carrier to change the mix and the required number of drivers for the different types of drivers with a single run of the model. This allowed them to estimate the marginal value of each driver type and converge to the best combination of drivers and their domiciles. In this research, the focus of finding better solutions against solutions obtained with previous methods developed by the authors such as Topaloglu and Powell (2006) was more on the type of drivers to use and less on the number of drivers needed. The ADP algorithm developed in this research proved to be a suitable approach to provide high quality solutions in the matter of returning drivers home and also matching historical statistics in average length of haul for various types of drivers. Moreover, the ADP algorithm can be applied in cases with uncertain parameters such as random customer demands and travel times. A synthesis of the economic benefits for Schneider National resulting from the application of this research is included in Simão et al. (2010).

The problem of managing mobile assets (i.e., equipment such as trailers or containers) to minimize repositioning costs has also been studied using OR. A major problem faced by large TL carriers is the load request imbalance in both time and space that occurs when nodes with large incoming flows possess a surplus of empty equipment and nodes with large outgoing flows suffer a deficit of empty equipment to dispatch loads. Erera et al. (2009) developed a two stage robust optimization framework with uncertainty budgets (Ben Tal et al. 2004; Bertsimas and Sim 2003) for dynamic repositioning of empty transportation resources over time. The two stage robust optimization approach was applied on a flow optimization model over a time space network. In these networks, a feasible flow consists of empty resource management decisions (i.e., holding inventory of empty resources or repositioning empty resources between locations). The model was solved for two real world test cases to obtain plans over a long planning horizon.

Additional research studies involving the application of OR models in TL transportation under the traditional PtP dispatching method are described in the surveys by Gifford (2010) and Gorman et al. (2014).

3.4 Alternative Dispatching Methods for TL Transportation

In this section, we discuss different alternative dispatching methods for TL transportation that have been proposed in the literature and classify them according to the OR modeling and solution approaches used to either optimize their design or evaluate their performance. A series of alternative TL dispatching methods analyzed using simulation are presented in Section 3.4.1. Section 3.4.2 presents research studies in which mathematical programming was used to model a particular alternative TL dispatching method based on relay networks. Finally, Section 3.4.3 shows other algorithmic approaches used for the design of alternative TL dispatching methods.

3.4.1 Simulation Studies

In this section, we present research studies that have applied simulation with the goal of designing and evaluating alternative dispatching methods for TL trucking as opposed to PtP dispatching. Figure 4 summarizes the simulation studies that are included in this survey.

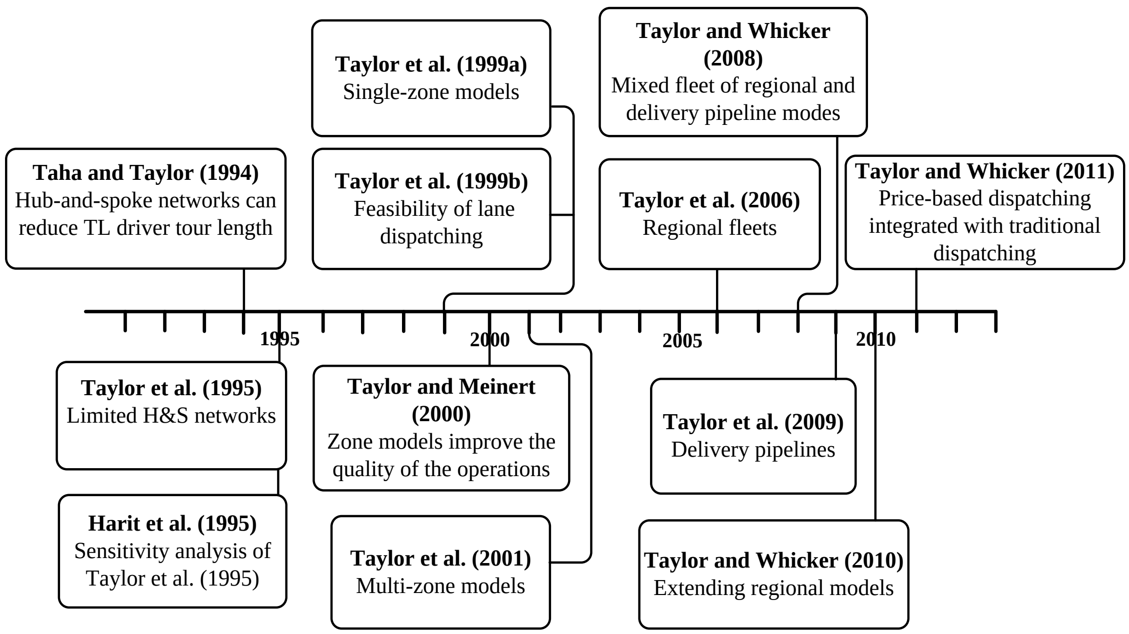

Figure 4: Summary of Simulation Studies Addressing Alternative TL Dispatching Methods.

In one of the earliest studies in alternative TL dispatching methods, Taha and Taylor (1994) completed the first formal study of the implementation of hub and spoke (H&S) networks in TL transportation. The authors completed a comprehensive survey of H&S networks such as the ones used in airlines and large LTL companies, and identified the potential benefits for TL trucking systems from the application of such networks to alleviate the problem of driver retention through more regular tours for the drivers. They explored the feasibility of H&S networks in TL trucking by implementing a simulation system named HUBNET. The authors evaluated several performance metrics such as percent circuity (i.e., the percentage of out of route miles driven from origin to destination when visiting hubs), first dispatch empty miles and tour length values in a case study of company operations for one of the largest TL carriers in the United States (J.B. Hunt Transport Inc.) and proved the feasibility of this alternative TL dispatching method.

In a related study, Taylor et al. (1995) tried to quantify the effects of the application of H&S networks in the TL trucking industry using real data provided by J.B. Hunt Transport Inc. Their objective was to investigate if the H&S networks in TL trucking would perform as effectively as in other transportation systems such as airlines and LTL trucking knowing that the most relevant feature of H&S networks such as load consolidation is not applicable in TL trucking. The authors anticipated that using hubs would help TL motor carriers to reduce driver tour lengths and driver turnover costs. They conducted their study using the HUBNET simulator and historical data provided by J.B. Hunt Transport, Inc. to evaluate the performance of H&S networks in terms of operational profits and associated costs. According to the experimental results obtained in this study, the authors proved that a partial implementation of H&S networks (i.e., while still maintaining some shipments PtP) would be useful, especially in relation to driver tour lengths. Even though a partial implementation of H&S networks sacrifices some other important operational criteria, trade-offs observed between the associated costs made it an appealing alternative for TL dispatching.

In another early study, Harit et al. (1995) completed additional experimental tests and performed a sensitivity analysis of the implementation of H&S networks for TL transportation extending the work of Taylor et al. (1995). The authors tried to find the best scenario for the implementation of H&S networks in TL transportation. They evaluated partial H&S networks looking at particular performance measures such as driver tour length, average miles per driver per day, circuity, and first dispatch empty miles. Then, they completed a sensitivity analysis by changing the limitations for those measures. For example, percent circuity was required not to be very high to meet the quality requirements of the network. Among different scenarios tested in their sensitivity analysis, the one in which almost one half of the total truckloads travel through the H&S network performed the best. This validated the idea that using a partial H&S network would be a viable alternative. In general, these original studies about the use of H&S networks in truckload trucking provided a solid foundation for more research studies in this area.

Later in a more extensive study, Taylor et al. (1999a) used simulation to compare different scenarios made of combinations of three alternative TL dispatching methods: delivery lanes, zone dispatching and H&S networks. Zone dispatching models make use of zone hubs within regions where drivers pick up and deliver loads. In this model, two types of drivers are used: over the road (OTR) drivers move truckloads between zones hubs located at zone boundaries and regional drivers move truckloads that originate or terminate at a zone. In this configuration, regional drivers have much shorter tour lengths when compared to those needed for PtP delivery. In this specific study, the authors sought to find methods for regularizing tours for long haul TL drivers and therefore reduce the amount of driver turnover for J.B. Hunt Transport Inc. in the Southeast region of the United States. The authors considered on time pick ups and deliveries as a key metric of customer satisfaction in the extremely competitive TL trucking industry. Actual data and historical load information provided by the carrier were used in the analysis. The authors explored different scenarios using discrete event simulation. All of the evaluated alternatives were successful in regularizing tours for the drivers, but only some of them resulted in significantly better performance metrics and seemed to be serious competitors to the PtP approach. According to their results, a zone model had the best performance in the region considered. The authors also implemented the same approach to another region in the Northeast of the United States to verify that the results were valid in other regions and the results obtained for this other region validated the robustness of the configuration studied in this research.

Regardless of the results obtained in the previous study, Taylor et al. (1999b) used a simulation model to extensively examine the concept of delivery lanes for TL dispatching proposed by Taylor et al. (1999a) to see if it was operationally feasible to be implemented in practice. In this configuration, a percentage of the loads are moved through well-defined delivery lanes that have high freight density as well as a one-day drive length. The goal of using regular delivery lanes is to reduce driver tour length while achieving high service level from the customer perspective and high driver utilization from the carrier perspective. Through the simulation outputs obtained and their statistical analysis, the factors affecting the design of the structure of the delivery lanes were identified and the critical operational measures were evaluated to examine the performance of the different lane configurations. The authors concluded that lane delivery had the potential to be used in the TL industry, and also that a partial implementation of delivery lanes in addition to traditional PtP dispatching might lead to better results in practice.

Considering the potential of zone dispatching models, Taylor and Meinert (2000) simulated several single zone model configurations for TL dispatching with different number of hubs, length of haul, and freight density distributions (i.e., dispersed or concentrated) to find the best scenario that improves the quality of service for all stakeholders: customers, drivers and carrier. Two simulation models were developed. The results of this study were the baseline for a more detailed sensitivity analysis to determine the effect of changing some of the operational factors in the amount of zone configuration usage in practice. For example, the suitable length of haul to be dispatched via the zone configuration, allowable circuity and minimum distance of pick-up and delivery from hubs were found to be determinant factors in zone participation. The results of the computational experiments were validated using actual freight data from J.B. Hunt Transport Inc. and were intended to help the carrier to find the best design of a zone model for implementation that would be able to meet the metrics that are crucial from customer, driver and carrier perspectives.

Later in Taylor et al. (2001), a supplementary study of Taylor et al. (1999a) and Taylor and Meinert (2000) was performed to evaluate different zone dispatching configurations. In this study, a simple primary structure for multi zone dispatching and a traditional dispatching scenario were considered as baselines for comparisons of various multi zone dispatching configurations. The authors conducted their experiments using a simulation model and historical data provided by J. B. Hunt Transport Inc. In each simulated scenario, some modifications and assumptions were imposed on the structure of the zones such as zone area boundaries and number of hubs to find any significant improvements in performance metrics, especially in driver tour length. According to the results obtained, all of the scenarios seemed applicable in practice and effective as compared to the baseline methods. The authors also noted that the scenario that minimized zone imbalance also provided shorter driver tour lengths. Moreover, in this scenario, a relatively high percentage of truckloads were dispatched via the zone configuration and high resource utilization was achieved. As a result of the analysis, multi zone dispatching was suggested for practical implementation.

As an alternative to multi zone dispatching, Taylor et al. (2006) used simulation to quantify the effects of using a regional fleet in a TL trucking setting. In the regional fleet, PtP movements are not abandoned, but the concepts of regional drivers and OTR drivers are considered so that regional drivers drive only in particular regions and the OTR drivers deliver long haul loads, both in PtP mode. Thus, in this delivery network, TL carriers do not need to make changes in the system and face the operational limitations that apply to alternative TL dispatching methods. The authors simulated various regional fleet configurations using realistic data provided by J.B. Hunt Transport Inc. and then examined several performance metrics (e.g., total miles per driver per day, empty miles per dispatch, and lateness) for different scenarios. Region centroids, region sizes and market areas to create regions are the main features that separate various configurations. According to the experimental results, regional fleets worked appropriately when compared to a baseline scenario considering traditional PtP. The quantified effects of regional fleets on the performance metrics for the two driver types showed that the system had a positive effect on driver retention, and therefore it may be an adequate alternative TL dispatching method while still maintaining the traditional PtP configuration of the system.

In yet another simulation study, Taylor et al. (2009) introduced another alternative TL dispatching method defined as delivery pipelines. Delivery pipelines use dense and balanced routes and highways for long haul movements and additional local drayage movements for pick-up and delivery of loads. The authors claimed that this configuration is very similar to a train intermodal system with the exception that the vehicle is a truck instead of a train and that the loads are not consolidated in trucks. In general, delivery pipelines are considered to be an evolved version of the delivery lanes proposed by Taylor et al. (1999a) and Taylor et al. (1999b). In this configuration, three drivers are required in each delivery pipeline to carry the truckloads from origin to one endpoint of the pipe, through the pipe, and from the other pipeline endpoint to the destination as opposed to one driver handling the load from origin to destination as in the PtP and delivery lane dispatching systems. Also, the service areas at the two endpoints of the delivery pipelines are not as restricted as in lane dispatching. This structure divides the drivers into several categories and guarantees frequent returns to their domiciles for all driver types with the exception of the remaining PtP drivers. The experimental results obtained by using a discrete event simulation model with data sets provided by J.B. Hunt Transport Inc. indicated that this method did not compromise the efficiency of the PtP drivers, and generally was a feasible TL dispatching alternative, especially for large companies.

In a related study, Taylor and Whicker (2008) discussed the development of an alternative TL dispatching method in which regional dispatching (Taylor et al. 2006) and delivery pipelines (Taylor et al. 2009) are integrated with traditional PtP dispatching to form a combined TL dispatching system. The objective of the study was to design a mixed system where the three dispatching methods can perform effectively when operating concurrently. Four groups of simulation experiments each consisting of several scenarios were completed. Various performance measures related to the benefits for carriers, drivers and customers were defined and evaluated and the results indicated that the baseline scenario of regional dispatching provided in Taylor et al. (2006) showed the best performance when the region centroids were integrated with pipelines and the dispatching priority belonged to regions instead of pipelines. In all, the results in Taylor and Whicker (2008) showed significant improvements in carrier operations when compared to PtP dispatching in all metrics, and to regional solutions in terms of important metrics such as regularizing regional driving jobs and miles driven per driver per day.

In another study, Taylor and Whicker (2010) extended the work presented in Taylor et al. (2006). The authors analyzed several combinations of regional dispatching with some of the previous potential TL dispatching alternatives such as delivery lanes and pipelines to improve the percentage of drivers that are partitioned into those mixed fleet configurations instead of being assigned to drive as PtP drivers. Five scenarios of extended regional models based on structural factors such as region centroids and service areas, and also priorities in using freight methods were developed and simulated. Various performance measures including the effect of the model on metrics for PtP drivers were evaluated. The combinations of lanes and regional models decreased the percentage of PtP drivers significantly and therefore showed great potential to improve operations in TL trucking.

Finally, Taylor and Whicker (2011) focused on the maximization of revenue in dispatching systems and introduced a framework to take into consideration revenue management within operational decisions. In spite of the several pricing systems already used by some TL carriers, the authors tried to integrate profit based dispatching methods that attempt to maximize the profit of the next dispatch with traditional systems where the minimization of empty repositioning is the main objective. They defined and simulated several scenarios based on system design, dispatch mode, priority status, freight volume and freight utilized. The authors collected statistics for several operational metrics such as the average length of haul for loaded moves and the average miles driven per driver per day as the performance measures of interest to the drivers, and the average deadhead per load and the total profit earned as the metrics of interest to the carriers. Then, the authors conducted an analysis of variance of the simulation results. This study provides a useful framework for future price based TL dispatching research studies.

All of these simulation studies benefited from a close collaboration between academic researchers and an industry partner which allowed the development of comprehensive descriptive models of the proposed alternative TL dispatching systems for their practical evaluation. However, the design and optimization of particular configurations could really benefit from the application of OR prescriptive models as described in the next section.

3.4.2 Mathematical Programming

In this section, we extend our survey of the literature to include studies that suggest potential alternative TL dispatching methods by taking advantage of mathematical programming formulations for system modeling and optimization. Figure 5 summarizes the research studies that make use of mathematical programming that are included in this survey.

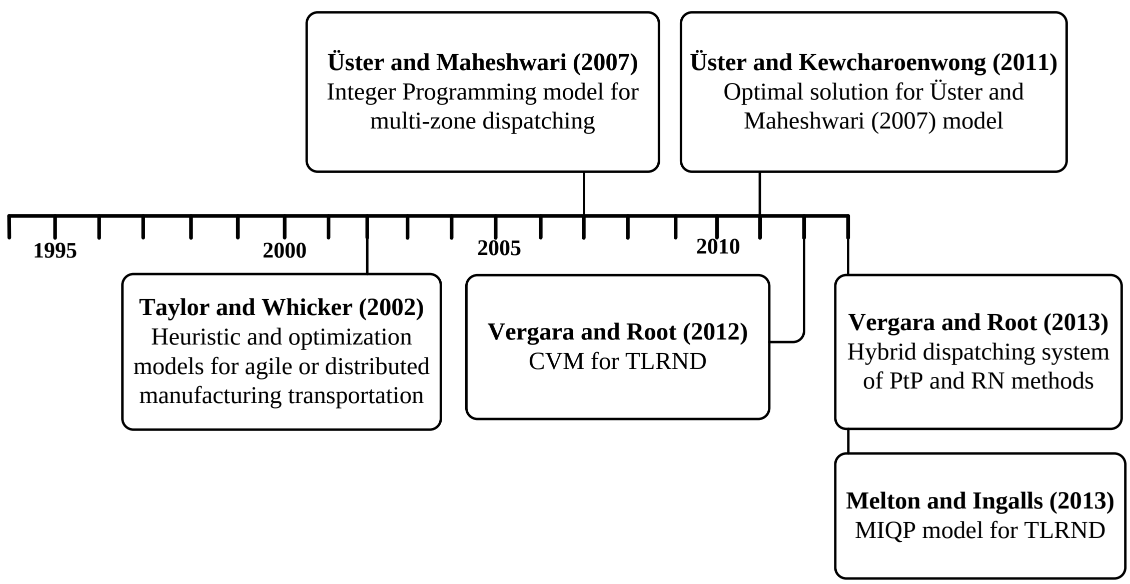

Figure 5: Summary of Research Studies on Alternative TL Dispatching Methods using Mathematical Programming.

First, Taylor and Whicker (2002) proposed an optimization model and a heuristic approach for the design of agile distributed manufacturing transportation systems in cases where fast performance is needed or facilities are very distant from each other. In particular, they focused on the TL trucking area and tried to find regular driving routes using partial networks where nodes with high density traffic are partitioned into a network with more regularized tours, while the rest of the nodes are either origins or destinations for PtP dispatching. A number of dispatching methodologies were implemented using a heuristic model written in a simulation language and operational statistics of the system were computed. The authors presented an integer programming (IP) model to maximize material movements between facilities of a supply chain while deciding the number of movements and showed its capability to solve real test cases for J.B. Hunt Transport Inc. Finally, a comparison between the models presented in this paper and the tools for tour regularization implemented by J.B. Hunt Transport Inc. at the time was conducted. Both models presented in Taylor and Whicker (2002) outperformed the planning tools being used by the carrier, and the heuristic model was able to generate acceptable solutions in comparison to the IP model with less computational complexity.

Later, Üster and Maheshwari (2007) developed an IP model for the multi zone dispatching configuration for alternative TL dispatching that was previously explored in Taylor et al. (2001). Based on this configuration, the authors formally introduced the TL relay network design (TLRND) problem. In TL relay networks, RPs play the role of hubs in an H&S system so that each zone has an RP that truckloads must visit when departing or arriving to a zone. However, no consolidation occurs at the RPs and their installation may require a very small capital investment. At RPs, drivers swap trucks or loads so that it facilitates having them turn back and return to their home domiciles more frequently. In this scenario, the TLRND problem jointly looks at how the relay network is structured and the freight routed through the network. Figure 6 shows a partial relay network configuration.

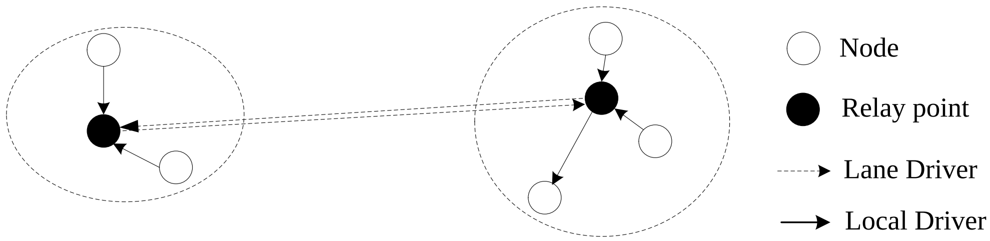

Figure 6: Relay Network for Truckload Transportation.

The mathematical programming formulation for TLRND presented in Üster and Maheshwari (2007) incorporates both the multi commodity flow and the hub location models. Implementing RPs requires defining two types of drivers: local and lane drivers. Local and lane tour length limitations, load circuity and load imbalance constraints are enforced to design the system and be able to obtain benefits for drivers, customers and carriers. The mathematical programming formulation presented in Üster and Maheshwari (2007) follows:

$$Min\ Z = \sum_i \sum_k T_1 d_{ik} \sum_j (w_{ij} + w_{ji}) X_{ik} + \sum_i \sum_j \sum_k \sum_l T_2 d_{kl} w_{ij} y_{kl}^{ij} + \sum_k F_k X_{kk} \quad (1)$$

Subject to:

$$d_{ik} x_{ik} \leq \Delta_1 \quad \forall\ i, k\ \in N, \quad (2)$$

$$d_{kl} y_{kl}^{ij} \leq \Delta_2 \quad \forall\ [i,j] \in Q, \forall\ k, l \in N, \quad (3)$$

$$\sum_m y_{mk}^{ij} - \sum_m y_{km}^{ij} = x_{jk} - x_{ik} \quad \forall\ [i,j] \in Q, \forall\ k \in N, \quad (4)$$

$$\sum_i \sum_j w_{ij} X_{ik} - \sum_i \sum_j w_{ij} X_{jk} \leq \psi \sum_i \sum_j w_{ij} X_{ik} \quad \forall k \in N, \quad (5)$$

$$\sum_i \sum_j w_{ij} X_{jk} - \sum_i \sum_j w_{ij} X_{ik} \leq \psi \sum_i \sum_j w_{ij} X_{jk} \quad \forall k \in N, \tag{6}$$

$$\left(\sum_k d_{ik} x_{ik} + \sum_k \sum_l d_{kl} y_{kl}^{ij} + \sum_k d_{jk} x_{jk} \right) - d_{ij} \leq \Omega\, d_{ij} \quad \forall\, [i,j] \in Q, \tag{7}$$

$$\sum_k x_{ik} = 1 \quad \forall\, i \in N, \tag{8}$$

$$x_{ik} \leq x_{kk} \quad \forall\, i,k \in N, \tag{9}$$

$$y_{kl}^{ij} \leq x_{kk}, y_{kl}^{ij} \leq x_{ll} \quad \forall\, [i,j] \in Q, \forall\, k,l \in N, \tag{10}$$

$$x_{ik}, y_{kl}^{ij} \in \{0,1\} \quad \forall\, i,j,k,l \in N. \tag{11}$$

The objective function minimizes the total cost of transportation as well as the cost of installation of RPs. The decision variables x_{ik} and y_{kl}^{ij} represent the selection of RPs and the assignment of nodes to the RPs as well as the route each truckload will use, respectively. Accordingly, x_{ik} = 1 if node *i* is assigned to the RP located at node *k*, and 0 otherwise; also, $y_{kl}^{ij} = 1$ if a truckload originating from node *i* and destined to node *j* uses the arc between the RP at node *k* and the RP at node *l*, and 0 otherwise. In constraints (2) and (3), Δ_1 and Δ_2 represent local and lane tour length restrictions, respectively. N is the set of nodes and Q is the set of arcs in the network. Flow conservation constraints are enforced in constraint (4). Load balance constraints (5) and (6), restrict the difference in the amount of outgoing and incoming loads for any given zone. Load circuity is the amount of additional travel through RPs as compared to direct PtP dispatching and is not allowed to exceed a certain amount as enforced in constraint (7). Constraint (8) ensures assigning each node to exactly one RP. Constraints (9) and (10) enforce the hub location constraints. Finally, constraint (11) defines the decision variables as binary variables.

Since optimal solutions for moderate size problem instances using this formulation were difficult to obtain using a commercial solver, the authors applied a construction heuristic method after relaxing constraints (5), (6) and (7) (i.e., circuity and load imbalance constraints) and were able to produce high quality initial solutions that were then improved using a tabu search (TS) based heuristic (Glover and Laguna 1997). In this procedure, all of the nodes are sorted based on the amount of loads originating from and destined to them in non-increasing order. Then, the nodes with high number of loads are chosen as RPs. Lane driver tour length restrictions need to be satisfied between the RPs that are selected. Also, when an RP is determined, the nodes that are located within the local driver tour limitation are assigned to that RP. After an initial solution is obtained, a tabu search based heuristic is used to improve the solution. To obtain alternative solutions, RP nodes and non-RP nodes in the initial solution are exchanged alternately and the corresponding objective function values are calculated. A move function was defined to reduce unnecessary RPs generated in the construction heuristic. Acceptable solutions in terms of quality and time were achieved for networks of up to 20 nodes using the proposed heuristic solution approach.

Later, Üster and Kewcharoenwong (2011) proposed an exact solution approach using a Benders decomposition based algorithm (Benders 1962) to solve a modified version of the model presented by Üster and Maheshwari (2007). The Benders decomposition based technique divided the problem into a master problem and a subproblem and resulted in an effective solution method for the TLRND problem. To implement this solution method, the authors applied an ε optimal Benders decomposition based algorithm that was improved and accelerated using several techniques such as strengthened Benders cuts, cut disaggregation schemes, and a procedure to improve the upper bounds for a version of the model without the circuity constrains. Then, since incorporating the circuity constraints worsened the optimality gap and also resulted in infeasible solutions, a surrogate constraint was derived to handle these issues. The authors were able to solve larger networks of up to 80 nodes with optimality gaps of up to 2%. In addition, the authors noted some insights provided by the computational results obtained about the impact of using PtP dispatching for some of the truckloads with short origin destination distance or those faced with high circuity in the relay network, and how that would result in overall cost reduction. Thus, the authors provided support to the idea of combining the network configuration with PtP dispatching as beneficial in a similar way to the discussion made on several of the simulation studies presented in Section 3.4.1. In this regard, they provided a priori and a posteriori approaches to develop hybrid TL dispatching networks.

In another study, Vergara and Root (2012) reformulated the TLRND problem using a composite variable model (CVM) (Armacost et al. 2002) where feasible routes are defined as composite variables. Using this approach, they were able to incorporate important operational constraints such as circuity and local and lane driver tour length limitations implicitly within the composite variable definition so there was no need to include those constraints in the mathematical programming formulation. They used the CVM as a tool to tackle the tractability issues resulting from the circuity constraints that were observed in Üster and Maheshwari (2007) and Üster and Kewcharoenwong (2011). Furthermore, the authors included a limitation on the number of RPs that a truckload is allowed to visit along its route. The CVM facilitated the creation of TL routes that do not violate operational constraints on circuity, lane and local length and maximum number of RPs on a route as infeasible routes are not produced and explored at all in the enumeration method created for variable generation. Each composite variable represents a feasible movement of a load from its origin to its destination, and the feasibility of the composite variables is determined by using templates in an enumeration based procedure developed by the authors. Optimal solutions for randomly generated complete networks with 50 and 100 nodes and different freight densities were obtained using the commercial solver CPLEX. The effects of network size and truckload flow density on computational time and solutions of the model were investigated. The number of composite variables increased significantly as networks increased in size. An exact method using branch and price was developed and used to find optimal solutions for networks with 50 nodes. However, tractability issues affected the time required to compute solutions for larger networks with 100 nodes. Solutions for larger networks were obtained by applying a heuristic approach that considered only a subset of the templates used to generate the composite variables that were observed to be the most used in the exact solutions. The quality of the solutions obtained by this heuristic and its computational time efficiency were verified in networks with 50 nodes and the method was used to solve randomly generated problems with 100 and 150 nodes, as well as a real network consisting of 623 nodes representing the East U.S. network of a major carrier (J.B. Hunt Transport Inc.). The observed low usage of some RPs in relatively low dense regions and the high cost of RP installation reinforced the idea of the potential efficiency of combining the relay network system and the PtP system together in a mixed fleet dispatching system.

In this regard, Vergara and Root (2013) studied the hybrid structure supported by the empirical results of Üster and Kewcharoenwong (2011) and Vergara and Root (2012), as well as the general insights presented in simulation studies about the potential performance of simultaneously using the PtP and TL relay networks for dispatching as compared to a pure relay network or a PtP system. To this end, the authors presented an extension to the CVM formulation introduced in Vergara and Root (2012) to represent the mixed fleet structure in which the mode of dispatching the loads via a traditional PtP method or via the relay network is also a decision variable using the following integer programming (IP) model:

$$Min\ Z = \sum_{r\in R} c_r x_r + \sum_{t\in T} p_t z_t + \sum_{k\in N} f_k Y_k \tag{12}$$

Subject to:

$$\sum_{r\in R_t} x_r + z_t = b_t \quad \forall\ t \in T, \tag{13}$$

$$\sum_{r\in R_t} \theta_{kr} x_r \le b_t\, y_k \quad \forall\ t \in T, k \in N_r{:}\, r \in R_t, \tag{14}$$

$$\sum_{r:\eta_{kr=-1}} x_r - \sum_{r:\eta_{kr=1}} x_r \le \delta \sum_{r:\eta_{kr=-1}} x_r \quad \forall\ k \in N, \tag{15}$$

$$\sum_{r:\eta_{kr=1}} x_r - \sum_{r:\eta_{kr=-1}} x_r \leq \delta \sum_{r:\eta_{kr=1}} x_r \quad \forall\, k \in N, \tag{16}$$

$$\sum_{r \in R} \theta_{kr} x_r \geq v\, y_k \quad \forall\, k \in N, \tag{17}$$

$$\sum_{t \in T} z_t \leq \rho \sum_{t \in T} b_t, \tag{18}$$

$$x_r \; integer \quad \forall\, r \in R, \tag{19}$$

$$y_k \in \{0,1\} \quad \forall\, k \in N, \tag{20}$$

$$z_t \; integer \quad \forall\, t \in T. \tag{21}$$

The objective function minimizes the transportation cost for truckloads using the relay network, the transportation cost of direct PtP shipments, and the fixed cost of installation of RPs. Decision variables x_r and z_t represent the number of truckloads that are shipped through a relay network route or using PtP dispatching, respectively. In addition, $y_k = 1$ denotes that an RP is located at node *k*, and 0 otherwise. Constraint (13) enforces demand satisfaction by selecting a dispatching mode for truckloads between the alternatives of using RPs and PtP dispatching. Constraint (14) requires that an RP should be open at node *k* if it is visited by a relay network route. Constraints (15) and (16) are associated with load balance at RP nodes by restricting the difference between outgoing and incoming loads at each RP. In this formulation, the authors also incorporated additional constraints associated with the design of the hybrid system such as a limitation on the minimum truckload volume required to justify opening an RP in constraint (17), and a limitation on the maximum proportion of truckloads that can be dispatched PtP in constraint (18). Constraints (19), (20) and (21) are the variable type constraints. In this formulation, *N* is the set of nodes in the network, *T* is the set of origin/destination (O-D) pairs with truckload demand in the network, and R_t is the set of feasible routes (i.e., composite variables) for the O-D pair *t*. The proposed solution method for this model reduces the number of composite variables by using templates consisting of a maximum of two RP nodes and pre-processing truckloads that have O-D node pairs that fall below a given threshold as PtP loads. Solutions were obtained using CPLEX for networks with 50, 100 and 150 nodes and different freight densities.

A comparison between PtP-only, relay network-only and the hybrid mixed fleet dispatching system confirmed a better performance of both of the network based structures over the PtP-only system. Furthermore, the authors observed a better performance of the mixed fleet dispatching system over the relay network-only system, especially as the fixed cost of installation of RPs increased.

Finally, Melton and Ingalls (2013) presented an additional formulation for the TLRND problem. They modeled a highway transportation network using a mixed integer quadratic program (MIQP) to decide in which locations RPs should be established for a relay network dispatching system. Their objective function included key transportation costs including annual transportation cost between locations, annual fixed amortized cost of building RPs, annual driver turnover cost, and truck and trailer depreciation cost. Several factors such as limitations on the length of haul, different fixed costs for locating RPs depending on the location, and the maximum average weekly miles driven per driver were incorporated in constraints of the model to establish RPs at appropriate locations. Then, a case study was used to evaluate the performance of an RP scenario as compared to a non-RP scenario from operational and economic viewpoints. According to the results obtained, with the same driver quantity and pay, the RP scenario performed significantly better than the PtP method in terms of critical operational performance measures such as driver work hours and driver home time as well as from the cost perspective.

3.4.3 Other Modeling and Solution Techniques for Alternative TL Dispatching

In this section, we discuss a couple of contributions in the literature that apply other OR modeling and solution techniques to the problem of designing alternative dispatching methods for TL transportation.

First, Hunt (1998) used the physical roadway network of the United States Southeast region to design TL relay networks. Hunt (1998) used a three step algorithmic method to solve a routing and RP location problem. The first step was to solve a routing problem on a network using a shortest path heuristic without considering RPs. Then, assuming that the RPs can be located anywhere in the network, using an iterative algorithm termed as the *spring algorithm*, RPs were assigned to the routes created in the first step. In the last step, given the locations of the RPs found in the second step, the approach used in the first step was implemented again to ship loads but using RPs this time around. Excess miles (i.e., additional miles compared to PtP movement), circuity (i.e., excess miles divided by shortest path distance) and excess service time (i.e., additional delivery time compared to PtP movement) were the major criteria examined to observe the performance of a TL relay network. This study provided a method to improve driver tour lengths; however the author claimed that using a partial TL relay network would be more effective in terms of eliminating excessive circuity for some of the loads.

In another study, Ali et al. (2002) presented heuristic models for “straight route” (i.e., shortest path or PtP) and “detour” scenarios including “semi detour” and “*d* detour” versions representing H&S dispatching configurations that minimize the number of RPs on a highway transportation network. The authors considered constraints on the maximum distance of travel before taking a rest and the maximum additional distance (i.e., circuity) for a truckload. The three scenarios were graphically depicted and the algorithms were implemented in C using initial random graphs generated by a random graph model. The proposed method showed that “detour” scenarios had better performance when compared to the straight route approach in terms of the number of RPs (i.e., selecting fewer number of RPs) and traveling distances. However, the algorithms for “detour” scenarios required longer execution times to obtain solutions compared to the straight route algorithm.

3.5 Concluding Remarks and Future Challenges

Alternative dispatching methods for TL transportation have received increasing attention from researchers and carriers in the last two decades, and several papers have addressed the essential design problem from strategic, tactical and operational perspectives. We have completed a review of existing research that identifies OR techniques that have been applied in order to design and evaluate specific alternative dispatching methods in TL transportation. In this paper, research contributions in this area are classified into three categories based on the modeling and solution techniques used: simulation models, mathematical programming, and other algorithmic approaches. These techniques have been used in strategic, tactical and operational levels of decision making including decisions involving establishment of hubs or RPs, delivery lanes, the routing of freight, and the assignment of drivers to loads. Figure 7 presents the distribution of research studies exploring alternative TL dispatching methods using different approaches. According to Figure 7, the majority of the contributions in this area have focused on the use of simulation models followed by mathematical programming approaches in recent years.

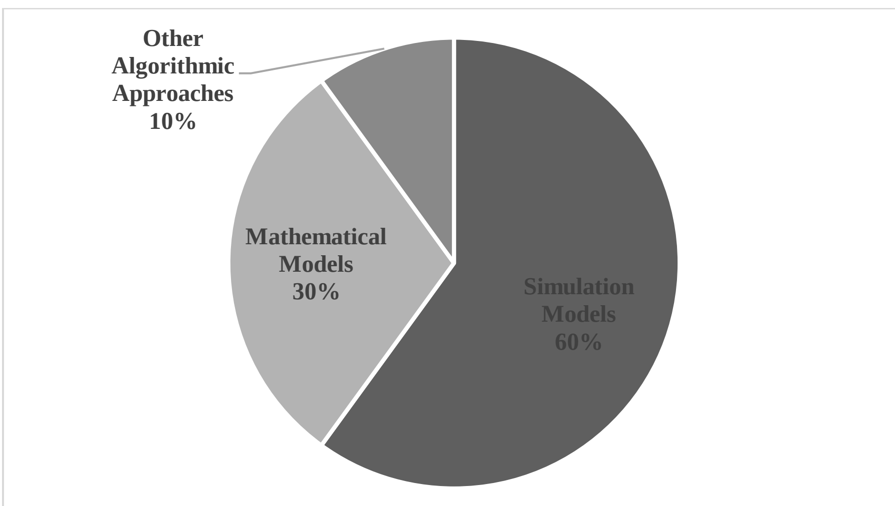

Figure 7: Distribution of Research Studies on Alternative TL Dispatching Methods.

As observed in Figure 4 and Figure 5, most of the early work in this area considered the use of simulation tools to recommend new TL dispatching methods, and just recently more mathematical programming and algorithmic approaches have emerged and matured. Another trend exists in the evolution of the different perspectives associated with this problem. As determined in our survey, the earlier studies mostly tried to create pure alternative methods of dispatching, but gradually a better understanding of the models and solutions proved the benefits of hybrid systems including the traditional PtP dispatching system. Thus, we see a growth in the number of studies that develop more complicated mixed fleet transportation structures using simulation techniques, mathematical programming and heuristic approaches. Although numerous studies highlight the benefits of such systems, there are still significant challenges that need to be overcome to precisely quantify such benefits and improve current modeling and solution methods for their design.

Since mathematical modeling of the design problem of alternative TL dispatching systems is an emerging research area, the number of studies is still limited and more development of exact and heuristics methods and their comparison remain as open research areas. Moreover, there is no literature on applying a multi objective optimization approach to this problem. An integrated approach to optimize total costs and service level performance measures might be an interesting area for future study in order to increase the likelihood of implementation of design results in real applications. Further investigation of extended types of network topologies could be useful as well.

In addition, it seems that successful solution methods have been obtained for deterministic environments using both pure and hybrid alternative TL dispatching systems. Given that the majority of studies considered deterministic parameters of the problem, there is a significant opportunity for research studies that would take into account the uncertain nature of the TL trucking environment in order to discover more realistic and potentially implementable solutions. As mentioned in our survey, demand and travel times are examples of components of the system that can be considered uncertain (Simão et al. 2009). Thus, further development of robust and stochastic OR techniques and heuristics incorporating uncertainty within the context of TL transportation could be an interesting area for future research. Some early work on this area includes the robust formulation for the TLRND problem presented by Vergara and Mokhtari (2014).

Finally, as more research on alternative dispatching systems in the literature focus on the strategic design of these systems as opposed to more tactical and operational aspects, future work on this area will need to address related planning problems at these levels of decision making. For example, more work is needed to model and solve problems such as the allocation of drivers to terminals or the allocation of drivers and equipment (i.e., load matching) to loads for alternative dispatching systems. Early work on these types of problems has been presented by Root and Vergara (2012) and Melton and Ingalls (2013), however more research is still required to address these challenging problems that would support decision making as alternative dispatching methods are implemented and tested by carriers.

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4 Strategic Design of Robust Truckload Relay Networks under Demand Uncertainty[2]

4.1 Abstract

A robust optimization approach with controllable level of conservatism is applied to find solutions to the strategic truckload relay network design problem that perform well under any possible realization of the demand instead of generally optimizing the problem assuming the most likely value of the parameters. This approach was used to develop the robust counterpart of an existing mathematical model for deterministic truckload relay network design with mixed-fleet dispatching. The results obtained for different network instances show how incorporating uncertainty affects the total facility installation and transportation costs as well as other characteristics of the resulting truckload relay networks.

Keywords: truckload transportation; relay networks; uncertainty; robust optimization; heuristic

4.2 Introduction

The design of alternative dispatching methods for full truckload transportation has received the attention of carriers and researchers in recent years due to the potential of these alternative methods to improve both the quality of life for drivers (thus reducing driver turnover) and resource utilization for carriers. One particular alternative dispatching method considers using RPs in a network to dispatch loads from origin to destination using multiple drivers. The truckload relay network design (TLRND) problem has been previously studied in the literature by Üster and Maheshwari (2007), Üster and Kewcharoenwong (2011), Vergara and Root (2012), Vergara and Root (2013), and Melton and Ingalls (2013) using deterministic mathematical programming

[2] This work will be submitted for publication to *Transportation Research Record* and is an extension of (Vergara and Mokhtari 2014)

techniques. In the TLRND problem, loads are not transported directly from origin to destination using a point-to-point (PtP) dispatching method, but are shipped via one or more RPs. In an extension to this basic configuration, a hybrid method of transportation would be allowed in which a load can be shipped either PtP or via RPs. The design of the latter method is known as the truckload relay network design with mixed fleet dispatching (TLRND-MD) problem (Vergara and Root 2013). In this paper, we incorporate the uncertain nature that exists in the trucking industry in the design of relay networks for TL transportation to obtain more realistic solutions that could be implemented in practice with minimal reconfiguration. In particular, the problem that we study in this paper incorporates demand uncertainty in the TLRND-MD problem.

The TLRND and the TLRND-MD problems are large scale optimization problems affected by an extremely large number of variables and constraints as well as complex operational constraints that need to be considered when designing TL transportation networks. Their complexity increases even more when parameter uncertainty is explicitly considered. Here, we develop a robust optimization model for the TLRND-MD problem under demand uncertainty that would allow us to obtain solutions for large size instances of this problem in reasonable computational times. For this purpose, we developed a robust counterpart formulation to the integer programming model presented by Vergara and Root (2013). The robust counterpart is obtained by applying the robust optimization approach by Bertsimas and Sim (2003) when demand uncertainty between origin-destination pairs in the network is considered. As opposed to other robust optimization approaches that are highly conservative and consider the worst case value of all uncertain parameters, the Bertsimas and Sim (2003) approach allows us to adjust the level of uncertainty of the parameters. The approach assumes that the uncertainty is captured in an uncertainty set that is represented by bounded and symmetric intervals of demand fluctuation around a nominal value. We aim to exploit the strength of a heuristic solution method developed in Vergara and Root (2013) for the deterministic TLRND-MD problem to also solve its robust counterpart. Numerical results obtained for the robust counterpart are presented and compared to solutions with deterministic truckload demand to investigate how the network design will be affected by demand uncertainty. Moreover, different levels of demand uncertainty are examined and studied to show the robustness of the results.

The remainder of this chapter is organized in the following way. In Section 4.3, a brief review of previous research on truckload relay network design as well as studies addressing uncertainty in transportation network design problems are presented. Section 4.4 presents the deterministic TLRND-MD problem followed by the mathematical formulation of its corresponding robust counterpart, and the proposed solution approach. Section 4.5 describes the numerical experiments completed, and presents the corresponding results. Finally, Section 4.6 summarizes some concluding remarks and provides directions for future work.

4.3 Literature Review

To overcome some of the challenges TL carriers experience with the PtP dispatching method, alternative dispatching methods have been studied by practitioners and academic researchers over the last two decades. A particular alternative dispatching method considers the use of relays for the movement of TL shipments. Relay networks for TL transportation have evolved from the integration of the hub-and-spoke (H&S) configuration used by less-than-truckload (LTL) carriers to deliver loads, and the multi-zone dispatching methods that have been trial-tested by large TL companies. In Section 4.3.1, we study the previous research in the development of relay networks for TL transportation. Section 4.3.2 describes modeling approaches and solution methods that have been applied to incorporate uncertainty in strategic network design and facility location problems. Both traditional network design and facility location problems are closely related to the current research on the design of relay networks for TL transportation.

4.3.1 Relay Networks for Truckload Transportation

Taha and Taylor (1994) completed the first formal study of the potential implementation of H&S networks in TL transportation. Later, using the configuration introduced in the previous study and the HUBNET simulator, Taylor et al. (1995) completed additional computational experiments to quantify the effects of the application of H&S networks in the TL trucking industry. Extending the work of Taylor et al. (1995), Harit et al. (1995) completed additional experimental tests and performed a sensitivity analysis of the factors affecting the implementation of TL H&S networks. Then, Taylor et al. (1999) used discrete event simulation to compare different scenarios made of combinations of three methods: delivery lanes, zone dispatching, and H&S networks. Later, Taylor and Meinert (2000) simulated several single-zone configurations for TL dispatching and Taylor et al. (2001) evaluated the performance of different zone dispatching configurations.

Alternatively to the simulation studies, Hunt (1998) used the United States Southeast physical roadway network to design TL relay networks. The author used a three step algorithmic method to solve a routing and RP location problem. The author claimed that using a partial TL relay network is more effective in terms of eliminating excessive circuity for some of the loads. In another study, Ali et al. (2002) presented heuristic methods for “straight route” (i.e., shortest path or PtP) and “detour” scenarios corresponding to H&S configurations that minimize the number of RPs on a highway transportation network. They showed that the “detour” scenarios outperformed the “straight route” scenario in terms of the number of RPs and traveling distances. Later, Tsu and Agarwal (2009) used relays to improve the operations of a private fleet for a large retailer. They compared the solutions for the problem without relays and the problem using relays. The results showed a 6% reduction in the weekly transportation cost and a significant increase of about 30% in utilization for the inbound private fleet tours.

The early studies on hub-based TL dispatching systems were mainly devoted to the development of descriptive models and providing insights on their benefits. More recently, researchers have tried to optimize the design of these systems and quantify their benefits by developing prescriptive models. Üster and Maheshwari (2007) formally introduced the TL Relay Network Design (TLRND) problem and formulated it using a binary integer program (BIP). The mathematical programming formulation developed by Üster and Maheshwari (2007) incorporates both the multi-commodity network flow and the single-allocation hub location models in an arc-based formulation that considers some operational constraints. Since optimal solutions for medium-size problem instances were difficult to obtain, the authors relaxed circuity and load imbalance constraints and applied a heuristic method to produce high quality initial solutions. Although this research study presents the first comprehensive mathematical model for TL relay network design, acceptable solutions in terms of quality and time were only achieved for networks of up to 20 nodes.

Later, Üster and Kewcharoenwong (2011) proposed an exact approach to solve a modified version of the model presented in Üster and Maheshwari (2007) using a Benders decomposition-based algorithm. The authors were able to solve networks of up to 80 nodes with optimality gaps of up to 2%. In addition, the authors noted some insights about the impact of using PtP dispatching for some of the truckloads. They determined that it would be preferable to use PtP dispatching for truckloads with short origin-destination distance or those faced with high circuity in the RP-network.

Based on the definition for the TLRND problem developed in Üster and Maheshwari (2007) and Üster and Kewcharoenwong (2011), Vergara and Root (2012) formulated a composite variable model (CVM) for the TLRND problem where only feasible routes are defined as composite decision variables. Using this approach, the authors were able to incorporate important operational constraints implicitly within the composite variable definition. Optimal solutions for randomly generated complete networks with 50 and 100 nodes were obtained using an exact solution method using branch-and-price. For larger networks, solutions were obtained by applying a heuristic approach for randomly generated problems with 50, 100 and 150 nodes, as well as a real network consisting of 623 nodes. They observed that combining the relay network system and the PtP system together in a mixed fleet dispatching system would be beneficial.

Regarding this, Vergara and Root (2013) studied the hybrid structure of combining the PtP and TL relay networks for dispatching. They presented an extension to the CVM formulation introduced in Vergara and Root (2012) to design the mixed fleet dispatching structure. In this model, the dispatching mode for loads via the PtP method or via the relay network is also a decision variable. The heuristic method used in Vergara and Root (2012) was also applied in this study and solutions were obtained for networks with 50, 100 and 150 nodes. The experimental results confirmed a better performance of relay network-only and the hybrid mixed fleet dispatching system over the PtP-only system.

Later, Melton and Ingalls (2013) modeled a highway transportation network using a mixed integer quadratic program to decide in which locations RPs should be established for a relay network dispatching system. A case study was presented to verify the better performance of an RP scenario as compared to a non-RP scenario from operational and economic viewpoints. According to the obtained results, the RP scenario performs significantly better than the PtP method in terms of critical operational performance measures.

4.3.2 Robust Optimization Applications in Transportation Network Design and Hub Location

Ben-Tal and Nemirovski (1999) , El Ghaoui et al. (1998), and Bertsimas et al. (2011) have all developed robust optimization approaches that account for the worst case performance of a system with respect to an uncertain parameter that fluctuates within an uncertainty set. In this type of approach, no specific distribution for the uncertain parameter is considered, but an uncertainty set has to be defined for it. In particular, Bertsimas and Sim (2003) assumed that the uncertainty set can be defined as a bounded and symmetric interval of fluctuation around an expected value for the uncertain parameter. Bertsimas and Sim (2003) developed a robust optimization approach for discrete optimization problems in which the level of uncertainty of the parameters is adjustable. Implementing this robust optimization approach involves creating a deterministic equivalent of the mathematical program with uncertain parameters that is referred to as the robust counterpart.

In the context of transportation network design, Gutiérrez et al. (1996) proposed a Benders decomposition algorithm to solve an uncapacitated *p*-robust network design problem. In this *p*-robust optimization approach that relies on the minimax regret approach, the goal is to find network designs for any possible scenario of the uncertain parameter whose relative regret is no more than *p*% of the optimal solution. The transportation cost and the volume of products (i.e., flow) to be transported were considered as the uncertain input data.

In another study, Ukkusuri et al. (2007) used a Genetic Algorithm (GA) to solve a capacitated network design problem under demand uncertainty in which fixed costs were associated to arc capacity. The strategic decision was to establish the capacities for arcs in the network. The authors considered robustness in the objective function by integrating the expected total system travel time and the standard deviation of total system travel time in a single objective function.

Atamtürk and Zhang (2007) presented a two-stage robust optimization approach for a network design and flow routing problem with demand uncertainty. In this approach, network design decisions were made in the first stage before demand realization. Decisions on flow routing were deferred until the demand was observed in the second stage. In a similar research study, Zeng and Zhao (2013) developed two-stage robust optimization formulations for an integrated location-transportation problem. Two different approaches were used for solution including a Benders decomposition algorithm and a column-and-constraint generation algorithm, respectively. The results showed that the column-and-constraint generation algorithm had better performance than the Benders decomposition algorithm. In both of these studies, budget uncertainty sets were applied to incorporate demand uncertainty in the formulations.

In another research study, Ordonez and Zhao (2007) used a robust optimization approach to solve the problem of expanding arc capacities in a network considering demand and travel time uncertainty. They showed that under a certain set of assumptions regarding the network structure as well as the definition of the uncertainty sets for the uncertain parameters, the resulting mathematical formulation is tractable. The authors concluded that the robust solutions can reduce the worst case total transportation cost while slightly losing optimality in a trade-off.

Also, a robust capacitated network design problem assuming single origin and destination per commodity was studied by Mudchanatongsuk et al. (2008). Demand and transportation cost were considered uncertain and were assumed to be fluctuating in independent closed convex uncertainty sets. The authors developed a tractable mathematical model to approximate the robust solution and showed that the approximate robust solution can reduce the worst case cost while resulting in modest sub-optimality.

In the context of hub location problems, Alumur et al. (2012) studied a robust multimodal hub location problem where the setup costs for the hubs and the demand between origin-destination (O-D) pairs in the network were considered to be uncertain. It was shown that the resulting structure of hub network was highly sensitive to the inclusion of uncertainty in the model. According to the results obtained, deterministic solutions yield hub locations that are sub-optimal. Moreover, the experimentation showed that there might be a significant increase in the total cost if uncertainty is not explicitly considered. Finally, they also showed that the solutions are more affected by setup cost uncertainty rather than demand uncertainty.

In a similar study, Shahabi and Unnikrishnan (2014) developed a robust formulation for the uncapacitated single and multiple allocation hub location problems with uncertain demand. The uncertain parameter was considered to lie in an ellipsoidal uncertainty set. The authors reformulated a mixed integer nonlinear model for the robust hub location problem into a conic quadratic mixed integer program The computational results indicated that the hub arrangement and network cost were very sensible to the inclusion of uncertainty and the uncertainty level.

More comprehensive reviews of strategic facility location problems under uncertainty can be found in Snyder (2006), and more recently in Gabrel et al. (2014).

4.4 TLRND-MD Robust Optimization Formulation and Solution Approach

In this research, we develop a robust counterpart to the integer programming model for the TLRND-MD problem presented by Vergara and Root (2013) when demand is assumed to be uncertain. Mixed fleet dispatching allows truckloads to be dispatched either through the relay network or directly PtP. The deterministic model for TLRND-MD minimizes the total costs of RP installation and transportation by selecting the number and location of RPs, the dispatching method for the expected loads, and the paths from origin to destination for the loads. In addition, limitations on out-of-route miles, equipment balance at nodes, maximum number of RPs allowed to be visited on a relay network route, maximum distances for local and lane movements, minimum volume required to open an RP, and maximum proportion of loads dispatched PtP are enforced. Vergara and Root (2013) provided a composite variable (CV) formulation where these constraints were enforced either implicitly as part of the generation of feasible routes (i.e., composite variables) or explicitly as constraints in the formulation. In the current study, we assume that demand is not constant anymore and that there is a need to explicitly account for this uncertain parameter in the strategic design of the mixed fleet dispatching system with relays.

4.4.1 Robust Optimization Formulation

Robust optimization is a technique that has been applied to other integrated planning problems under uncertainty as described in Section 4.3. We use the following notation to present the robust counterpart to the TLRND-MD mathematical formulation presented by Vergara and Root (2013) by applying the robust optimization approach of Bertsimas and Sim (2003).

Sets

N = set of nodes k,

R = set of feasible routes (i.e., composites) r,

T = set of O-D pairs t with truckload demand,

R_t = set of composites r for O-D pair t, $R_t \subset R$,

R_k = set of composites r that visit node k, $R_k \subset R$.

Parameters

c_r= cost of composite r, $\forall\ r \in R$,

f_k = fixed cost of RP k, $\forall\ k \in N$,

p_t = cost of dispatching a truckload for O-D pair t using PtP dispatching, $\forall t \in T$,

b_t = expected demand for O-D pair t (in number of truckloads), $\forall t \in T$,

δ = maximum acceptable percentage of equipment imbalance at nodes,

ρ = maximum proportion of truckloads to be dispatched direct PtP,

υ = minimum volume (in number of truckloads) required to open an RP,

η_{kr} = -1 if node k is the origin RP of composite r,

1 if node k is the destination RP of composite r, $\forall\ k \in N;\ r \in R$,

0 otherwise,

θ_{kr} = 1 if composite r visits RP k, $\forall\ k \in N;\ r \in R$,

0 otherwise.

Decision Variables

x_r = number of times composite r is used, $\forall r \in R$,

y_k = 1 if an RP is opened at node k, $\forall\, k \in N$,

0 otherwise,

z_t = number of truckloads sent direct PtP for O-D pair t, $\forall t \in T$.

Deterministic Mathematical Formulation

Using the notation presented above, the deterministic mathematical model for TLRND-MD follows (Vergara and Root 2013).

TLRND-MD:

$$\min \sum_{r \in R} c_r x_r + \sum_{t \in T} p_t\, z_t + \sum_{k \in N} f_k y_k \tag{22}$$

subject to

$$\sum_{r \in R_t} x_r + z_t \geq b_t \quad \forall t \in T \tag{23}$$

$$\sum_{r \in R_t} \theta_{kr}\, x_r \leq b_t y_k \quad \forall t \in T,\ k \in N_r; r \in R_t \tag{24}$$

$$\sum_{r:\eta_{kr}=-1} x_r - \sum_{r:\eta_{kr}=1} x_r \leq \delta \sum_{r:\eta_{kr}=-1} x_r \quad \forall k \in N \tag{25}$$

$$\sum_{r:\eta_{kr}=1} x_r - \sum_{r:\eta_{kr}=-1} x_r \leq \delta \sum_{r:\eta_{kr}=1} x_r \quad \forall k \in N \tag{26}$$

$$\sum_{r \in R} \theta_{kr} \, x_r \geq \, v \, y_k \qquad \forall k \in N \tag{27}$$

$$\sum_{t \in T} z_t \leq \, \rho \sum_{t \in T} b_t \tag{28}$$

$$x_r \text{ integer} \qquad \forall r \in R \tag{29}$$

$$y_k \in \{0,1\} \qquad \forall k \in N \tag{30}$$

$$z_t \text{ integer} \qquad \forall t \in T \tag{31}$$

The objective function minimizes the total transportation and RP installation costs. Demand satisfaction either through the relay network or by PtP dispatching is enforced in constraint (23). Constraint (24) ensures that composites visit only open RPs. Constraints (25) and (26) enforce equipment balance at the nodes in the network. Constraint (27) enforces a minimum volume required at a node to justify choosing it to serve as an RP. Constraint (28) limits the proportion of loads that are to be dispatched PtP. The purpose of applying constraint (28) is to increase the utilization of the relay network and attain the benefits of this alternative dispatching method over PtP. Finally, constraints (29), (30), and (31) are the variable-type constraints.

4.4.2 Application of Robust Optimization Approach

Demand is the uncertain parameter considered in this research. To incorporate demand uncertainty in the deterministic formulation presented above, we assumed that demand takes a value in a symmetric interval centered around the nominal (i.e., expected) value of demand. In this case, any demand observation $b_t{}' \in [b_t - \hat{b}_t, b_t + \hat{b}_t]$, where b_t is the nominal (i.e., expected) value of demand for O-D pair *t* (in number of truckloads), and $\hat{b}_t$ is the maximum amount of fluctuation from the mean value for O-D pair *t*. The worst case scenario would be obtained when the values of demand for all O-D pairs are at the upper bound of the uncertainty interval $\left(b_t + \hat{b}_t, \forall t \in T\right)$. However, using the worst case scenario would lead to obtaining highly conservative solutions.

Speaking intuitively, it is unlikely that all the demands will take their worst case value. In this implementation, we assumed that all the O-D pairs *t* are subject to demand uncertainty and our goal is to be protected against all cases in which up to Γ_i of the uncertain coefficient in constraint i is allowed to change.

The robust optimization approach used in this research introduces a number Γ_i , for every *i*, to represent the number of "coefficients" in a constraint *i* that take their worst case value. This parameter is regularly used to adjust the level of robustness of the solutions obtained. We define J_i , as the set of coefficients of row *i* that are subject to uncertainty. Therefore, Γ_i takes value in the interval $[0, |\mathrm{J}_i|]$ and Γ_i is not necessarily integer. As mentioned before, the intuition behind this approach is that, it is unlikely that all of the coefficients in constraint *i* will change to adversely affect the solution.

Applying robust optimization, the constraints on demand satisfaction (i.e., Constraints (23)) as well as the constraint that limits the proportion of total PtP loads (i.e., Constraint (28)) in the deterministic model will be modified in the robust counterpart formulation. In our application, the uncertainty happens in the right-hand-side values of these constraints. Moreover, following this robust optimization approach, more constraints and variables need to be added to the base model to form the robust counterpart formulation as described below. This approach was first explored in Vergara and Mokhtari (2014) for this problem and its use is expanded and thoroughly tested in the current research.

The first step to apply the robust optimization approach of Bertsimas and Sim (2003) requires modifying the original Constraints (23) and (28) in the deterministic model as follows:

Additional Notation

J_i = set of demand coefficients in constraint *i* that are *subject to uncertainty*; *i*=23, 28,

S_i = set of demand coefficients in constraint *i* that *take their worst case value*; *i*=23, 28

In the robust counterpart, we account for the maximum deviation from the nominal value for the uncertain demand coefficients. Thus, the following inner maximization terms are considered:

$$\sum_{r\in R_t} x_r + z_t \geq b_t + \max_{\{S_{23t}\cup\{t'\}|S_{23t}\subset J_{23t}, |S_{23t}|\leq\lfloor\Gamma_t\rfloor, t'\in J_{23t}\setminus S_{23t}\}} \left\{ \sum_{j\in S_{23t}} \hat{b}_j + (\Gamma_t - \lfloor\Gamma_t\rfloor)\hat{b}_t . a_{t'} \right\} \quad \forall t \in T \tag{23-1}$$

$$\sum_{t\in T} z_t \leq \rho \sum_{t\in T} b_t + \max_{\{S_{28}\cup\{t'\}|S_{28}\subset J_{28}, |S_{28}|\leq\lfloor\Gamma'\rfloor, t'\in J_{28}\setminus S_{28}\}} \left\{ \rho(\sum_{j\in S_{28}} \widehat{b_j} + \left(\sum_{j\in J_{28}\setminus S_{28}} (\Gamma_j - \lfloor\Gamma_j\rfloor)\widehat{b_j} \right) . a_{t'}) \right\} \tag{28-1}$$

Note that in Equation (28-1), $S_{28} = \bigcup_{t\,\epsilon T} S_{23t}$ and $\Gamma' = \sum_{t\,\epsilon T} \Gamma_t$. Moreover, note that a is a dummy variable that takes a value equal to 1 (i.e. $1 \leq a \leq 1$). The inner maximization terms make the robust counterpart non-linear. Thus, according to the Bertsimas and Sim (2013) robust optimization approach, the inner maximization problems can be written as linear optimization problems as follows:

$$\max\left[\hat{b}_t d_{23t}\right] \text{ subject to}: d_{23t} \leq \Gamma_t, 0 \leq d_{23t} \leq 1, \forall t \in T \tag{23-2}$$

$$\max[\rho \sum_{t\in T} \hat{b}_t\, d_{28}] \text{ subject to}: d_{28} \leq \Gamma', 0 \leq d_{28} \leq 1 \tag{28-2}$$

The dual formulations of the maximization problems presented above result in the following minimization problems, where q_t and p_t are the dual variables associated with $d_{23t} \leq \Gamma_t$ and $0 \leq d_{23t} \leq 1$ constraints, respectively. Moreover, q' and $p'$are the dual variables associated with $d_{28} \leq \Gamma'$ and $0 \leq d_{28} \leq 1$, respectively:

$$\min\,[\Gamma_t q_t + p_t] \text{ subject to: } q_t + p_t \;\geq\; \hat{b}_t, q_t \geq 0, p_t \geq 0\;, \forall t \in T \tag{23-3}$$

$$\sum_{t\in T} \min\,[\rho(\Gamma' q' + p')] \text{ subject to: } q' + p' \geq \rho \sum_{t\in T} \hat{b}_t\,, q' \geq 0\;\;, p' \geq 0 \tag{28-3}$$

Finally, the objective functions of (23-3) and (28-3) were incorporated into constraints (23) and (28) of the deterministic model, while the constraints associated with (23-3) and (28-3) were added to the formulation to obtain the final mathematical formulation of the robust counterpart for the TLRND-MD problem which we denote RO-TLRND-MD.

RO-TLRND-MD:

$$\min \sum_{r\in R} c_r x_r + \sum_{t\in T} p_t\, z_t + \sum_{k\in N} f_k y_k \tag{32}$$

subject to

$$\sum_{r\in R_t} x_r + z_t - \Gamma_t q_t - p_t \geq b_t \quad \forall t \in T \tag{33}$$

$$\sum_{r\in R_t} \theta_{kr}\, x_r \leq (b_t + \hat{b}_t)\, y_k \quad \forall t \in T,\ k \in N_r; r \in R_t \tag{34}$$

$$\sum_{r:\eta_{kr}=-1} x_r - \sum_{r:\eta_{kr}=1} x_r \leq \delta \sum_{r:\eta_{kr}=-1} x_r \qquad \forall k \in N \tag{35}$$

$$\sum_{r:\eta_{kr}=1} x_r - \sum_{r:\eta_{kr}=-1} x_r \leq \delta \sum_{r:\eta_{kr}=1} x_r \qquad \forall k \in N \tag{36}$$

$$\sum_{r\in R} \theta_{kr}\, x_r \geq v\, y_k \qquad \forall k \in N \tag{37}$$

$$\sum_{t\in T} z_t - \rho(\Gamma' q' + p') \leq \rho \sum_{t\in T} b_t \tag{38}$$

$$q_t + p_t \geq \hat{b}_t \quad \forall t \in T \tag{39}$$

$$q' + p' \geq \rho \sum_{t\in T} \hat{b}_t \tag{40}$$

$$q_t \geq 0\,, p_t \geq 0 \qquad \forall t \in T \tag{41}$$

$$q' \geq 0\ , p' \geq 0 \tag{42}$$

$$x_r \text{ integer} \qquad \forall r \in R \tag{43}$$

$$y_k \in \{0,1\} \qquad \forall k \in N \tag{44}$$

$$z_t \text{ integer} \qquad \forall t \in T \qquad (45)$$

Note that the demand parameter in Constraint (24) of the deterministic TLRND-MD model is used as a bound on a big M value required to enforce that selected composites can only visit RPs that are open. Thus, no concept of demand satisfaction is embedded in this constraint. Therefore, in RO-TLRND-MD the parameter was transformed into $b_t + \hat{b}_t, \forall t \in T$.

4.4.3 Solution Approach

To solve RO-TLRND-MD, we implement the heuristic solution approach developed by Vergara and Root (2013). The approach consists of a composite variable generation phase using templates to enumerate a subset of composite variables which are then used to solve the integer programming formulation of the problem with the help of a commercial solver. The composite variables represent feasible routes for truckloads as well as empty movements between O-D pairs. In the composite enumeration procedure, the composites that violate the limitations on the maximum percentage of out-of-route miles allowed, maximum local and lane distances allowed and the maximum number of RPs allowed to be visited are not generated. The feasible routes or composites can follow different templates (i.e., patterns) including one and two RPs. Since in practice more than two RPs could be visited in a route between origin and destination, the generated set of composites is only a subset of the complete feasible solution set. Figure 8 shows the set of templates that were used in this research to solve RO-TLRND-MD, where a square represents an RP and a circle is either an origin or a destination node.

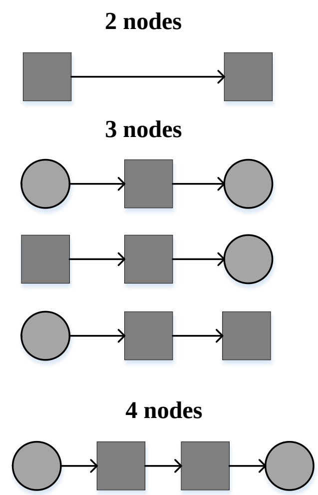

Figure 8: Templates Used for Composite Generation.

4.5 Computational Experiments

Computational experiments were completed to test the robust counterpart formulation for the TLRND-MD problem under demand uncertainty. The purpose of conducting these experiments was to evaluate the quality of the robust solutions in terms of performance measures such as solution value and network configuration, as well as developing insights on how these robust solutions differ from deterministic solutions. The computational performance of the solution approach described in Section 4.4.3 was also studied in terms of the computational time required to obtain the robust solutions for RO-TLRND-MD.

4.5.1 Computational Experiments Setup

Complete network instances (i.e., networks in which all pairs of nodes are connected by an arc) with 25, 50 and 100 nodes were generated assuming that the nodes are uniformly distributed in a squared area of size 1×1. Ten different network instances were created for each network size. Flow density was controlled by selecting 10%, 20% and 40% of the node pairs in the network as O-D pairs with truckload demand. Therefore, 60, 120 and 240 O-D pairs were selected for 25 node network instances, 245, 490 and 980 O-D pairs were selected for 50 node network instances, and 990, 1,980 and 3,960 O-D pairs were selected for 100 node network instances. The number of truckloads for an O-D pair t, b_t, is the uncertain parameter that belongs to the uncertainty set represented by the symmetric interval $[b_t - \hat{b}_t, b_t + \hat{b}_t]$. Values for the mean number of truckloads between O-D pairs, b_t, were randomly generated based on a uniform distribution between 10 and 20.

To obtain insights about how different levels of uncertainty can affect the solutions, we examined two different levels of uncertainty by considering $\Gamma_i = 0.5$ and $\Gamma_i = 1$ as the *number of coefficients* in constraint i, for *i*=23,28 that are allowed to change. Recall that in our application, there is only one coefficient in constraint *i* that is subject to uncertainty and can fluctuate. Therefore, Γ_i , for $i = 23{,}28$ will be at most 1.

For the cases that consider demand uncertainty, two different levels of fluctuation with respect to the mean number of truckloads were considered. Specifically, $\hat{b}_t$ was assumed to take the following values: 10 and 30. For example, if we assume a mean value of 15 for the number of truckloads for a particular O-D pair and 10 units of fluctuation, the uncertainty set for the demand of this O-D pair is the interval between 5 and 25 (i.e., 15 ± 10).

Table 1 summarizes the factors considered and their levels used to create distinct scenarios for the testing the RO-TLRND-MD formulation. Additional design parameters were fixed across all instances tested and include limitations on local and lane distances for relay network movements, percentage of out-of-route miles allowed, number of RPs allowed to be visited in a relay network route, equipment imbalance allowed, minimum volume required to open RPs, maximum proportion of PtP loads, fixed RP installation cost, and per mile transportation costs. Table 2 shows the values used for these fixed parameters.

Table 1: Computational Experiment Factors and Levels.

Factor	**Levels**
Size of the network (number of nodes)	25, 50, 100
O-D pairs with truckload demand (% of total node pairs)	10%, 20%, 40%
Level of uncertainty (fraction demand fluctuation)	0, 0.5, 1
Level of fluctuation (amount of fluctuation in the uncertainty set)	10, 30

Table 2: Fixed Parameter Values Used in Computational Experiments.

Parameter	**Value**
Local distance limitation (distance units)	0.3
Lane distance limitation (distance units)	0.5
Maximum percentage of out-of-route miles allowed (%)	25
Number of RPs allowed to be visited	2
Equipment imbalance allowed (%)	0
Minimum volume required to open RPs (as a % of total volume in the network)	0
Maximum proportion of PtP loads allowed (%)	100
Fixed installation cost of RPs (cost units)	10
Per mile local transportation cost (cost units)	1
Per mile lane transportation cost (cost units)	1.3
Per mile PtP transportation cost (cost units)	1.5

4.5.2 Computational Results

The formulation for RO-TLRND-MD and the composite variable generation method were implemented in Python and all instances were solved using CPLEX 12.2 on a 2.83 GHz Pentium computer with 8 GB of RAM. Unless noted otherwise, the results presented below are averages of ten different network instances. The responses that were collected to address characteristics of the solutions obtained were the *solution* *value* (i.e., objective function value) and the *number of RPs open*. Also, the *computational time* was the response considered to address the efficiency of the mathematical model and the solution approach used in this research.

4.5.2.1 Small Network Results

This section presents the results obtained with the heuristic solution approach presented in Section 4.4.3 for 25 node networks. Table 3 shows the solutions obtained for the baseline case with zero uncertainty (i.e., the deterministic case).

Table 3: Experimental Results for 25 Node Networks with Deterministic Demand.

Number of O-D pairs	**Solution Value (units)**	**Number of RPs Open**
60	899.196	11
120	1,930.5	15.4
240	2,924.74	16.8

The results obtained for instances with uncertain demand are reported in Table 4 for the different levels of O-D pair density, respectively. In addition to the values obtained for the responses, their differences with respect to the baseline deterministic scenario are also provided. The differences in *solution value* are reported as percentages, while the differences in *number of RPs open* are reported as differences in number.

According to the results presented in Table 4, *solution value* increased when uncertainty was incorporated when compared to the deterministic case. The increase goes from slightly above 15% for instances with low uncertainty to more than 100% for instances with high uncertainty. The percentage difference did not seem to vary significantly from the instances with fewer O-D pairs to the instances with more O-D pairs.

Table 4: Experimental Results for 25 Node Networks.

O-D Pairs	Demand Change (units)	Variability Parameter	Solution Value (units)	Diff.	Number of RPs Open	Diff.
60	10	0.5	1,055.01	17.33%	11.5	0.5
		1	1,203.21	33.81%	11.8	0.8
	30	0.5	1,340.61	49.09%	12	1
		1	1,753.39	94.99%	12.7	1.7
120	10	0.5	2,235.49	15.80%	15.8	0.4
		1	2,580.52	33.67%	16.3	0.9
	30	0.5	2,802.13	45.15%	16.9	1.5
		1	3,770.82	95.33%	17.9	2.5
240	10	0.5	3,497.77	19.59%	17.4	0.6
		1	4,052.36	38.55%	18.1	1.3
	30	0.5	4,543.66	55.35%	18.2	1.4
		1	6,098.50	108.51%	19.3	2.5

Similarly, the average *number of RPs open* increased in the uncertain demand scenarios, however only slightly from about 0.4 more RPs for instances with low uncertainty to 2.5 additional RPs open for instances with high uncertainty. The difference in number of RPs did not seem to vary significantly from instances with fewer O-D pairs to instances with more O-D pairs.

As robust optimization attempts to find solutions that remain feasible under any realization of the uncertain parameter, more RPs are required to protect the solutions against worst case scenarios of demand for the O-D pairs that are subject to uncertainty which results in higher fixed RP installation costs. Also, as the level of uncertainty increases, the robust approach assumes that more demand exists in the network which results in an increase of the transportation costs to move the additional loads.

Also, according to the results, we observe that the number of the RPs that are replaced in the robust solutions when compared to the deterministic solutions increases as the network size and the level of uncertainty increase. Still, even in the cases with the highest number of new robust locations, most of the deterministic RP locations are kept open in the robust solution. For example, for the instances with largest network size and highest uncertainty, we observed that the difference in the number of open RPs between deterministic and robust solutions is at most 4. Moreover in these instances, there are cases in which all the nodes open as RPs in the deterministic solution are still open in the robust solution, and in the worst case at most two of them are replaced in the robust solution. In contrast, for smaller instances with lower levels of uncertainty, in most cases the locations of selected RPs are exactly the same for robust and deterministic scenarios.

Another interesting observation from the results for the robust instances is the reduction in the number of deadhead composites required (i.e., empty trips to balance equipment) with respect to the deterministic solutions. A potential explanation for this response is that by increasing the total amount of loads to be dispatched in the uncertain scenarios, there were more opportunities to use loaded composites instead of deadhead composites in order to balance the equipment at the nodes. Therefore, some of the deadhead composites selected in deterministic solutions (which are more expensive than loaded composites) will be replaced by loaded composites in the robust solutions. The same response is also observed when we increase the level of uncertainty for robust instances in the sense that for higher levels of uncertainty there are fewer number of deadhead composites. For example, in a 25-node network instance with 10% O-D pair density we observed that five deadhead movements in the deterministic solution were reduced to three deadhead movements in the robust solution. While in the same instance, 44 loaded composites in the deterministic scenario were increased to 49 loaded composites in the robust scenario. Among those five additional composites representing loaded movements in the robust solution, some are substituting for the deadhead movements that were eliminated in the robust solution. This observation is made by looking at the composites used in the robust solution for those situations in which a deadhead was eliminated between two nodes. For example, in the instance described above, a deadhead (i.e., empty movement) was established between nodes 1 and 6 in the deterministic solution, but it was eliminated in the robust solution, and instead an additional loaded movement was used between these nodes in the robust solution. The same observation was made in most other instances.

Regarding traffic at the RPs, we observed that even though new RPs are to be opened in the robust solutions, generally the same amount of traffic goes through the RPs that remain open in both deterministic and robust solutions. More precisely, the additional amount of loads that need to be dispatched due to demand uncertainty are distributed in the network in a way that the traffic at the RPs does not change significantly between the two scenarios. For example, in the above instance, we observed that the number of open RPs in the deterministic solution was increased from 11 to 12 for the robust scenario. However, from the 12 RPs in the robust solution, two RPs replaced other locations from the deterministic solution, and only one additional RP location was selected. For the nine RPs that remained open in both solutions, we observed that the percentage of traffic going through them was almost the same in the deterministic and robust scenarios. In this instance, the highest value for the difference in percentage of traffic flow through these RPs was only 3%. We observed similar results for most other instances.

4.5.2.2 Network Size Effect

The effect of larger network instances on the robust solutions was studied by considering the uncertain demand scenarios with the highest level of fluctuation (e.g. 30 units above the expected value of demand). Figure 9 shows the solution values obtained for all network sizes and O-D pair densities for the deterministic scenario as well as the uncertain scenarios with different uncertainty levels (i.e., different proportion of O-D pairs with uncertain demand). As shown in Figure 9, for all instances, a general increasing trend for *solution value* was observed as the uncertainty level increased. The magnitude of increase was more significant for 100 node network instances. This is mostly due to the higher truckload demand experienced by the system in the scenarios with demand uncertainty, especially for the instances with 20% and 40% O-D pair density (e.g., 100-1,980 and 100-3,960). Similarly, Figure 10 shows that the *number of RPs open* increased as the network size increased, especially for 100 node instances.

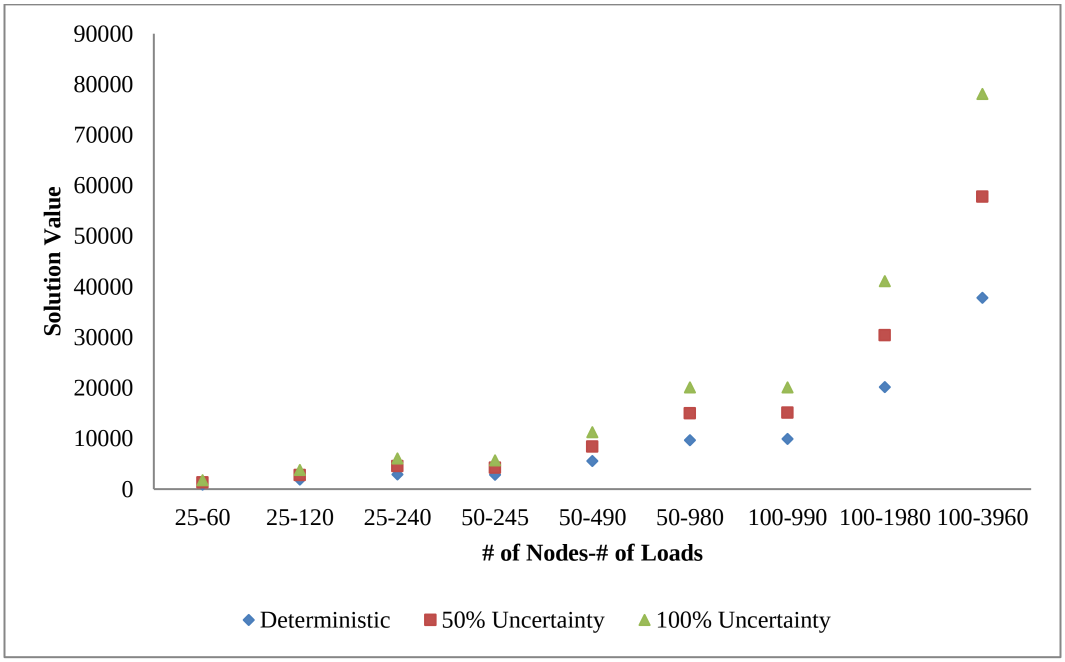

Figure 9: Solution Values for Deterministic and Uncertain Demand Scenarios solved with RO-TLRND-MD (30 units of fluctuation).

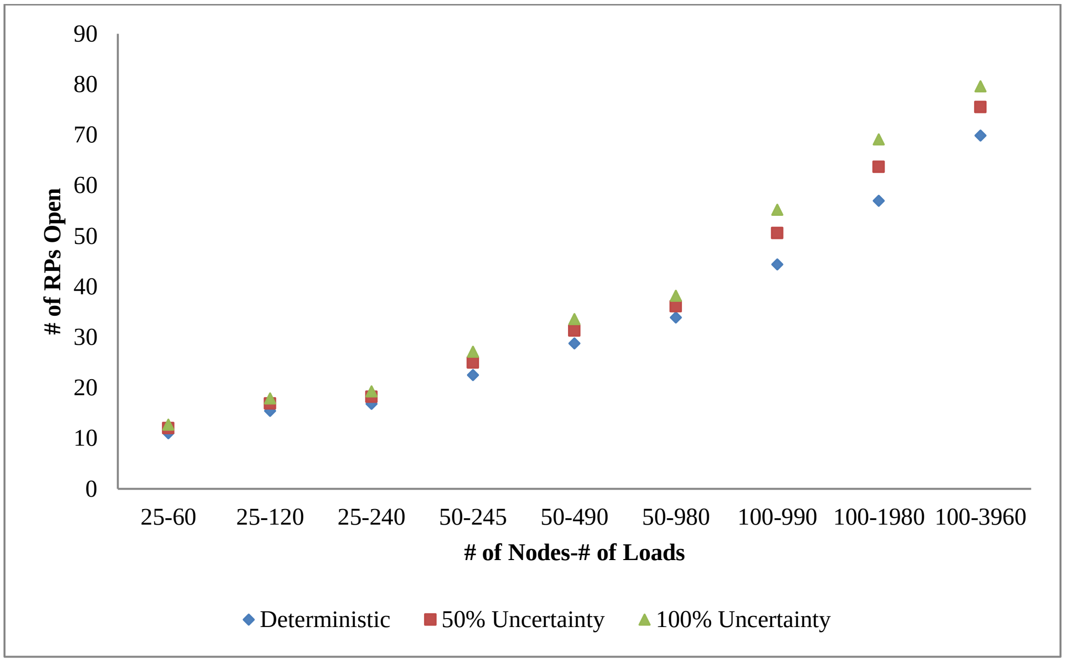

Figure 10: Number of RPs Open for Deterministic and Uncertain Demand Scenarios solved with RO-TLRND-MD (30 units of fluctuation).

In addition to *solution value* and *number of RPs open*, we also investigated *computational time* as a performance measure to assess how incorporating demand uncertainty affects the tractability of the mathematical formulation of RO-TLRND-MD. Figure 11 shows the average *computational times* observed for deterministic and uncertain demand scenarios under different levels of uncertainty and demand fluctuation. The results indicate that even for high uncertainty levels with high demand fluctuation, the *computational time* was not affected when compared to the deterministic case. This seems to indicate that the robust optimization approach that we implemented helped us to hedge against the effects of uncertainty in the input data while at the same time it did not add to the complexity of the mathematical formulation as compared to TLRND-MD. Larger network instances still required more *computational time*, especially for 100 node instances where we start to observe that the *computational time* increases exponentially. However, the largest instances were still solved in less than ten minutes showing the efficiency of the mathematical formulation and solution approach for RO-TLRND-MD.

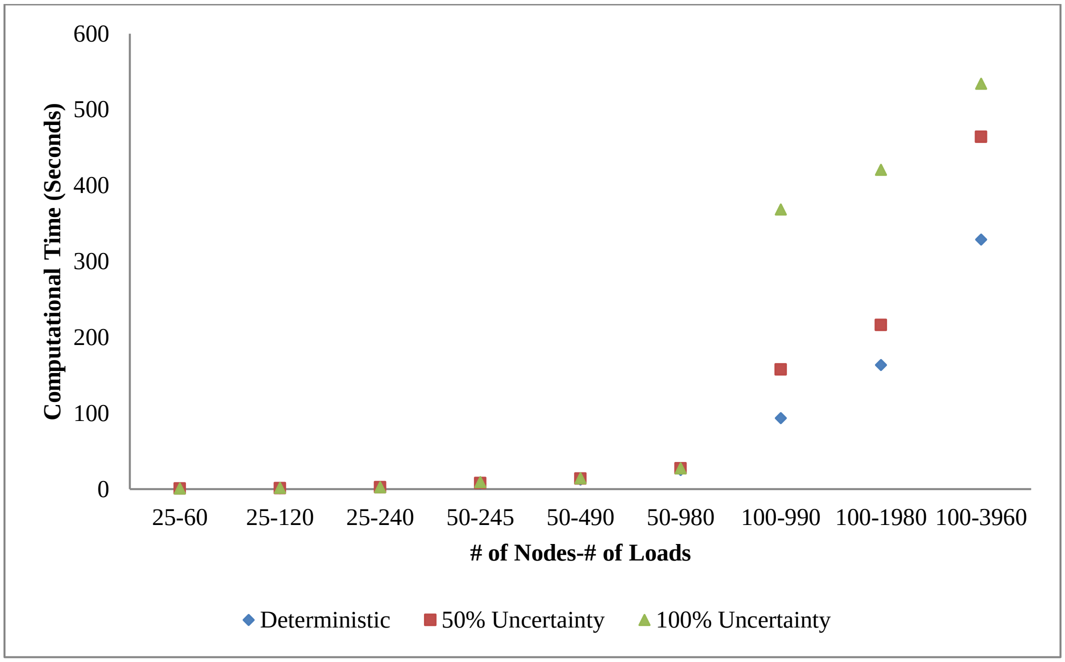

Figure 11: Computational Time for Deterministic and Uncertain Demand Scenarios solved with RO-TLRND-MD (30 units of fluctuation).

4.5.2.3 Fixed Cost Effect

Figure 12 shows the proportion of the total *solution value* that corresponds to the fixed RP installation cost as the size of the networks increased for both deterministic and uncertain demand scenarios. The results show that the proportion of fixed RP installation cost in *solution value* decreased as the level of uncertainty increased, especially for the smaller instances. We can conclude that while the fixed RP installation cost increased due to the larger number of RPs open in the cases under demand uncertainty, the weight of the increase in transportation cost due to the additional load demand in the system seems to be more significant in the total *solution value*.

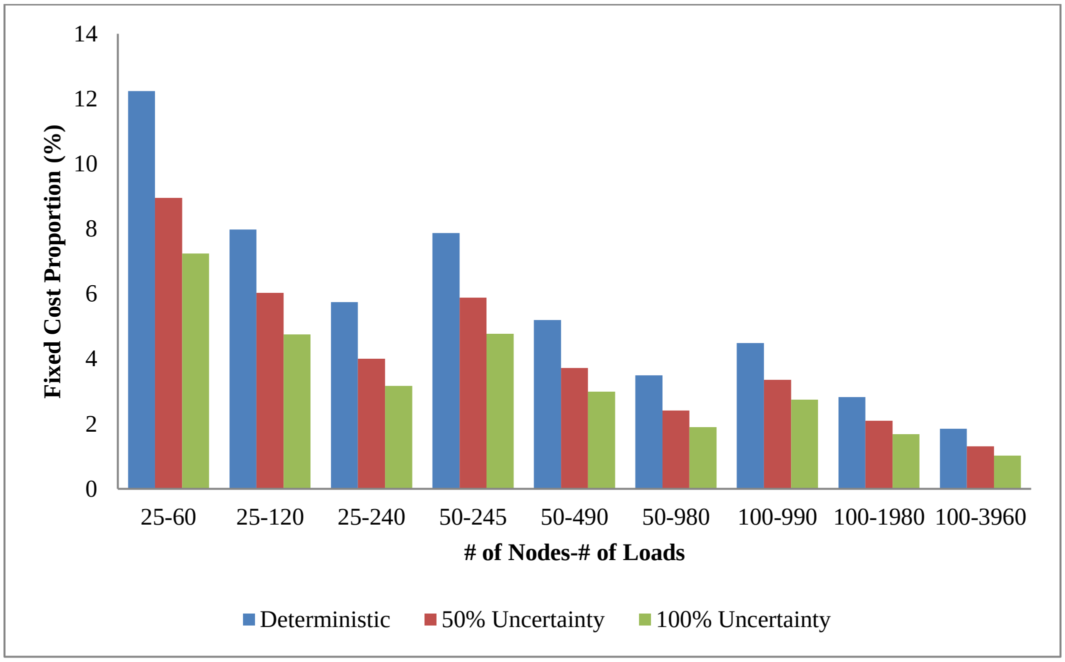

Figure 12: Fixed RP Installation Cost Proportion for Deterministic and Uncertain Demand Scenarios solved with RO-TLRN-MD (30 units of fluctuation).

To evaluate the effect of a larger fixed RP installation cost, solutions were obtained for deterministic and uncertain demand scenarios for 25, 50 and 100 nodes network instances with 10%, 20% and 40% O-D pair density when the fixed RP installation cost was modified from 10 to 100. Figure 13 shows the *number of RPs open* while Figure 14 shows *solution value* when the fixed RP installation cost was increased for these instances.

According to Figure 13, the *number of RPs open* decreased when the fixed RP installation cost increased from 10 to 100. This had an effect on the configuration of the network and resulted in different selections for the dispatching method and the route for the relay network loads. Note in Figure 13 that the *number of RPs open* for the case with 100% uncertainty and fixed RP installation cost equal to 100 was always less than the *number of RPs open* for the deterministic case and fixed RP installation cost equal to 10. This shows that the effect of increasing the fixed RP installation cost from 10 to

100 was more significant than assuming that all O-D pairs have uncertain demands fluctuating as much as 30 units from their nominal values.

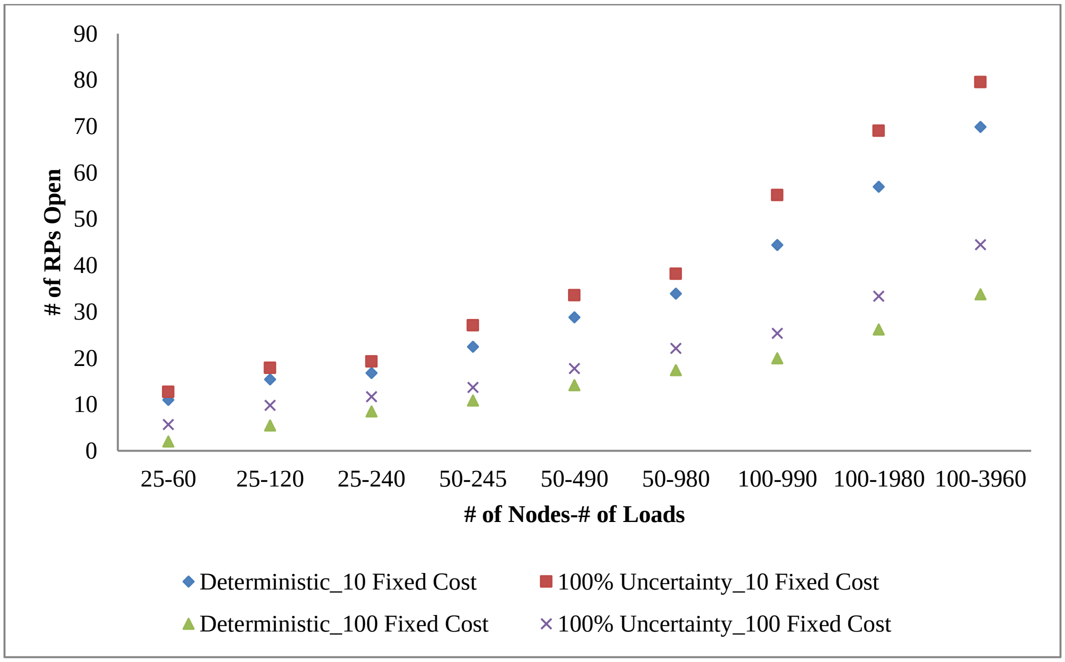

Figure 13: Number of RPs Open for Deterministic and Uncertain Demand Scenarios (30 units of fluctuation) for Different Fixed RP Installation Costs.

In Figure 14, we observe that in both deterministic and uncertain scenarios, a higher fixed cost value results in a higher solution value. This increase is not very significant since fewer RPs are open when the fixed cost is equal to 100 instead of 10.

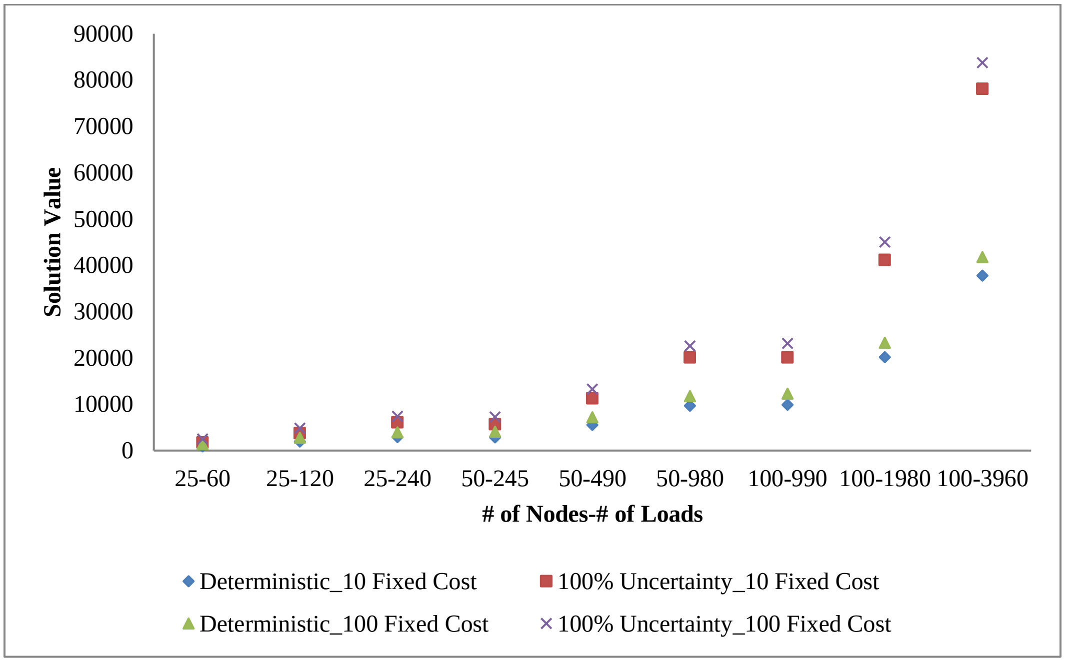

Figure 14: Solution Values for Deterministic and Uncertain Demand Scenarios (30 units of fluctuation) for Different Fixed RP Installation Costs.

Figure 15 shows that the proportion of the total fixed RP installation cost as part of the *solution value* increased when the parameter changed from 10 to 100. For the high value of fixed RP installation cost and for 25 nodes network instances with 10% density (i.e. 60 loads), we observed that the proportion of the total fixed RP installation cost as part of the *solution value* was higher in the deterministic scenario. However, for the larger instances, the two scenarios had almost the same proportion, and gradually the proportion for the robust scenario started to decrease when compared to the deterministic scenario.

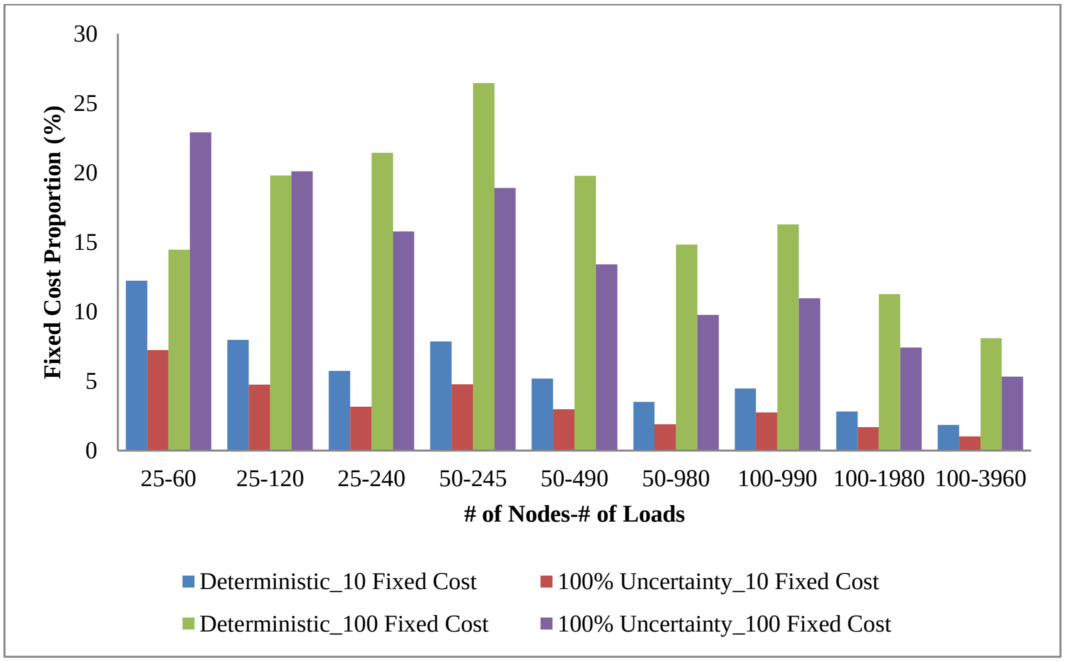

Figure 15: RP Installation Cost Proportion for Deterministic and Uncertain Demand Scenarios (30 units of fluctuation) and Different Fixed RP Installation Costs.

Finally, to evaluate the effect of fixed cost changes on the computational performance of the proposed formulation and solution approach for RO-TLRND-MD, Figure 16 shows the effect of a higher fixed RP installation cost on *computational time*. The results in Figure 16 show that *computational time* was not affected for the larger network instances in the deterministic scenario. However, the *computational time* increased significantly for robust solutions with the higher fixed RP installation cost.

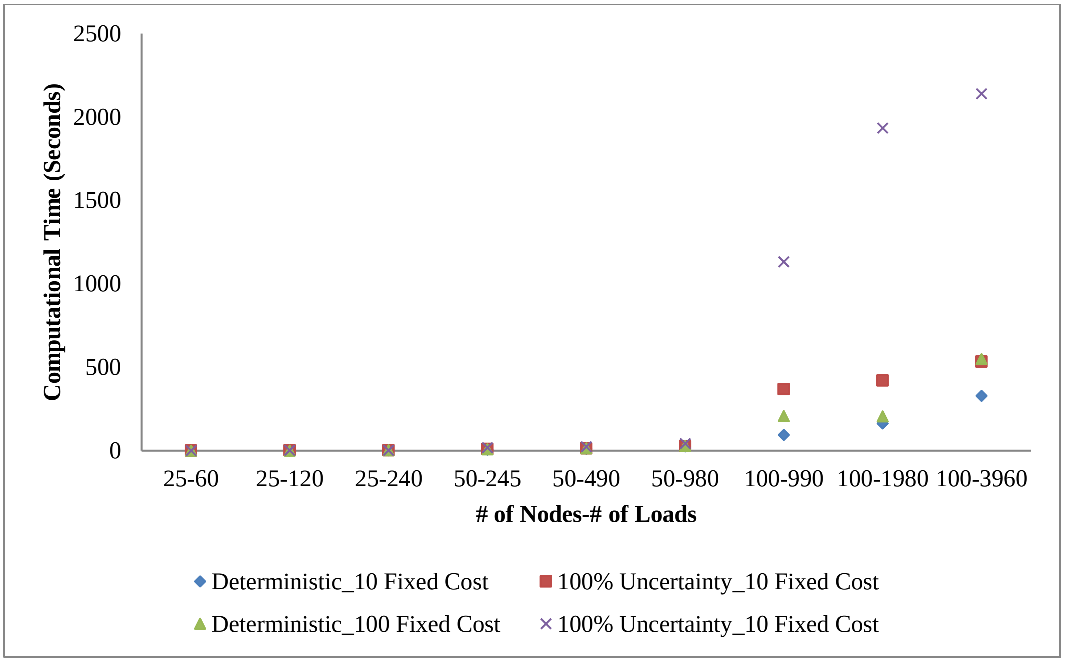

Figure 16: Computational Time for Deterministic and Uncertain Demand Scenarios (30 units of fluctuation) and Different Fixed RP Installation Costs.

4.6 Conclusions and Future Research

In this research, we studied the robust truckload relay network design problem under demand uncertainty. In this problem, we are interested in determining the locations of RPs as well as the routes for shipping loads when demand between the O-D pairs can fluctuate in a symmetric interval. The contributions of this paper are twofold: (1) we present a robust counterpart formulation for the TLRND-MD problem under demand uncertainty using the robust optimization approach introduced in Bertsimas and Sim (2003) in which the level of conservatism is controllable; and (2) we conduct a comprehensive analysis on how uncertainty affects different characteristics of the solutions obtained.

The robust counterpart of the TLRND-MD problem under demand uncertainty was formulated as a mixed integer programming model using composite variables. The formulation of RO-TLRND-MD was solved using a heuristic solution approach.

Comprehensive computational experiments were completed on different network instances to assess the effects of uncertainty on the structure of the relay network and total solution cost as well as on the tractability of the robust optimization model. The numerical results indicated that incorporating uncertainty resulted in opening more RPs to handle the additional loads in the network as well as higher total cost for the network. The increase on the number of RPs required in robust solutions seemed to become more significant for larger network instances and extreme cases of uncertainty. Interestingly, computational times were not significantly affected by uncertainty. We also observed that although the number of open RPs increases in robust solutions, most of the nodes serving as RPs in deterministic solutions remained open in the robust solutions as well. Moreover, the traffic at the RPs that are kept remained almost the same between the two scenarios. Another interesting observation was that some deadhead movements were eliminated in the robust solution and were replaced with loaded movements due to the additional freight loads in the network considered in the robust approach to handle demand uncertainty.

As a possible extension to this research, the methodology developed here can be applied to the TLRND-MD problem under multiple uncertain parameters (e.g., considering uncertain demand and transportation costs). Moreover, examining advanced uncertainty sets such as ellipsoidal uncertainty sets and asymmetric uncertainty sets can be another future research direction. Also, another interesting area of future research might be the application of stochastic optimization techniques to solve this problem assuming a fully known probability distribution for the uncertain demand as an alternative for cases in which more information about the demand is available and less conservatism in the solutions is desired.

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5 Stochastic Optimization Approach for Truckload Relay Network Design under Demand Uncertainty[3]

5.1 Abstract

We consider the strategic design of a truckload relay network with mixed fleet dispatching under demand uncertainty. A two-stage stochastic programming formulation is developed to capture the uncertainty and observe the effects of demand uncertainty on the design of the network as well as on the total installation and transportation costs. A Monte-Carlo simulation-based sampling algorithm known as Sample Average Approximation (SAA) strategy is used as the solution approach that allows examining a large number of scenarios. Results are compared with the solutions obtained for deterministic parameters.

Keywords: truckload transportation, relay networks, uncertainty, stochastic optimization

5.2 Introduction

Truckload relay network design (TLRND) is an application of relay networks in transportation where the trailers are switched at facilities called RPs. As opposed to the hub-and-spoke (H&S) architecture in which loads with several origins are consolidated at hubs, in relay networks there is no consolidation and a full truckload is assigned to a single origin and destination (O-D) pair. The idea behind the use of the TLRND configuration is to route the commodities between O-D pairs using multiple drivers for each delivery as opposed to the traditional Point-to-Point shipments (e.g. assigning a single driver to each delivery). This configuration has received considerable attention by researchers and trucking carriers to overcome the significant driver turnover rate which is a crucial issue in this industry. In the TLRND problem, the long-term strategic

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decision of locating RPs as well as the tactical decision of route selection for sending the commodities will be determined so as to minimize the total installation and flow costs.

Applying different assumptions has resulted in several variants of mathematical formulations and solution approaches for the TLRND problem. Üster and Maheshwari (2007), Üster and Kewcharoenwong (2011), Vergara and Root (2012), Melton and Ingalls (2013), and Vergara and Root (2013) have studied this problem. In particular, Vergara and Root (2013) analyzed the potential performance of a hybrid structure that simultaneously uses the PtP and TL relay networks for dispatching as compared to a pure relay network or a pure PtP system. To this end, the authors presented an extension to the CVM formulation introduced in Vergara and Root (2012) to represent the mixed fleet structure in which the mode of dispatching the loads via a traditional PtP method or via the relay network is also a decision variable. This problem is known as the truckload relay network design with mixed fleet dispatching (TLRND-MD) problem.

However, the majority of research on TLRND and TLRND-MD problems assumes deterministic characteristics and parameters when designing the network while the strategic and tactical decisions that are to be made in these problems are typically affected by uncertainty. In fact, customer demand, transportation cost, and travel time can be quite uncertain even after determining the locations of RPs. As a result, assuming known and deterministic characteristics and data can result in sub-optimality. To avoid this, we suggest incorporating uncertainty in the TLRND-MD problem to achieve more practical solutions. An extremely high number of variables and constraints in the mathematical models developed in the aforementioned references as well as the complexity of the operational constraints considered in the design of TL transportation networks are the main factors that make the TLRND-MD problem a hard one to solve. This complexity gets even worse when uncertainty in the environment is explicitly taken into account. In this research, we attempt to develop an efficient stochastic programming formulation and find high quality solutions for the TLRND-

MD problem under demand uncertainty. We are interested in using a solution approach that incorporates a significantly large number of scenarios of the uncertain parameter in order to obtain promising solutions.

The remainder of this chapter is organized as follows. In Section 5.3, a brief review of research on truckload relay network design with mixed fleet dispatching as well as studies addressing uncertainty in transportation network design problems is presented. Section 5.4 provides an introduction of the deterministic capacitated TLRND-MD problem followed by the mathematical formulation of the corresponding stochastic programming formulation and the solution approach that has been developed. Section 5.5 describes the numerical experiments conducted as well as the corresponding results and discussion. Finally, Section 5.6 presents some concluding remarks and provides future work directions.

5.3 Literature Review

5.3.1 Relay Networks for Truckload Transportation

The hub-and-spoke (H&S) configuration for TL dispatching was first introduced with the work of Taha and Taylor (1994) and has been studied extensively as an alternative dispatching method for TL transportation. Most of the preliminary work considered simulation approaches such as Taha and Taylor (1994), Taylor et al. (1995), Harit et al. (1995) Taylor et al. (1999), Taylor and Meinert (2000), and Taylor et al. (2001).

In addition to the simulation studies discussed above, Hunt (1998) designed TL relay networks using the United States Southeast physical roadway network using an algorithmic approach. Based on the findings, Hunt (1998) pointed out the benefits of using a partial TL relay network in terms of eliminating excessive circuity for some of the loads. Later, Ali et al. (2002) proposed heuristic methods to minimize the number of RPs on a highway transportation network for different scenarios considering a H&S configuration.

More recently, several studies have developed mathematical programing formulations for the TLRND problem and some of its variants. Üster and Maheshwari (2007) studied the design of hub-based TL dispatching systems and formally introduced the TLRND problem. They formulated a binary integer program (BIP) to model the problem. Due to tractability issues, the mathematical programming formulation was relaxed and solved using a heuristic method for medium size instances. Later, Üster and Kewcharoenwong (2011) solved a modified version of the model presented in Üster and Maheshwari (2007) using an exact solution approach based on a Benders decomposition algorithm. In another study, Vergara and Root (2012) formulated the TLRND problem using a composite variable model (CVM) where only feasible routes are considered as decision variables. In this way, important operational constraints were incorporated implicitly within the composite variable definition. In their results, they observed that a combination of the relay network system and the PtP system together in a mixed fleet dispatching outperforms both methods when used solely. Based on this, Vergara and Root (2013) studied the hybrid structure of combining the PtP and TL relay networks for TL dispatching. They extended the CVM formulation introduced in Vergara and Root (2012), so that the dispatching mode for loads via the PtP method or via the relay network is also a decision variable. At the same time, Melton and Ingalls (2013) used a mixed integer quadratic program to model a highway transportation network to decide on the location of RPs in a relay network dispatching system.

More recently, in order to address uncertainty, Vergara and Mokhtari (2014) proposed the robust counterpart formulation of the TLRDN-MD problem using a robust optimization approach with controllable level of uncertainty. In this study, demand was assumed to be fluctuating in a symmetric uncertainty set around its expected value and solutions were obtained for the worst case value of demand for each O-D pair.

5.3.2 Stochastic Optimization Applications in Transportation Network Design and Facility Location

Stochastic optimization utilizes the distribution of the uncertain parameters to find solutions to optimization problems under uncertainty. A common goal in most stochastic optimization techniques is to optimize the expected value of an objective function (Rosenhead et al. 1972). Many of these techniques attempt to minimize the expected cost or maximize the expected profit of a system in which uncertainty exists for one or more parameters. Other techniques of stochastic optimization consider a probabilistic approach to find a solution (i.e., maximizing the probability that the performance is good or constraining the probability that it is bad) (Snyder 2006).

In addition to facility location and transportation network design applications, the use of stochastic optimization has extended to incorporate uncertain parameters in supply chain network design problems. In particular, supply chain network design under demand uncertainty has received significant attention in the last fifteen years. For instance, Mirhassani et al. (2000) developed a two-stage stochastic model for the strategic multi-period capacity planning of supply chain networks. Demand uncertainty was investigated in this study and the proposed model was solved by applying Benders decomposition. Tsiakis et al. (2001) considered a multi-product, multi-echelon supply chain under demand uncertainty. The decisions considered included the selection of middle-echelon facility locations and capacities, transportation links, and flows. Transportation cost was defined as a piecewise linear concave function in their formulation.

Santoso et al. (2005) studied a global supply chain network design problem under uncertainty with continuous distribution for the uncertain parameters, and thus an infinite number of scenarios. Costs, demands, and capacities were considered to be uncertain. The problem was to decide where to build facilities and what machines to procure at each facility to minimize the total expected cost. The problem was formulated as a two-stage stochastic program with binary first-stage variables for the facility location problem and continuous recourse variables for the remaining decisions. The two-stage stochastic program was solved using accelerated Benders decomposition.

Azaron et al. (2008), Schütz et al. (2009), El-Sayed et al. (2010), Bidhandi and Yusuff (2011), Cardona-Valdés et al. (2011) are other examples of the application of stochastic optimization for the design of supply chain networks where usually strategic location decisions are considered as first stage decisions and operational decisions are the second stage decisions. More recently, Razmi et al. (2013) developed a bi-objective two-stage mixed integer linear programming model for redesigning a reliable warehouse distribution network. The authors considered uncertainty in customer demand, costs of warehousing and transportation, and facilities failures. These parameters were expressed in a number of probabilistic scenarios and the proposed model was validated and verified by applying it to a real industrial case.

In another study, Contreras et al. (2011) developed a two-stage stochastic optimization model for the multiple allocation uncapacitated hub location problem under demand and transportation cost uncertainty. They considered a known probability distribution for the uncertain parameters. A Monte-Carlo simulation-based framework integrating a sample average approximation (SAA) algorithm with a Benders decomposition technique was used to solve the problem. The authors showed that the SAA algorithm resulted in estimated optimality gaps that were always less than 0.3% for the instances with up to 50 nodes.

Although there are several studies that apply operations research techniques to the TLRND problem and even a larger body of literature addressing uncertainty in strategic network design problems, there is a lack of studies evaluating the effects of uncertainty using a stochastic optimization approach in the design of relay networks for the TL trucking industry.

5.4 Methodology

We first introduce a deterministic mathematical formulation for the capacitated version of the TLRND-MD problem. Vergara and Root (2013) proposed a mathematical formulation for TLRND-MD problem which does not consider any restriction on the capacity of the RPs in accommodating truckloads going through the facilities. In practice, there exists a limitation on the number of the truckloads that can be served by an RP that needs to be incorporated in the mathematical formulation to limit traffic flow at the RPs. In this research we developed the capacitated TLRND-MD mathematical formulation using the following notation:

<u>Sets</u>

R = set of composites r,

T = set of O-D pairs t with truckload demand,

N = set of nodes k,

R_t = set of composites r for O-D pair t, $R_t \subset R$,

R_k = set of composites r that visit node k, $R_k \subset R$.

<u>Parameters</u>

c_r= cost of composite r, $\forall\ r \in R$,

f_k = fixed cost of RP k, $\forall\ k \in N$,

p_t = cost of dispatching a truckload for O-D pair t using PtP dispatching, $\forall t \in T$,

b_t = demand for O-D pair t (in number of truckloads), $\forall t \in T$,

C_k = capacity at RP k, $\forall\ k \in N$,

δ = maximum acceptable percentage equipment imbalance,

ρ = maximum proportion of truckloads to be dispatched direct PtP,

υ = minimum volume (in number of truckloads) required to open an RP,

η_{kr} = -1 if node *k* is the origin RP of composite *r*,

1 if node *k* is the destination RP of composite *r*, $\forall\ k \in N;\ r \in R$,

0 otherwise,

θ_{kr} = 1 if composite *r* visits RP *k*, $\forall\ k \in N;\ r \in R$,

0 otherwise.

Decision Variables

x_r = number of times composite *r* is used, $\forall r \in R$,

y_k = 1 if an RP is opened at node *k*, $\forall\ k \in N$,

0 otherwise,

z_t = number of truckloads sent direct PtP for O-D pair *t*, $\forall t \in T$.

Using the notation presented above, the deterministic mathematical model for capacitated TLRND-MD problem follows:

$$Minimize\ Z\ = \sum_{r \in R} c_r x_r + \sum_{t \in T} p_t\, z_t + \sum_{k \in N} f_k y_k \tag{46}$$

subject to

$$\sum_{r \in R_t} x_r + \ z_t \geq \ b_t \qquad \forall t \in T \tag{47}$$

$$\sum_{r \in R_t} \theta_{kr}\, x_r \leq\ b_t y_k \qquad \forall t \in T,\ k \in N_r; r \in R_t \tag{48}$$

$$\sum_{r \in R} \theta_{kr}\, x_r \leq C_k y_k \qquad \forall k \in N \tag{49}$$

$$\sum_{r:\eta_{kr}=-1} x_r - \sum_{r:\eta_{kr}=1} x_r \leq\ \delta \sum_{r:\eta_{kr}=-1} x_r \qquad \forall k \in N \tag{50}$$

$$\sum_{r:\eta_{kr}=1} x_r - \sum_{r:\eta_{kr}=-1} x_r \leq\ \delta \sum_{r:\eta_{kr}=1} x_r \qquad \forall k \in N \tag{51}$$

$$\sum_{r \in R} \theta_{kr}\, x_r \geq\ v\, y_k \qquad \forall k \in N \tag{52}$$

$$\sum_{t \in T} z_t \leq\ \rho \sum_{t \in T} b_t \tag{53}$$

$$x_r \text{ integer} \qquad \forall r \in R \tag{54}$$

$$y_k \in \{0,1\} \qquad \forall k \in N \tag{55}$$

$$z_t \text{ integer} \qquad \forall t \in T \tag{56}$$

In this integer programming formulation, a composite variable *r* is defined as a feasible path for a truckload between an O-D pair. This definition of the composites requires enforcing the constraints related to local and lane distance limitations, maximum number of RPs visited in a path, and maximum percent circuity allowed. Since these constraints are implicitly enforced when generating the composites, they do not have to be explicitly included as constraints in the mathematical model presented above.

The objective function minimizes the sum of the transportation costs for truckloads using RPs, the transportation costs of direct PtP shipments, and the fixed cost of installation of RPs. The decision variables, x_r and z_t represent the number of truckloads that are shipped through a relay network route or PtP, respectively. Constraint (47) enforces demand satisfaction for O-D pairs with truckload demand by selecting a dispatching mode for the truckloads between the relay network and PtP dispatching. Constraint (48) requires that an RP should be open at node k if it is visited by a relay network path. Constraint (49) limits the number of composites that visit an RP. Constraints (50) and (51) enforce equipment balance at RP nodes by restricting the difference between outgoing and incoming loads at each RP. The limitation on the minimum truckload volume required to open an RP is enforced in Constraint (52), and the limitation on the maximum proportion of truckloads that can be dispatched PtP is enforced in Constraint (53). Finally, Constraints (54), (55) and (56) are the variable type constraints.

In this research, we develop a two-stage stochastic optimization corresponding to the integer programming model for the capacitated TLRND-MD problem when demand is assumed to be uncertain. We assume that demand is not fixed anymore and there is a need to explicitly account for this uncertain parameter in the strategic design of the mixed fleet dispatching system with relays.

An approach to incorporate demand uncertainty in the capacitated TLRND-MD problem is the application of a two-stage stochastic optimization model with recourse. In this approach, the decision variables are divided into a set of first-stage decisions, and a set of second-stage decisions that depend on the first-stage decisions and the realizations of the uncertain parameters. Unlike robust optimization approaches that do not assume any information about the distribution of the uncertain parameter, a probability distribution is assumed for demand when using the stochastic optimization approach. In this research, we assume that demand follows a uniform probability distribution. The following sub-sections describe the application of this approach to the capacitated TLRND-MD problem under demand uncertainty.

5.4.1 Stochastic Formulation of the Capacitated TLRND-MD Problem

A two-stage stochastic optimization method has been selected to be used in the current research to incorporate demand uncertainty in the formulation of the capacitated TLRND-MD problem. In this research, the first-stage decisions are the network configuration decisions (i.e., the number and location of RPs), and the second-stage decisions are the transportation decisions after demand realization (i.e., the selection of dispatching mode and relay network routes used to satisfy a specific realization of demand in the network). Using this approach, it is assumed that the decisions related to RP location are to be made prior to and regardless of the realization of the uncertain demand.

Demand uncertainty can be addressed by considering multiple scenarios in which the uncertain parameter takes specific values that come from a probability distribution. We define $\boldsymbol{\xi} = (\xi^1, \xi^2, \dots, \xi^S)$ as a vector consisting of demand values for S different scenarios. Given that for the two-stage stochastic optimization method, the optimal dispatching of truckloads depends on the actual realization of demand (represented by a particular scenario ξ^s), we need to consider dispatching decision variables (i.e., composites and PtP movements) for each possible scenario ξ^s. For example, $x_r(\xi^s)$, $\forall r \in R$ is the set of composites r generated for scenario ξ^s, and $z_t(\xi^s), \forall t \in T$ is the set of decision variables related to direct PtP dispatching for scenario ξ^s.

Consequently, the capacitated TLRND-MD problem under demand uncertainty is reformulated as the two-stage stochastic optimization model presented below. In this formulation, $b_t(\boldsymbol{\xi})$ is a random variable representing the demand for truckload *t* under each scenario in $\boldsymbol{\xi}$ and E_{ξ} represents the expectation of the transportation costs for the scenarios in $\boldsymbol{\xi}$. As a result, the objective function of the two-stage stochastic optimization model is to minimize the current RP installation costs, $\sum_{k \in N} f_k y_k$, and the *expected* transportation costs $E_{\xi}\left(\sum_{r \in R} c_r x_r(\boldsymbol{\xi}) + \sum_{t \in T} p_t z_t(\boldsymbol{\xi})\right)$. In this model, the second-stage variables and constraints are defined for every possible scenario in $\boldsymbol{\xi}$. More precisely, we (hypothetically) assume that there exist separate second-stage decision variables $x_r(\xi^S)$ and $z_t(\xi^S)$ for each scenario s = 1, 2,…, S. Therefore, for example, the demand satisfaction constraint is represented for each demand scenario between a particular O-D pair. It should be noted that, this is just the case for the second-stage decisions and the first-stage decision, y_k, is still represented as it was in the deterministic model. The stochastic capacitated TLRND-MD model becomes:

$$Minimize\ Z' = E_\xi\left(\sum_{r\in R} c_r x_r(\boldsymbol{\xi}) + \sum_{t\in T} p_t\, z_t(\boldsymbol{\xi})\right) + \sum_{k\in N} f_k y_k \tag{57}$$

subject to

$$\sum_{r\in R_t} x_r(\boldsymbol{\xi}) + z_t(\boldsymbol{\xi}) \geq b_t(\boldsymbol{\xi}) \qquad \forall t \in T \tag{58}$$

$$\sum_{r\in R_t} \theta_{kr}\, x_r(\boldsymbol{\xi}) \leq b_t(\boldsymbol{\xi})\, y_k \qquad \forall t \in T,\ k \in N_r; r \in R_t \tag{59}$$

$$\sum_{r\in R} \theta_{kr}\, x_r(\boldsymbol{\xi}) \leq C_k y_k \qquad \forall k \in N \tag{60}$$

$$\sum_{r:\eta_{kr}=-1} x_r(\boldsymbol{\xi}) - \sum_{r:\eta_{kr}=1} x_r(\boldsymbol{\xi}) \leq \delta \sum_{r:\eta_{kr}=-1} x_r(\boldsymbol{\xi}) \qquad \forall k \in N \tag{61}$$

$$\sum_{r:\eta_{kr}=1} x_r(\boldsymbol{\xi}) - \sum_{r:\eta_{kr}=-1} x_r(\boldsymbol{\xi}) \leq \delta \sum_{r:\eta_{kr}=1} x_r(\boldsymbol{\xi}) \qquad \forall k \in N \tag{62}$$

$$\sum_{r\in R} \theta_{kr}\, x_r(\boldsymbol{\xi}) \geq v\, y_k \qquad \forall k \in N \tag{63}$$

$$\sum_{t\in T} z_t(\boldsymbol{\xi}) \leq \rho \sum_{t\in T} b_t(\boldsymbol{\xi}) \tag{64}$$

$$x_r(\boldsymbol{\xi}) \text{ integer} \qquad \forall r \in R \tag{65}$$

$$y_k \in \{0,1\} \qquad \forall k \in N \tag{66}$$

$$z_t(\boldsymbol{\xi}) \text{ integer} \qquad \forall t \in T \tag{67}$$

5.4.2 Solution Approach for the Stochastic Capacitated TLRND-MD Formulation

The key difficulty in solving the above formulation is the evaluation (i.e., calculation as well as optimization) of the expectation term in the objective function (Santoso et al. 2005; Contreras et al. 2011). In this case, a Monte-Carlo simulation-based algorithm known as Sample Average Approximation (SAA) was used to deal with this problem (Kleywegt et al. 2002). In SAA, a single sample is formed by considering a vector $\boldsymbol{\xi}$ consisting of demand realizations for *S* different scenarios. Then, *M* different samples of size *S* are considered to approximate the expected transportation cost. Accordingly, each value $\xi^1, \xi^2, \ldots, \xi^S$ in a vector $\boldsymbol{\xi}$ represents a scenario of demand (i.e., a value of demand generated from a probability distribution), and the second stage expectation, $E_{\xi}\left(\sum_{r\in R} c_r x_r(\boldsymbol{\xi}) + \sum_{t\in T} p_t z_t(\boldsymbol{\xi})\right)$ for a single sample can be approximated using the sample average function given in Equation (68).

$$\frac{1}{S}\sum_{s=1}^{S}\left(\sum_{r\in R} c_r x_r(\boldsymbol{\xi}) + \sum_{t\in T} p_t z_t(\boldsymbol{\xi})\right) \tag{68}$$

Therefore, the objective function of the two-stage stochastic optimization formulation presented above is approximated by the following function (Equation (69)):

$$Minimize\ Z'' = \frac{1}{S}\sum_{s=1}^{S}\left(\sum_{r\in R} c_r x_r(\boldsymbol{\xi}) + \sum_{t\in T} p_t z_t(\boldsymbol{\xi})\right) + \sum_{k\in N} f_k y_k \tag{69}$$

We define v_S and $\hat{y}_S$ as the optimal value and the optimal solution, respectively, for the SAA optimization problem represented by Equation (69). Since the term inside the parenthesis in Equation (69) is deterministic for a single sample of demand scenarios, the mathematical model can be optimally solved using optimization techniques. The number of scenarios in a single sample *S* determines the trade-off between the quality of the optimal solution obtained with SAA, and the computational performance to find such solution. The reason why *S* is the trade-off factor is that, each scenario of demand requires a set of second stage variables (e.g., $x_r(\xi^s)$ and $z_t(\xi^s)$ for scenario ξ^s) as well as constraints associated with the new set of variables which significantly increase the size of the problem and consequently its computational complexity.

As a single sample might not be enough to evaluate the expected value of the transportation costs, the SAA technique requires generating *M* independent samples each containing *S* scenarios of demand and solves the optimization problem for each sample. Then, these optimal solutions are used to compute statistical lower and upper bounds for the optimal solution value of the two-stage stochastic optimization problem. The optimality gap is computed using three different solutions: an average of the optimal solutions that are obtained for the *M* samples, a feasible solution of the two-stage stochastic optimization problem, and the average solution for a single sample formed by a large number of scenarios of the uncertain parameter. More precisely, the procedure that the SAA technique follows to obtain the optimality gap for the two-stage stochastic optimization problem is summarized in the following four steps.

Step 1. *M* samples of demand scenarios each of size *S* are generated using a probability distribution function for the demand. The SAA problem (i.e., the one using Equation (69) as the objective function) is solved for each of the *M* samples. Let, v_S^j and $\hat{y}_S^j$ for *j*= 1,…, *M* represent the optimal objective function value and the optimal solution, respectively.

Step 2. An unbiased estimator of $E[v_s]$ can be computed by obtaining $\bar{v}_{S,M} = \frac{1}{M}\sum_{j=1}^{M} v_S^j$ with a variance of $\sigma^2_{\bar{v}_{S,M}} = \frac{1}{M(M-1)}\sum_{j=1}^{M}(v_S^j - \bar{v}_{S,M})^2$ (Santoso et al. 2005). Since $\bar{v}_{S,M}$ is the unbiased estimator of $E[v_s]$, and it can be proved that $E[v_s] \le v^*$ where v^* is the optimal value of the two-stage stochastic optimization problem, then $E[\bar{v}_{S,M}] \le v^*$ (Mak et al. 1999; Norkin et al. 1998). This means that $\bar{v}_{S,M}$ serves as a statistical estimate for a lower bound on v^*which is the optimal value of the two-stage stochastic optimization problem.

Step 3. In this step, the upper bound on the two-stage stochastic optimization objective value corresponding to a feasible solution (e.g. $\bar{y} \in Y$) such as $\hat{y}_S^j$ is estimated. To evaluate the objective function, another sample of demand scenarios of size S' is generated independently from the one used to solve the SAA problem when obtaining $\hat{y}_S^j$. S' can be chosen much larger than S. This step involves solving S' independent second-stage sub-problems when second stage decisions $\hat{y}_S^j$ are fixed across all the S' sub-problems. Then, the following unbiased estimator of $f(\bar{y})$ is calculated in Equation (70).

$$\tilde{f}_{S'}(\bar{y}) = \sum_{k\in N} f_k \bar{y}_k + \frac{1}{S'}\sum_{s=1}^{S'}\left(\sum_{r\in R} c_r x_r(\boldsymbol{\xi}) + \sum_{t\in T} p_t z_t(\boldsymbol{\xi})\right) \tag{70}$$

Assuming $\tilde{f}_{S'}(\bar{y})$ is an unbiased estimator of $f(\bar{y})$ (i.e. $\hat{y}_S^j$) and considering that $\bar{y}$ is chosen as a feasible solution to the two-stage stochastic optimization problem, we can conclude that $f(\bar{y}) \ge v^*$. Thus, $\tilde{f}_{S'}(\bar{y})$ estimates the upper bound of the solution to the two-stage stochastic optimization problem. The variance of this estimator is obtained with Equation (71).

$$\sigma_{S'}^2(y) = \frac{1}{(S'-1)S'} \sum_{s=1}^{S'} \left(\sum_{k \in N} f_k \bar{y}_k + \sum_{r \in R} c_r x_r\,(\boldsymbol{\xi}) + \sum_{t \in T} p_t\, z_t(\boldsymbol{\xi}) - \tilde{f}_{S'}(\bar{y}) \right)^2 \quad (71)$$

Step 4. In this step, the lower bound estimation from step 2 and the objective value estimation from step 3 are used to estimate the optimality gap for solution $\bar{y}$ (Equation (72)).

$$gap_{S,M,S'}(\bar{y}) = \tilde{f}_{S'}(\bar{y}) - \bar{v}_{S,M} \quad (72)$$

That has a variance of

$$\sigma_{gap}^2 = \sigma_{S'}^2(y) + \sigma_{\bar{v}_{S,M}}^2 \quad (73)$$

When choosing a solution to serve as $\bar{y}$, we tend to choose the one with the smallest estimated objective function value to obtain a better gap. Numerical experiments are needed to examine the performance of the proposed methodology. This SAA algorithm was used to solve stochastic optimization problems with discrete first-stage variables for the first time by Kleywegt et al. (2002). Section 5.6 describes the approach that was used to complete our numerical experiments with the stochastic optimization model for the capacitated TLRND-MD problem by applying the SAA algorithm.

5.4.3 Benders Decomposition

Benders decomposition is a cutting plane method that can be helpful in solving two-stage problems such as the SAA problem (Equation (69)). The algorithm requires decomposing the problem into a master problem to minimize the facility installation cost and a sub-problem to minimize the total transportation cost. The objective function values obtained by the master problem and the sub-problem provide a lower bound and an upper bound approximation to the SAA problem, respectively. The master problem is a mixed-integer problem dealing with N binary variables (y) and one continuous variable B, while the sub-problem contains only continuous variables x and z. The steps of a Benders decomposition algorithm to solve the two-stage stochastic problem are described as follows.

Initialization: Initialize lower and upper bounds $lb = -\infty$ and $ub = +\infty$, respectively. l denotes the iteration and we set the iteration counter $i = 0$.

Step 1: Solve the master problem

$$lb = \min \sum_{k \in N} f_k y_k + \frac{1}{S} \sum_{s=1}^{S} B_s \tag{74}$$

$$y_k \in \{0,1\} \qquad \forall k \in N \tag{75}$$

$$B_s \geq (a_l^s)^T y + b_l^s \qquad l = 1, \ldots, i, s = 1, \ldots, S \tag{76}$$

Where, y^i is the optimal solution of the master problem for iteration i.

Step 2: For s = 1, …, S, solve the sub-problem corresponding to y^i and ξ^s. The sub-problem is stated as follows.

$$Q\left(y^i, \boldsymbol{\xi}^s\right) = \min\left(\sum_{r\in R} c_r x_r\,(\boldsymbol{\xi}) + \sum_{t\in T} p_t\, z_t(\boldsymbol{\xi})\right) \tag{77}$$

subject to

$$\sum_{r\in R_t} x_r(\boldsymbol{\xi}) + z_t(\boldsymbol{\xi}) \geq b_t(\boldsymbol{\xi}) \quad \forall t \in T \qquad (\alpha) \tag{78}$$

$$\sum_{r\in R_t} \theta_{kr}\, x_r(\boldsymbol{\xi}) \leq b_t(\boldsymbol{\xi})\, y_k^i \quad \forall t \in T,\ k \in N_r; r \in R_t \qquad (\beta) \tag{79}$$

$$\sum_{r\in R} \theta_{kr}\, x_r(\boldsymbol{\xi}) \leq C_k y_k^i \quad \forall k \in N \qquad (\gamma) \tag{80}$$

$$\sum_{r:\eta_{kr}=-1} x_r(\boldsymbol{\xi}) - \sum_{r:\eta_{kr}=1} x_r(\boldsymbol{\xi}) \leq \delta \sum_{r:\eta_{kr}=-1} x_r(\boldsymbol{\xi}) \quad \forall k \in N \qquad (\mu) \tag{81}$$

$$\sum_{r:\eta_{kr}=1} x_r(\boldsymbol{\xi}) - \sum_{r:\eta_{kr}=-1} x_r(\boldsymbol{\xi}) \leq \delta \sum_{r:\eta_{kr}=1} x_r(\boldsymbol{\xi}) \quad \forall k \in N \qquad (\lambda) \tag{82}$$

$$\sum_{r\in R} \theta_{kr}\, x_r(\boldsymbol{\xi}) \geq v\, y_k^i \quad \forall k \in N \qquad (\pi) \tag{83}$$

$$\sum_{t\in T} z_t(\boldsymbol{\xi}) \leq \rho \sum_{t\in T} b_t\,(\boldsymbol{\xi}) \qquad (\omega) \tag{84}$$

$$x_r(\boldsymbol{\xi}) \text{ integer} \quad \forall r \in R \tag{85}$$

$$z_t(\boldsymbol{\xi}) \text{ integer} \quad \forall t \in T \tag{86}$$

In the above formulation, the Greek letters in parentheses are the corresponding dual variables of the sub-problem. The objective function values of the above formulation solved for S samples are used in Equation (87) to obtain an upper bound.

$$\hat{f}_S(y^i) = \sum_{k\in N} f_k y^i + \frac{1}{S}\sum_{s=1}^{S} Q(y^i, \boldsymbol{\xi}^s) \tag{87}$$

Where, $\hat{f}_S(y^i)$ is the objective function value corresponding to the current feasible solution y^i. If $\hat{f}_S(y^i) < ub$, the upper bound will be updated to $ub = \hat{f}_S(y^i)$ and the incumbent solution is set to $\hat{y} = y^i$.

The dual sub-problem formulation is presented below and uses the following notation.

<u>Sets</u>

O = set of origin nodes of all composites,

D = set of destination nodes of all composites,

N = set of nodes k,

R_d= set of deadhead composites,

T_k= set of O-D pairs that their composites have visited node k,

$$\begin{aligned} Maximize\ Z\ = & \sum_{t\in T} b_t(\boldsymbol{\xi})\alpha_t + \sum_{k\in N}\sum_{t\in T_k} b_t(\boldsymbol{\xi})\hat{y}_k\beta_k + \sum_{k\in N} C_k\hat{y}_k\,\gamma_k \\ & + \sum_{k\in N} v\hat{y}_k\,\pi_k + \rho\sum_{t\in T} b_t\,(\boldsymbol{\xi})\,\omega \end{aligned} \tag{88}$$

Subject to

$$\alpha_t - \mu_o + \mu_d + \lambda_o - \lambda_d + \pi_o + \pi_d + \gamma_o + \gamma_d + \sum_{k\in Nr} \beta_k \le c_r \quad \forall\, r \in R \tag{89}$$

$$-\mu_o + \mu_d + \lambda_o - \lambda_d \leq c_r \quad \forall\, r \in R_d \tag{90}$$

$$\alpha_t + \ \omega \ \leq p_t \qquad \forall\, t \in T \tag{91}$$

$$\alpha \geq 0, \beta \ \leq 0, \gamma \leq 0, \mu \leq 0, \lambda \leq 0, \pi \geq 0, \omega \leq 0 \tag{92}$$

Step 3: With the new lb, ub, and a pre-specified tolerance $\delta \geq 0$, if $ub - lb < \delta$, the algorithm stops. The optimal solution and the optimal objective function value will be $\hat{y}$ and ub, respectively; otherwise proceed to Step 4.

Step 4: Compute the cut coefficients using the optimal dual solutions for the sub-problem solved for y^i and $\boldsymbol{\xi}^s$. Update the iteration counter $i = i+1$ and go to step 1.

5.4.3.1 Difficulties in Applying Benders Decomposition

Cutting plane algorithms such as Benders decomposition require enhancement strategies to improve their convergence. In general, decomposition techniques tend to oscillate between different sections of the feasible region in early iterations. Moreover, these iterations are highly time-consuming in particular for the problems with large number of integer variables (such as the RP installation variables in our formulation). Therefore, the implementation of Benders decomposition requires being enhanced using accelerating strategies. We observed a very slow convergence behavior of the Benders decomposition method in our application, and therefore we applied two enhancement strategies.

In the first strategy, referred to as cut disaggregation, we added S cuts at each iteration instead of adding only one cut per iteration to the master problem. The S cuts were obtained by solving the sub-problem for scenario $s = 1,\ldots, S$. According to Tang et al. (2013), these cuts include exactly the same information as the primal Benders cut, but will also impose a more accurate restriction on the solution space of the master problem.

In the second strategy, we solved the problem for the deterministic scenario (considering the expected value of demand) and obtained a solution on the number of RPs. Then, Benders decomposition is applied with a fix number of open RPs. However, considering that instances have 25, 50 and 100 nodes as potential RP locations, searching for RP locations was dramatically time-consuming. For example, knowing that the number of RPs in a deterministic solution for a 25-node network instance was 13, the master problem tried to investigate all combinations of selecting 13 out of 25 nodes which results in 5,200,300 possibilities.

Since using accelerating techniques did not provide a significant reduction in computational time in our preliminary testing, we concluded that Benders decomposition would not be an appropriate approach to solve the SAA problem presented in Section 5.4.2. We observed that solving the standard implementation of the SAA problem is much faster than applying the accelerated Benders decomposition approach for this problem. As previously mentioned, the reason behind this observation is the large number of integer variables to locate the RPs.

5.5 Computational Experiments

In order to evaluate the performance of SAA algorithm in solving the stochastic capacitated TLRND-MD problem under demand uncertainty, we designed a set of experiments as follows.

5.5.1 Computational Experiments Setting

We have randomly generated a set of benchmark instances that consider different levels of magnitude for the network and SAA parameters. Table 5 presents the levels of the factors that have been examined in order to create distinct scenarios of the stochastic capacitated TLRND-MD problem. The parameters related to network design were fixed across all instances including limitations on local and lane distances for relay network movements, percentage of out-of-route miles allowed, number of RPs allowed to be visited in a relay network route, equipment imbalance allowed, minimum volume required to open RPs, maximum proportion of PtP loads, fixed RP installation cost, and per mile transportation costs. These parameters and their values are presented in Table 6. The capacity parameter provided in this table is determined based on the number of O-D pairs in the network and is set in a way that each RP would be able to serve several load demand in the network.

Table 5: Computational Experiment Factors and Levels.

Factor	**Levels**
Number of Nodes	25 and 50 nodes are uniformly distributed in a 1×1 rectangular area
Number of O-D Pairs	10%, 20% and 40% of all possible O-D pairs
Freight Demand	Uniformly distributed value between 10 and 20
Sample Size	20, 50 and 100 scenarios
Number of Samples	5 samples
Upper Bound Sample Size	200

Table 6: Fixed Parameter Values Used in Computational Experiments.

Parameter	**Value**
Local distance limitation (distance units)	0.3
Lane distance limitation (distance units)	0.5
Maximum percentage of out-of-route miles allowed (%)	25
Number of RPs allowed to be visited	2
Equipment imbalance allowed (%)	0
Minimum volume required to open RPs (as a % of total volume in the network)	0
Maximum proportion of PtP loads allowed (%)	100
Fixed installation cost of RPs (cost units)	10

Per mile local transportation cost (cost units)	1
Per mile lane transportation cost (cost units)	1.3
Per mile PtP transportation cost (cost units)	1.5
Capacity at RPs	$\frac{4 * 20 * \#\text{ of O} - \text{D Pairs}}{\#\text{ of Nodes}}$

5.5.2 Computational Results

In this section, we present the results of the computational experiments that we completed to evaluate the performance of the SAA algorithm. Recall from Section 5.4.2 that the SAA algorithm solves *M* instances of the approximating stochastic program (Equation 69) each having *S* sample scenarios. Then, to investigate how accurate is the model in representing the true objective function, a candidate solution is selected out of the *M* solutions and solved for *S'* sample scenarios to obtain an approximation of the objective function upper bound. In our experiments, we used *S*=20, 50, 100, *M*= 5, and *S'*= 200. As the results below indicate, these values were sufficient to obtain high quality solutions. Table 7 shows the sizes of the deterministic equivalents of the SAA problems for one instance with 25 nodes and 60 O-D pairs, and illustrates the complexity of solving the SAA problem for different values of *S*. Note how large samples can dramatically change the problem size.

Table 7: Size of the Deterministic Equivalent of the SAA problem (*N*=25, *L*=60).

Sample Size	Constraints	Variables
1	361	663
20	5,301	6,895
50	13,101	16,735
100	26,101	33,135

In the computational experiments, we evaluated performance measures related to the SAA method such as SAA optimality gap, standard deviation for the SAA optimality gap, and SAA computational time. In addition, we analyzed measures describing the expected performance of the system and the design of the network when incorporating demand uncertainty. For the latter, we analyzed the difference between the expected total network cost in the deterministic and stochastic scenarios as well as the difference on the number of relay points selected by the two scenarios.

We first aimed to assess the convergence of the SAA algorithm based on different values of the sample size *S*. This was motivated by the intuition that increasing the sample size *S* would result in a better approximation of the objective function and tighter optimality gap which would trade-off with a higher computational time. Figure 17 and Figure 18 present the optimality gap obtained for different values of *S* corresponding to 25-node and 50-node network instances, respectively. We observe that the optimality gap for all of the 25-node network instances is below 0.4% which is sufficiently small and yields an accurate estimation of the objective function. In particular, we observe that by increasing the sample size, the optimality gap becomes tighter.

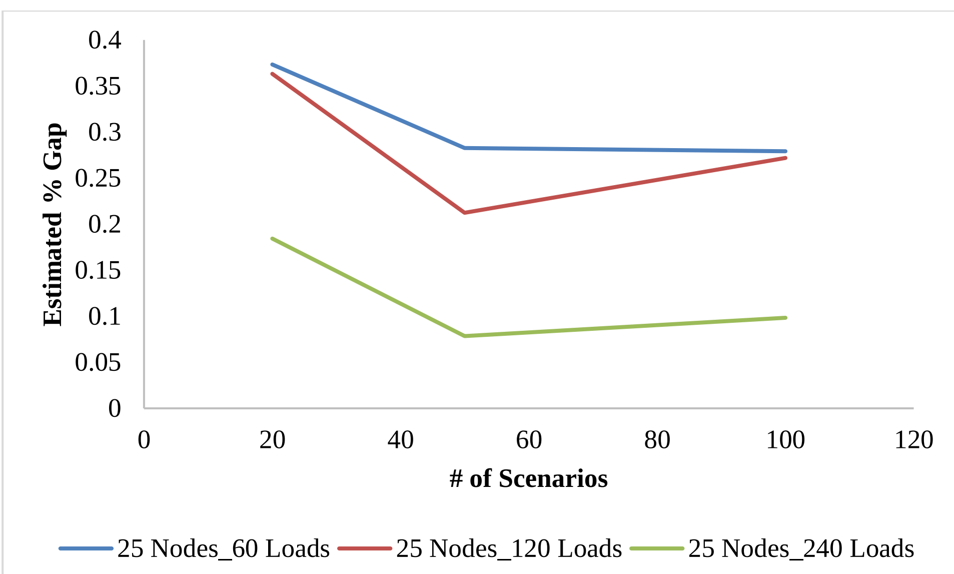

Figure 17: Optimality Gap for 25-Node Instances with Different Values of *S* (*N*=25).

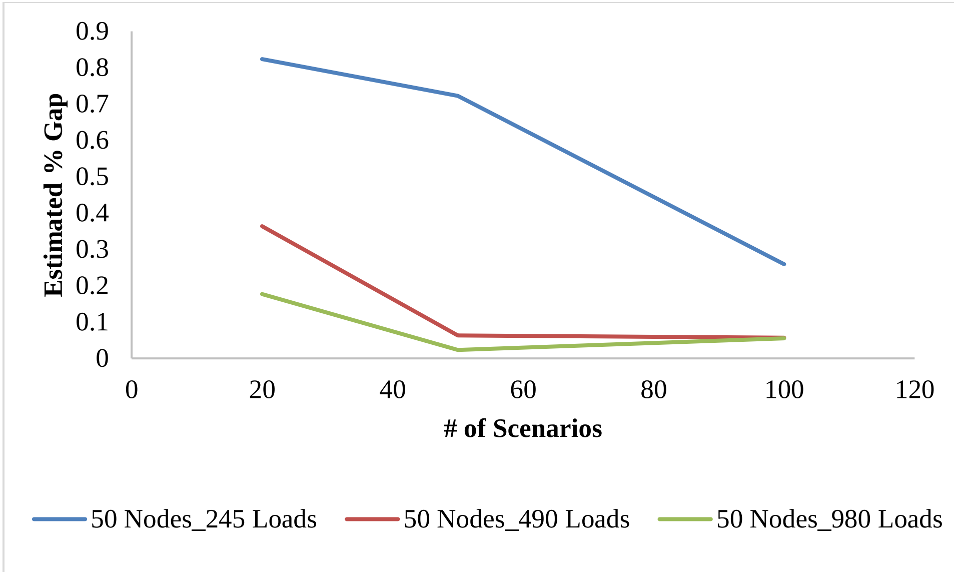

Figure 18: Optimality Gap for 50-Node Instances with Different Values of *S* (*N*=50).

As shown in Figure 18, the largest optimality gap obtained for 50-node network instances is about 0.9%, and the gaps become smaller as we increase the number of demand realizations. We also noticed a difference between the trends in Figure 17 and Figure 18. There is a considerable reduction in the optimality gap when the sample size increases from 50 to 100 scenarios for 50-node network instances with 245 O-D pairs. In Figure 17, we did not observe such sudden change in the optimality gap. Overall, Figure 17 and Figure 18 present similar trends in terms of optimality gap.

Figure 19 and Figure 20 show the estimated standard deviation for the optimality gap obtained for different values of *S* corresponding to 25-node and 50-node network instances, respectively. Standard deviation of the SAA gap provides a useful measure to investigate the variability of the gap for different samples drawn for demand realizations. We observe that in all cases except for the case with 50 nodes and 490 O-D pairs, as the sample size increases, the corresponding standard deviation for the optimality gap is significantly reduced. In this particular case, as we increase the sample size from 50 to 100, the standard deviation increases.

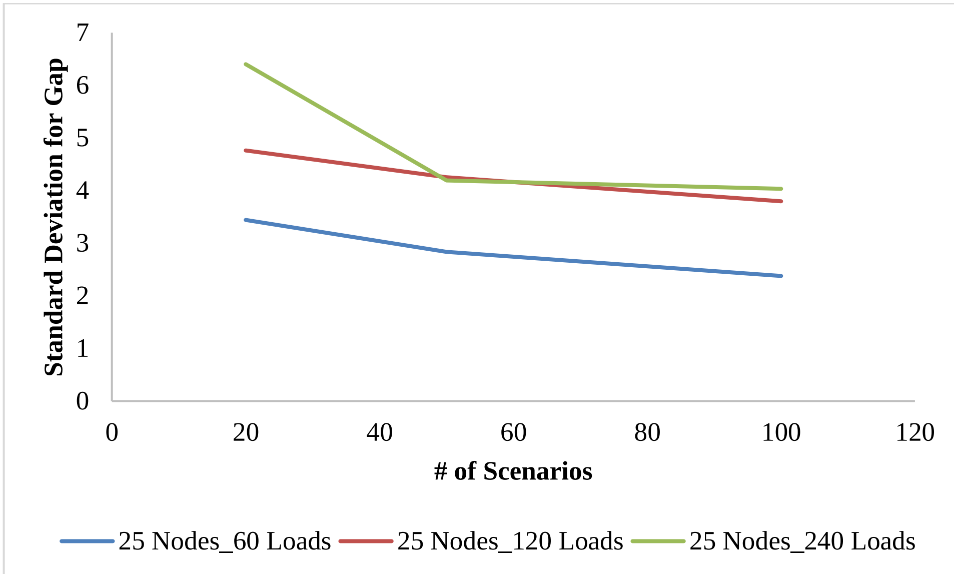

Figure 19: Standard Deviation for the Optimality Gap for 25-Node Instances with Different Values of *S* (*N*=25).

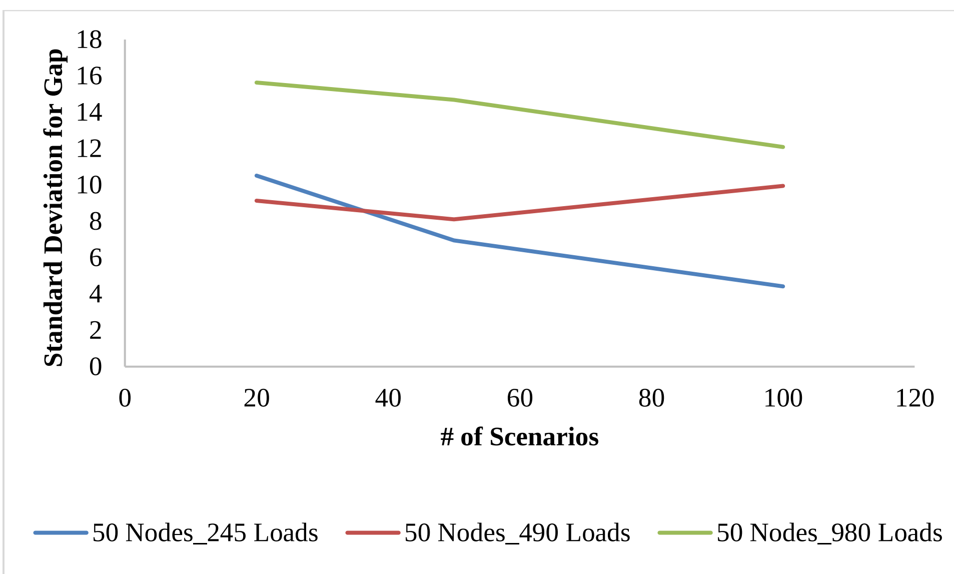

Figure 20: Standard Deviation for the Optimality Gap for 50-Nodes Instances with Different Values of *S* (*N*=50).

We now look at the computational performance of the solution method. Figure 21 and Figure 22 present the total CPU time required for the SAA algorithm for different values of *S* corresponding to 25-node and 50-node network instances, respectively. From these figures, we observe that the computational complexity for solving the SAA problems seems to increase as the sample size as well as the number of O-D pairs in the network increases.

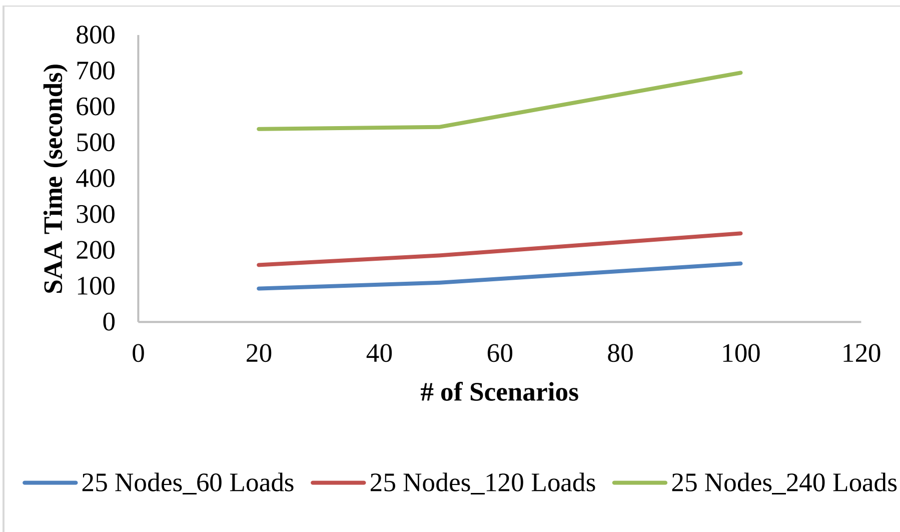

Figure 21: Total CPU Time for 25-Node Instances with Different Values of *S* (N=25).

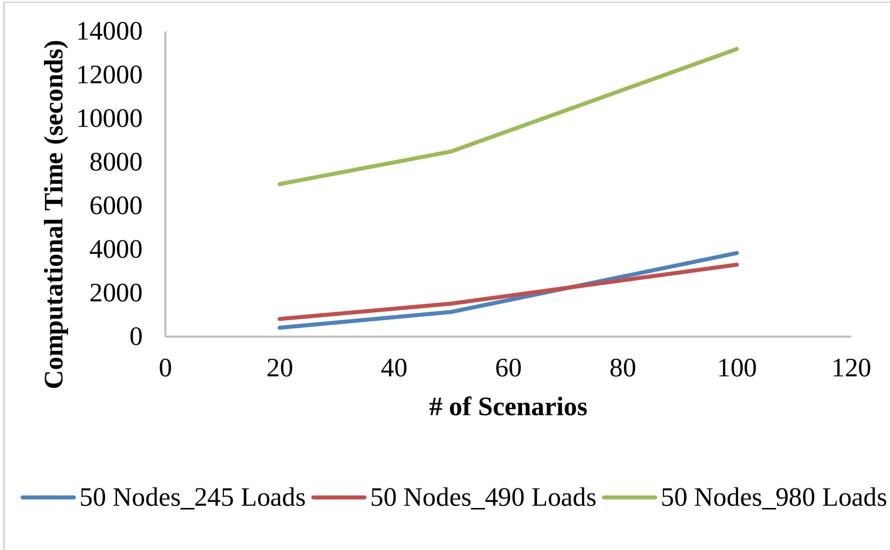

Figure 22: Total CPU Time for 50-Node Instances with Different Values of *S* (*N*=50).

In order to obtain insights about the impact of uncertainty on the solutions for the capacitated TLRND-MD problem, we present numerical results in Table 8 and Table 9. The values presented in Table 8 are averages of the results for 10 network instances under each parameter combination for problems with 25-node network instances. Due to computational complexity in solving 50-node problem sizes, we averaged the results of 5 network instances and reported those in Table 9. In Table 8 and Table 9, the number of O-D pairs and sample sizes are provided in the first two columns. Then, the objective values obtained for the deterministic expected value problem (EVP) and the SAA algorithm are presented in the next two columns. The EVP is the deterministic capacitated TLRND-MD problem presented in Section 5.4. Moreover, we report the % optimality gap for the SAA algorithm solutions. An important measure on the SAA optimality gap is the error intervals constructed using the SAA optimality gaps and the standard deviation (i.e., gap ± $2*\sigma_{gap}$) which are also presented in Table 8 and Table 9. The error intervals provide a useful measure of the variability of the optimality gap from the underlying sample. Tight error intervals represent small expected % gap for the solutions obtained by repeating the SAA algorithm for different samples of demand (i.e. less variation of % optimality gap with respect to different samples drawn for demand realizations). Finally, we also present the average number of open RPs in the EVP and SAA solutions.

Table 8: Comparison of Results Obtained for Deterministic and Stochastic Problems (N=25).

# of O-D Pairs	Sample Size	Objective Value EVP	Objective Value SAA	Optimality % Gap	Error Intervals for Gap at $\pm 2^*\sigma_{gap}$	# of RPs Open
60	1	905.51	-	-	-	11.3
	20	-	901.72	0.37	(-3.12, 10.65)	11.3
	50	-	903.05	0.28	(-2.94, 8.4)	11.2
	100	-	904.64	0.28	(-1.37, 8.14)	11.2
120	1	1936.3	-	-	-	16.2
	20	-	1881.49	0.36	(-2.91, 16.13)	15.4
	50	-	1882.26	0.11	(-6.4, 10.60)	15.6
	100	-	1884.71	0.27	(-2.27, 12.92)	15.5
240	1	2926.87	-	-	-	17.5
	20	-	2918.46	0.18	(-6.88, 18.72)	17.4
	50	-	2922.6	0.08	(-6.37, 10.40)	17.4
	100	-	2935.83	0.09	(-5.3, 10.83)	17.2

The results presented in Table 8 and Table 9 show that the solutions obtained for the deterministic EVP are sub-optimal compared to the SAA solutions that incorporate demand uncertainty. Moreover, in all cases except for 100 scenarios of network instances with 240 O-D pairs with demand (e.g., loads), the SAA algorithm achieves better solutions compared to the deterministic EVP. We observed that the SAA optimality gap for 25-node network instances does not exceed 0.37% and for the network instances with 240 O-D pairs, the SAA optimality gap becomes as small as 0.09%. Another interesting observation in Table 8 relates to the error intervals for the optimality gap of the solution obtained by the SAA algorithm. According to the results, the upper bounds of the error intervals never exceed 18.72 and an error of this magnitude represents a sufficiently small % gap with regard to the magnitude of the corresponding objective value (i.e. about 0.6%).

Table 9: Comparison of Results Obtained for Deterministic and Stochastic Problems (*N*=50).

# of O-D Pairs	Sample Size	Objective Value EVP	Objective Value SAA	Optimality % Gap	Error Intervals for Gap at ± 2*σ_{gap}	# of RPs Open
245	1	2734.37	-	-	-	26
	20	-	2701.39	0.82	(1.43, 43.48)	25.1
	50	-	2719.28	0.72	(5.75, 33.57)	25.1
	100	-	2716.47	0.26	(-1.790, 15.87)	25
490	1	5095.11	-	-	-	33.3
	20	-	5061.59	0.36	(0.226, 36.77)	32.9
	50	-	5089.78	0.06	(-13.00, 19.41)	33.7
	100	-	5081.75	0.06	(-16.97, 22.80)	31.2
980	1	9459.42	-	-	-	35.3
	20	-	9439.11	0.18	(-14.46, 48.06)	35.1
	50	-	9474.79	0.02	(-27.16, 31.59)	35.5
	100	-	9482.07	0.05	(-18.96, 29.37)	35.5

Generally, the same observations for Table 8 were made about the results presented in Table 9. We observed that except for the instances with 490 and 980 O-D pairs, the SAA solutions yield better objective values compared to the deterministic EVP. The estimated % optimality gap for 50-node network instances does not exceed 0.82%. Moreover, the largest upper bound in the error intervals is 48.06 which provides a reasonably small optimality % gap with respect to the magnitude of the objective function value.

We also observed that incorporating demand uncertainty using the stochastic program affected the number of the RPs to be open in the network when compared to the deterministic solutions. The results in the last column of both Table 8 and Table 9 show that the stochastic solutions tend to open fewer RPs when compared to the deterministic solution. These results confirmed that not accounting for the uncertainty can yield sub-optimality in the design of the network.

In terms of the design of network and the location of relay points, we observed that most of the relay points that were open in the deterministic solution remained open in the stochastic scenarios. In some instances, we observed that a few of the open relay points in the deterministic solution were replaced with different relay points in the SAA solutions. The new relay points were located very closely to the replaced ones and in some cases two relay points were replaced with one new relay point. The reason for this is the low traffic volume of shipments at those replaced relay points that now are being aggregated and moved through the new relay point in the SAA solution. This observation justifies opening slightly fewer relay points in the SAA solutions that was previously discussed. In addition since capacity is limited at the relay points, in some cases for the SAA solutions, a new relay point is added that is located very close to one of the relay points which is still open in the SAA solution as compared to the deterministic solution. This implies that the capacity at the relay points in the deterministic solution has been fully utilized so that a new relay point in the vicinity of the open relay point is needed to allow dispatching the loads.

In addition to the set of instances for which we presented the computational results above, we attempted to solve larger network instances with 100 nodes and 10% O-D pair density and 20 scenarios of demand realizations. The solution times for instances of this size were dramatically affected by the SAA algorithm, so we set a time limit of three hours to obtain a feasible solution and recorded the gap at that point. Even with the early termination of the optimization, we obtained an average of 0.28% optimality gap for these instances. It should be noted that due to the computational complexity, we only averaged solutions of 5 instances instead of 10 instances for the 100-node network instances.

5.6 Conclusions and Future Research

In this paper, we introduced the stochastic capacitated TLRND-MD problem under demand uncertainty. We developed a two-stage stochastic program considering installation decisions as first-stage decisions and transportation decisions as second-stage decisions. A SAA algorithm was implemented to approximate the true problem. The SAA algorithm allowed us to obtain solutions to problems with a very large number of scenarios. According to the computational results, the SAA solution approach is efficient and yields sufficiently small optimality gaps within tight confidence intervals. We obtained high quality solutions for benchmark instances with 25 and 50 nodes with optimality gaps less than 0.37% and 0.82%, respectively. Moreover, we showed that the SAA algorithm provides solutions that outperform those of the deterministic expected value problem showing that not accounting for uncertainty results in sub-optimal solutions. In this study, incorporating uncertainty resulted in opening slightly fewer number of relay points in the network when compared to deterministic solutions. The reason for this is that in some SAA solutions, a few relay points with low shipment traffic from the deterministic solution were replaced with one new relay point located in the vicinity of the replaced ones. The new relay point allows moving the aggregated shipment traffic that moved through the relay points in the deterministic solution. A potential future research direction to extend this study is to investigate the use of other probability distributions to describe demand uncertainty and study the effects of the choice of probability distribution on the performance measures and network characteristics. Moreover, since a Benders decomposition method failed at solving large size instances of the proposed SAA problem, developing a solution approach that efficiently solves large network instances is another relevant avenue for future research.

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6 A Stochastic Analysis via Robust Optimization for Truckload Relay Network Design under Demand Uncertainty[4]

6.1 Abstract

Stochastic optimization and robust optimization are the two main approaches in the literature to analyze and optimize systems under uncertainty. Stochastic optimization allows us to describe uncertainty using probability distributions while in robust optimization uncertainty is described deterministically using uncertainty sets. In this research, we develop an approach that bridges stochastic and robust optimization to solve the strategic truckload relay network design problem with mixed fleet dispatching where demand and the variability parameter in the robust counterpart formulation are the uncertain parameters.

Keywords: truckload transportation, relay networks, uncertainty, stochastic optimization, robust optimization

6.2 Introduction

RPs in relay networks play the role of hubs in hub-and-spoke (H&S) transportation networks except that in relay networks no consolidation of loads at RPs occurs when full truckloads are shipped from origin to destination. Dispatching full truckloads over a relay network is an alternative to traditional Point-to-Point (PtP) shipments, where a single driver delivers a load from origin to destination. In relay networks, several drivers are responsible for different legs of the trip of a truckload which is expected to reduce driver tour lengths and alleviate the high driver turnover rate in full truckload transportation (Üster and Maheshwari 2007). In the truckload relay network design (TLRND) problem, the strategic decision of locating RPs as well as the tactical decision

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[4] This work will be submitted for publication to Transportation Research Part E

of routing the commodities are made such that the total installation and transportation cost is minimized (Üster and Maheshwari 2007).

A hybrid configuration integrating PtP and relay network dispatches has also been studied and has been shown to outperform a pure PtP shipment system or a pure relay network. Vergara and Root (2013) presented a mathematical formulation for the truckload relay network design with mixed fleet dispatching (TLRND-MD) problem that also considers the mode of delivery (i.e., PtP or via the relay network) as another decision variable.

However, the TL transportation industry is exposed to significant uncertainty which has not been explicitly considered in much of the existing literature related to the TLRND and TLRND-MD problems. The design of relay networks with deterministic parameters might result in solutions that are suboptimal in practice. For example, customer demand, transportation cost, and travel times can be quite uncertain and will affect routing decisions, while the strategic location of RPs is often made regardless of the uncertainty. Considering this, Chapter 4 and Chapter 5 investigated the use of a robust optimization and a two-stage stochastic optimization approach to analyze the performance of stochastic TLRND-MD and capacitated TLRND-MD systems, respectively. In Chapter 4, the robust optimization approach introduced by Bertsimas and Sim (2003) that allows the system designer to adjust the level of conservatism was utilized when assuming that the demand fluctuates in a symmetric uncertainty set. In this approach, a variability parameter that controls the size of the uncertainty set determines the conservatism preferences of the designer. Larger values of the variability parameter result in including extreme scenarios of demand that directly affect the worst case performance measure. However, optimizing the average behavior of the system using robust optimization requires capturing the choice of values for the variability parameter which can be a major challenge. Furthermore, in Chapter 5, demand is treated as a random variable following a specific probability distribution. In this way, a large number of demand realizations are used to optimize the system with respect to the expected transportation cost over the different demand values. A two-stage stochastic optimization approach was used in Chapter 5.

In this research, we propose a framework to integrate robust optimization and stochastic optimization in which the variability parameter in the robust counterpart for the capacitated TLRND-MD problem under demand uncertainty is treated as a random variable. We assume that this parameter follows a posited probability distribution from which we can observe realizations of variability parameter values. As discussed above, robust optimization obtains worst case solutions at each level of conservatism that directly depend on the value of the variability parameter. However, since the choice of variability parameter value is a challenge, we propose to average the worst case solutions over the possible realizations of the variability parameter. As the main contribution of this paper, we aim to bridge the stochastic and robust optimization approaches within the context of designing TL relay networks and obtain an uncertainty modeling framework that minimizes the average worst case cost of the system.

The remainder of this chapter is organized as follows. In Section 6.3, a brief review of related research is presented. Section 6.4 introduces the uncertainty modeling framework proposed in this research and the corresponding mathematical formulation. Moreover, Section 6.4 presents the solution approach that has been developed. Section 6.5 describes the setting of the numerical experiments performed as well as the corresponding results and their discussion. Finally, Section 6.6 presents conclusions and provides some future work directions.

6.3 Literature Review

Alternative dispatching methods to overcome the challenges of traditional PtP delivery in TL transportation have been studied extensively in the last twenty years. Section 6.3.1 presents a review of existing work in the development of relay networks as an alternative dispatching configuration for TL transportation. Earlier studies in this context are dedicated to simulation approaches while more recently researchers have attempted to develop mathematical programming formulations for this network configuration. Then, Section 6.3.2 summarizes research that incorporates uncertainty by means of the application of robust optimization and stochastic optimization.

6.3.1 Relay Networks for Truckload Transportation

Taha and Taylor (1994) introduced the hub-based configuration of relay networks in TL dispatching as an alternative dispatching method to PtP delivery using a simulation approach. Extending this work, Taylor et al. (1995) and Harit et al. (1995) completed additional computational experiments and provided more insights on the potential of hub-based networks in the TL trucking industry. Later, Taylor et al. (1999) defined different scenarios made of combinations of three methods: delivery lanes, zone dispatching, and H&S networks and used discrete event simulation to investigate the effects of different scenarios on the operations in the network. In similar studies, Taylor and Meinert (2000) used a simulation approach to investigate the performance of several single-zone configurations for TL dispatching, while Taylor et al. (2001) evaluated the performance of different zone dispatching configurations.

These preliminary studies motivated the development of algorithmic approaches to design TL relay networks. For instance, Hunt (1998), Ali et al. (2002), and Tsu and Agarwal (2009) designed TL relay networks using algorithmic and heuristic approaches to determine the number and location of RPs in the network. These studies confirmed the benefits of relay networks in improving the network operations and in particular suggested the practicality of partial TL relay networks that integrate traditional PtP with relay networks.

TL relay network design using a mathematical programming approach was originally studied by Üster and Maheshwari (2007) who developed the first mathematical formulation for the strategic design of TL relay networks. Then, Üster and Kewcharoenwong (2011) modified the model presented in Üster and Maheshwari (2007) and developed an algorithm based on Benders decomposition to solve larger instances. Later, Vergara and Root (2012) used a composite variable model (CVM) to reduce the size of the problem by only considering the feasible routes as composite decision variables. They also observed that an integrated configuration of the relay network system with the PtP system would be beneficial. Based on this observation, Vergara and Root (2013) extended the mathematical programming formulation of the TLRND problem to incorporate mixed-fleet dispatching and extensively studied the strengths of the hybrid system. In their model, the dispatching mode for loads via the PtP method or via the relay network was also a decision variable. In another study, Melton and Ingalls (2013) formulated a highway transportation network using a mixed integer quadratic program trying to locate the RPs in a relay network dispatching system. More recently, Mokhtari and Vergara (2014) incorporated uncertainty in the TLRDN-MD problem using a robust optimization approach with controllable level of uncertainty. A symmetric uncertainty set was used for the uncertain demand and solutions were obtained for the worst case value of demand for each origin destination (O-D) pair.

6.3.2 Integrating Robust Optimization and Stochastic Optimization for Uncertainty Modeling

Two well-established approaches to explicitly incorporate uncertainty in mathematical modeling are stochastic optimization and robust optimization. Dantzig (1955) first introduced stochastic programming to account for uncertainty when the distribution of the uncertain parameter is available. On the other hand, when uncertainty can be defined in a set, robust optimization is a promising approach in terms of computational tractability. This technique was first introduced by Soyster (1973).

We note that the applicability of stochastic optimization depends on the ability to describe the uncertainty using probability distributions. As such, when it is difficult to have access to such information there is a need for an alternative uncertainty modeling approach. Given this challenge, robust optimization which is a set-based approach that assumes the uncertain parameters lie within some set has been introduced to model uncertainty. Robust optimization has been thoroughly studied and extended by several research studies in the last decade. The most conservative robust optimization accounts for the worst case scenario of the uncertain parameter. Ben-Tal and Nemirovski (1998), Ben-Tal and Nemirovski (1999), EI-Ghaoui and Lebret (1997), and El Ghaoui et al. (1998) are the leading studies in introducing this method. This approach aims to optimize the worst case performance of the system which in most cases leads to solutions that are too conservative. To alleviate conservatism, Bertsimas and Sim (2003) developed a less conservative robust optimization approach assuming that not all the coefficients in a mathematical program that are subject to uncertainty will take their worst case scenario. In this approach the level of uncertainty is controllable using a variability parameter. The advantage of robust optimization is that for the mathematical program with uncertain parameters a deterministic equivalent is developed that is known as robust counterpart. A comprehensive review on the evolution of robust optimization can be found in Ben-Tal et al. (2009) and Bertsimas et al. (2011).

The connection between robust optimization and the classical stochastic analysis approaches has been the subject of several recent investigations. In particular, Bandi et al. (2015) referred to an open challenge in the analysis of queueing networks under the probabilistic framework. According to Kingman (2009), if the arrival process in a queuing system cannot be modeled well using a Poisson process or one of its near relatives, it will be a challenge to model or analyze it simply and effectively. Kingman (2009) suggests describing arrival times in a different way than positing a probability distribution for them.

Bandi et al. (2015) propose a framework to model queueing systems based on optimization theory. They model the uncertainty in the arrivals and services using polyhedral uncertainty sets that allowed them to model heavy-tailed behavior characterized by bursts of rapidly occurring arrivals and long service times. They took a worst-case robust optimization approach to obtain closed-form upper bounds on the system time in a multi-server queue. However, more relevant to our research is the extension presented in Bandi et al. (2014). In this study, the authors build on their previous analysis on robust queuing theory and model the service/arrival process parameters via polyhedral uncertainty sets. These uncertainty sets are characterized by parameters that control the degree of conservatism of the model and the inter-arrival and service times belong to such uncertainty sets. Moreover, they break new ground and present an approach to average worst case values of system time. They carry out the averaging approach by treating the parameters characterizing the uncertainty sets as random variables and then averaging the worst case values obtained at different degrees of conservatism. This methodology provides good approximations for the expected system time relative to simulation.

In the current research, we aim to incorporate uncertainty in an extension of the TLRND-MD problem considering capacity at the RPs by integrating robust optimization and stochastic optimization. Motivated by previous studies, and in particular Bandi et al. (2014), we take advantage of the tractability of robust optimization and the strengths of stochastic optimization to propose an integrated framework to analyze and optimize average worst case performance of capacitated TLRND-MD problem under uncertainty.

6.4 Proposed Framework for Incorporating Uncertainty in Capacitated Robust TLRND-MD

In this research, we propose to analyze the average case behavior of TLRND-MD under demand uncertainty by averaging over the possible realizations of the variability parameter. In this framework, we first adopt the robust counterpart to the integer programming model for the TLRND-MD problem presented in Chapter 4 when demand is uncertain and extend it to the robust counterpart corresponding to the capacitated version of the TLRND-MD problem. Then, in this formulation, we try to optimize the average behavior of the system under variability parameter uncertainty. In this model, demand uncertainty is defined using symmetric uncertainty sets, while the uncertainty of the variability parameter is described using a uniform probability distribution. Therefore, the uncertainty of demand and of the variability parameter is incorporated using robust optimization and stochastic optimization, respectively.

The base deterministic model for capacitated TLRND-MD problem was introduced in Chapter 5.

6.4.1 Mathematical Formulation

In the current research, we first assume that demand is not constant anymore and can fluctuate in a symmetric interval centered on the expected value of demand for each load. We adopt the robust counterpart associated with the TLRND-MD problem developed in Chapter 4, and extend it to a robust capacitated TLRND-MD formulation when a limitation is enforced on the capacity of RPs. Then, in the robust counterpart formulation, we assume that the variability parameter, Γ, that allows choosing a trade-off between conservatism and performance is also subject to uncertainty following a uniform probability distribution. So, in order to incorporate uncertainty in the value of this parameter, we use the two-stage stochastic optimization approach previously used in Chapter 5 that optimizes the system's expected performance under uncertainty. The final two-stage stochastic program of the capacitated RO-TLRND-MD problem is as follows. For a review of the notations used in this model and the procedure to obtain the final formulation, we refer the reader to Chapter 4 and Chapter 5.

$$Minimize\ Z' = E_{\xi}\left(\sum_{r\in R} c_r x_r(\boldsymbol{\xi}) + \sum_{t\in T} p_t\, z_t(\boldsymbol{\xi})\right) + \sum_{k\in N} f_k y_k \tag{93}$$

subject to

$$\sum_{r\in R_t} x_r(\boldsymbol{\xi}) + z_t(\boldsymbol{\xi}) - \Gamma_t(\boldsymbol{\xi}) q_t(\boldsymbol{\xi}) - p_t(\boldsymbol{\xi}) \geq b_t \qquad \forall t \in T \tag{94}$$

$$\sum_{r\in R_t} \theta_{kr}\, x_r(\boldsymbol{\xi}) \leq (b_t + \hat{b}_t)\ y_k \qquad \forall t \in T,\ k \in N_r; r \in R_t \tag{95}$$

$$\sum_{r\in R_t} \theta_{kr}\, x_r(\boldsymbol{\xi}) \leq C_k y_k \qquad \forall t \in T,\ k \in N_r; r \in R_t \tag{96}$$

$$\sum_{r:\eta_{kr}=-1} x_r(\boldsymbol{\xi}) - \sum_{r:\eta_{kr}=1} x_r(\boldsymbol{\xi}) \leq \delta \sum_{r:\eta_{kr}=-1} x_r(\boldsymbol{\xi}) \qquad \forall k \in N \tag{97}$$

$$\sum_{r:\eta_{kr}=1} x_r(\boldsymbol{\xi}) - \sum_{r:\eta_{kr}=-1} x_r(\boldsymbol{\xi}) \leq \delta \sum_{r:\eta_{kr}=1} x_r(\boldsymbol{\xi}) \qquad \forall k \in N \tag{98}$$

$$\sum_{r\in R} \theta_{kr}\, x_r(\boldsymbol{\xi}) \geq v\, y_k \qquad \forall k \in N \tag{99}$$

$$\sum_{t\in T} z_t(\boldsymbol{\xi}) - \rho(\Gamma'(\boldsymbol{\xi})q'(\boldsymbol{\xi}) + p'(\boldsymbol{\xi})) \leq \rho \sum_{t\in T} b_t \tag{100}$$

$$q_t(\boldsymbol{\xi}) + p_t(\boldsymbol{\xi}) \geq \hat{b}_t \quad \forall t \in T \tag{101}$$

$$q'(\boldsymbol{\xi}) + p'(\boldsymbol{\xi}) \geq \rho \sum_{t\in T} \hat{b}_t \tag{102}$$

$$q_t(\boldsymbol{\xi}) \geq 0\,, \;\; p_t(\boldsymbol{\xi}) \geq 0 \quad \forall t \in T \tag{103}$$

$$q'(\boldsymbol{\xi}) \geq 0 \;\; , p'(\boldsymbol{\xi}) \geq 0 \tag{104}$$

$$x_r(\boldsymbol{\xi}) \text{ integer} \qquad \forall r \in R \tag{105}$$

$$y_k \in \{0,1\} \qquad \forall k \in N \tag{106}$$

$$z_t(\boldsymbol{\xi}) \text{ integer} \qquad \forall t \in T \tag{107}$$

Note that in the above model we assume that demand between the O-D pairs fluctuates in a symmetric interval centered around the nominal (i.e., expected) value of demand. In other words, demand realization for O-D pair *t* can be presented as $b_t{}' \in [b_t - \hat{b}_t, b_t + \hat{b}_t]$, where b_t is the nominal (i.e., expected) value of demand and $\hat{b}_t$ is the amount of expected fluctuation from the mean value for O-D pair *t*. Robust optimization attempts to protect the solution against all realizations of the uncertain parameter satisfying the uncertainty set and selects the realizations of demand that produce the worst case scenario.

Moreover, in the proposed framework in this research, we treat the variability parameter Γ as a random variable following some probability distribution. We define $\boldsymbol{\xi} = (\xi^1, \xi^2, \dots, \xi^S)$ as a vector consisting of Γ_t values for *S* different scenarios for each O-D pair *t*. In this formulation, $\Gamma_t(\boldsymbol{\xi})$ is a random variable representing the variability of demand for O-D pair *t* under each scenario in $\boldsymbol{\xi}$. In the two-stage stochastic program, dispatching decisions are considered as the second-stage decisions that need to be made after realizing the values of Γ_t. Therefore, we need to consider dispatching decision variables (i.e., composites and PtP movements) for each possible scenario ξ^s of Γ_t. For example, $x_r(\xi^s)$, $\forall r \in R$ is the set of composites *r* generated for scenario ξ^s, and $z_t(\xi^s), \forall t \in T$ is the set of decision variables related to direct PtP dispatching for scenario ξ^s. This is also the case for the variables associated with robust counterpart, q_t and p_t that are transformed to $q_t(\xi^s)$ and $p_t(\xi^s)$ in the above formulation.

We are interested in optimizing the system for average worst case demand scenarios. Given that, dispatching decisions are affected by uncertainty, E_{ξ} represents the expectation of the transportation costs for the scenarios in $\boldsymbol{\xi}$. As a result, the objective function of the two-stage stochastic optimization model is to minimize the current RP installation costs, $\sum_{k \in N} f_k y_k$, and the *expected* transportation costs over the variability parameter $E_{\xi}\left(\sum_{r \in R} c_r x_r\,(\boldsymbol{\xi}) + \ \sum_{t \in T} p_t\, z_t(\boldsymbol{\xi})\right)$.

6.4.2 Solution Approach for the Two-Stage Stochastic Program of the Capacitated RO-TLRND-MD Problem

To overcome the challenge of optimizing the expected value term in the objective function, we use a Monte-Carlo simulation-based sampling algorithm known as SAA algorithm to approximate the objective function (Kleywegt et al. 2002). The SAA algorithm attempts to find high quality solutions by calculating a lower bound and an upper bound for the true objective function (Equation (93)). In this algorithm, we generate a vector $\boldsymbol{\xi}$ consisting of S realizations (i.e., scenarios) of the variability parameter. Each value $\xi^1, \xi^2, \ldots, \xi^S$ in a vector $\boldsymbol{\xi}$ represents a scenario of the variability parameter, Γ, generated from a probability distribution. The expected transportation cost over the vector $\boldsymbol{\xi}$ can be approximated using the following sample average function.

$$\frac{1}{S}\sum_{s=1}^{S}\left(\sum_{r\in R} c_r x_r\,(\boldsymbol{\xi}) + \sum_{t\in T} p_t\, z_t(\boldsymbol{\xi})\right) \tag{108}$$

Accordingly, the true objective function of the two-stage stochastic program (Equation (93)) is approximated as follows.

$$Minimize\ Z'' = \frac{1}{S}\sum_{s=1}^{S}\left(\sum_{r\in R} c_r x_r\,(\boldsymbol{\xi}) + \sum_{t\in T} p_t\, z_t(\boldsymbol{\xi})\right) + \sum_{k\in N} f_k y_k \tag{109}$$

Equation (109) is deterministic for a single sample of Γ scenarios and therefore can be solved optimally using optimization techniques. It should be noted that, each scenario of Γ requires a set of second stage variables (e.g., $x_r(\xi^s)$ and $z_t(\xi^s)$ for scenario ξ^s) as well as constraints associated with this set of variables. These characteristics of the algorithm significantly add to the size of the problem and consequently its computational complexity. In this algorithm, sample size reflects the trade-off between the quality of the optimal solution obtained with SAA, and the computational complexity.

The four steps of the SAA algorithm to obtain the optimality gap for the two-stage stochastic optimization problem are described below.

Step 1. Generate *M* independent samples of Γ scenarios each of size *S*. Solve the following SAA problem for each of the *M* samples:

$$Minimize\ Z'' = \frac{1}{S}\sum_{s=1}^{S}\left(\sum_{r\in R} c_r x_r\,(\boldsymbol{\xi}) + \sum_{t\in T} p_t\, z_t(\boldsymbol{\xi})\right) + \sum_{k\in N} f_k y_k$$

Subject to (94) – (107)

Let, v_S^j and $\hat{y}_S^j$ for *j*= 1,…, *M* represent the optimal objective function value and the optimal solution, respectively.

Step 2. Compute the average of *M* optimal solution values from Step 1 and their variance.

$$\bar{v}_{S,M} = \frac{1}{M}\sum_{j=1}^{M} v_S^j \tag{110}$$

$$\sigma_{\bar{v}_{S,M}}^2 = \frac{1}{M(M-1)}\sum_{j=1}^{M}(v_S^j - \bar{v}_{S,M})^2 \tag{111}$$

According to Mak et al. (1999) and Norkin et al. (1998), the average $\bar{v}_{S,M}$ provides a statistical estimate for a lower bound on the optimal value of the true problem and $\sigma_{\bar{v}_{S,M}}^2$ provides an estimate of the variance of this estimator.

Step 3. In this step, choose a feasible solution of the true problem (e.g., $\bar{y} \in Y$), for instance one of the solutions obtained at Step 1, $\hat{y}_S^j$. Use this solution to obtain an estimate of the upper bound on the true objective function value as follows.

$$\tilde{f}_{S'}(\bar{y}) = \sum_{k \in N} f_k \bar{y}_k + \frac{1}{S'} \sum_{s=1}^{S'} \left(\sum_{r \in R} c_r x_r(\boldsymbol{\xi}) + \sum_{t \in T} p_t z_t(\boldsymbol{\xi}) \right) \tag{112}$$

In this equation, $\boldsymbol{\xi}$ is a sample of size S' that has been generated independently from the sample used in Step 1 to obtain $\hat{y}_S^j$. The value calculated at this step provides an unbiased estimator for the upper bound on the true optimal solution value. It is recommended to choose S' much larger than the sample size S to obtain a high quality upper bound estimator. The variance of this estimator is obtained as follows.

$$\sigma_{S'}^2(y) = \frac{1}{(S'-1)S'} \sum_{s=1}^{S'} \left(\sum_{k \in N} f_k \bar{y}_k + \sum_{r \in R} c_r x_r(\boldsymbol{\xi}) + \sum_{t \in T} p_t z_t(\boldsymbol{\xi}) - \tilde{f}_{S'}(\bar{y}) \right)^2 \tag{113}$$

Step 4. In this step, compute the absolute optimality gap and its variance using the lower and upper bound estimations on the true objective function value in Steps 2 and 3.

$$gap_{S,M,S'}(\bar{y}) = \tilde{f}_{S'}(\bar{y}) - \bar{v}_{S,M} \tag{114}$$

$$\sigma_{gap}^2 = \sigma_{S'}^2(y) + \sigma_{\bar{v}_{S,M}}^2 \tag{115}$$

The solution approach used in this research to solve the SAA problem is the heuristic algorithm used in Chapter 4 and Chapter 5. In Section 6.5, we present the computational experiments completed and the results obtained.

6.5 Computational Experiments

To evaluate the performance of the proposed framework and SAA algorithm for solving the stochastic capacitated RO-TLRND-MD problem under demand and variability parameter uncertainty, we designed the set of computational experiments presented below.

6.5.1 Computational Experiments

A set of benchmark instances considering different levels for the network parameters as well as the SAA parameters were randomly generated. Different levels of these parameters determine distinct scenarios for experimentation (Table 10). Moreover, Table 11 presents fixed parameters related to the design of the network across all instances and their values. These parameters include limitations on local and lane distances for relay network movements, percentage of out-of-route miles allowed, number of RPs allowed to be visited in a relay network route, equipment imbalance allowed, minimum volume required to open RPs, maximum proportion of PtP loads, fixed RP installation cost, and per mile transportation costs. The value of the capacity parameter provided in Table 11 depends on the number of O-D pairs in the network and is set in a way that each RP serves several truckloads in the network.

Table 10: Computational Experiment Factors and Levels.

Factor	**Levels**
Number of Nodes	25 and 50 nodes are uniformly distributed in a 1×1 rectangular area
Number of O-D Pairs	10%, 20% and 40% of all possible O-D pairs
Freight Demand	Uniformly distributed value between 10 and 20
Variability Parameter	Uniformly distributed value between 0 and 1
Sample Size	20, 50 and 100 scenarios
Number of Samples	5 samples
Upper Bound Sample Size	200
Level of Fluctuation in the Uncertainty Set	10, 30

Table 11: Fixed Parameter Values Used in Computational Experiments.

Parameter	**Value**
Local distance limitation (distance units)	0.3
Lane distance limitation (distance units)	0.5
Maximum percentage of out-of-route miles allowed (%)	25
Number of RPs allowed to be visited	2
Equipment imbalance allowed (%)	0
Minimum volume required to open RPs (as a % of total volume in the network)	0
Maximum proportion of PtP loads allowed (%)	100
Fixed installation cost of RPs (cost units)	10
Per mile local transportation cost (cost units)	1
Per mile lane transportation cost (cost units)	1.3
Per mile PtP transportation cost (cost units)	1.5
Capacity at RPs	$\frac{4 * 20 * \text{\# of O} - \text{D Pairs}}{\text{\# of Nodes}}$

6.5.2 Computational Results

In this section, the trends observed in the computational results in terms of solution quality performance measures such as the estimated % optimality gap, standard deviation for % gap, and total CPU time are presented first. Additionally, we analyze performance measures describing the resulting network cost and network design and compare them to solutions obtained by the deterministic scenario. The results are averaged over 10 instances for 25-node networks and 5 instances for 50-node networks.

First, the SAA optimality gaps are presented in Figure 23 and Figure 24 for 25-node instances with different sample sizes and 10 and 30 units of demand fluctuation, respectively. We observed that increasing the sample size of Γ realizations results in more accurate estimations of the true objective function value, and therefore smaller optimality gaps. According to Figure 23 and Figure 24, optimality gaps obtained by the SAA algorithm are sufficiently small and always below 0.7%.

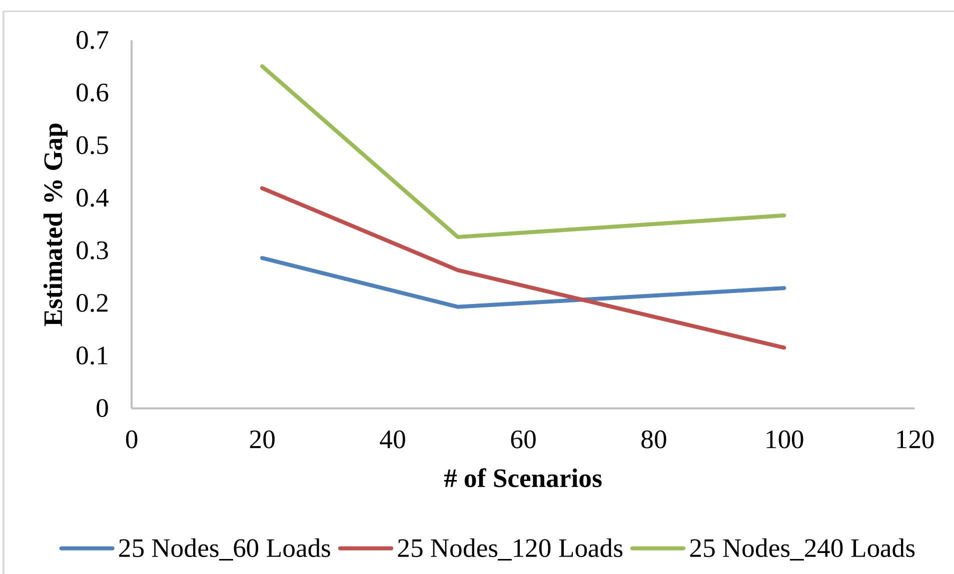

Figure 23: Optimality Gap for 25-Node Instances with Different Values of *S* (10 Units of Demand Fluctuation).

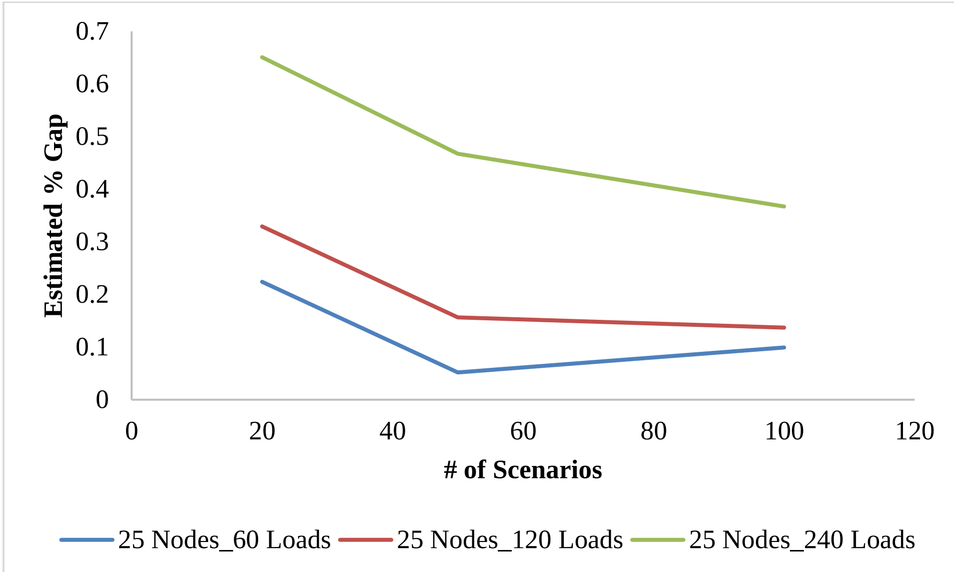

Figure 24: Optimality Gap for 25-Node Instances with Different Values of *S* (30 units of fluctuation).

Figure 25 and Figure 26 show the standard deviation of the SAA optimality gap for 25-node network instances with different sample sizes and 10 and 30 units of demand fluctuation, respectively. They show that by increasing the sample size, we obtain smaller standard deviations for the SAA optimality gap. This indicates that by incorporating more realizations of Γ in the SAA problem, the variation of the optimality gap decreases. Therefore, the method provides less variability of optimality gap under different samples drawn for Γ.

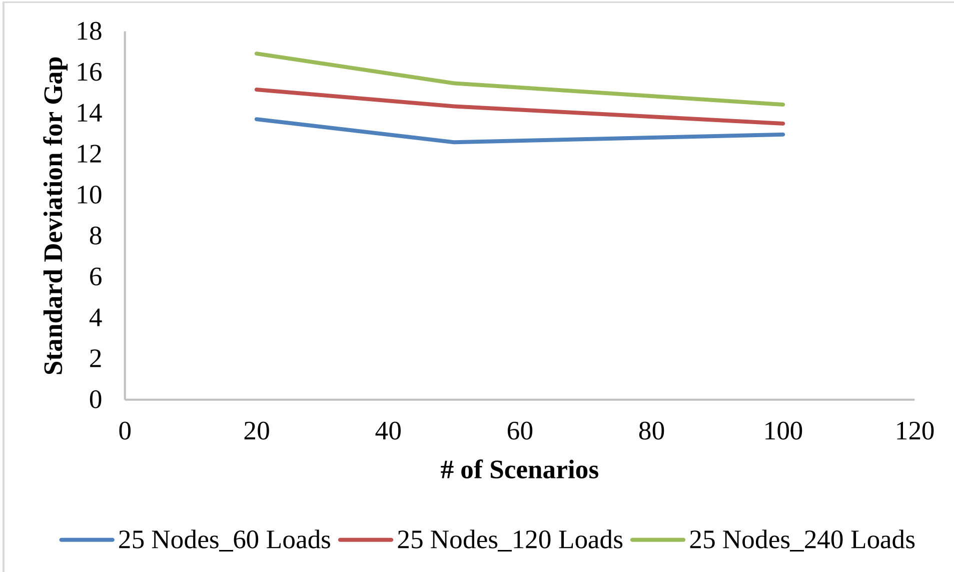

Figure 25: Standard Deviation for the Optimality Gap for 25-Node Instances with Different Values of *S* (10 Units of Demand Fluctuation).

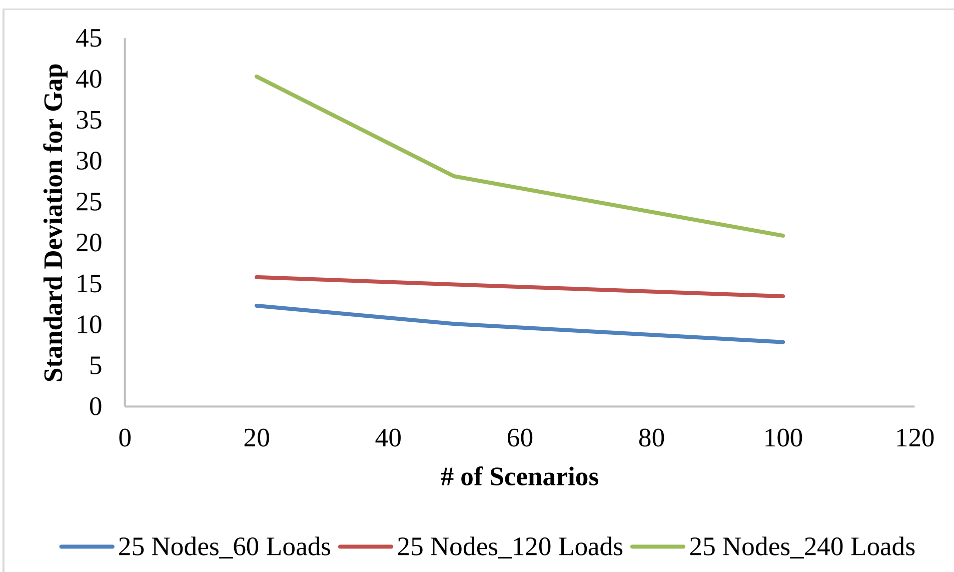

Figure 26: Standard Deviation for the Optimality Gap for 25-Node Instances with Different Values of *S* (30 Units of Demand Fluctuation).

In addition to optimality gap and its standard deviation, we also investigated computational time as a measure to assess how incorporating demand uncertainty via the integrated framework affects the tractability of the problem. We noticed that SAA solutions of higher quality are obtained in a trade-off with computational complexity since larger sample sizes represent solving larger size SAA problems. Figure 27 and Figure 28 show computational run times for 25-node network instances with different sample sizes and 10 and 30 units of demand fluctuation, respectively. According to Figure 27 and Figure 28, increasing the number of Γ scenarios increases the total CPU time and for network instances with 40% O-D pair density we observe a dramatic increase in computational time.

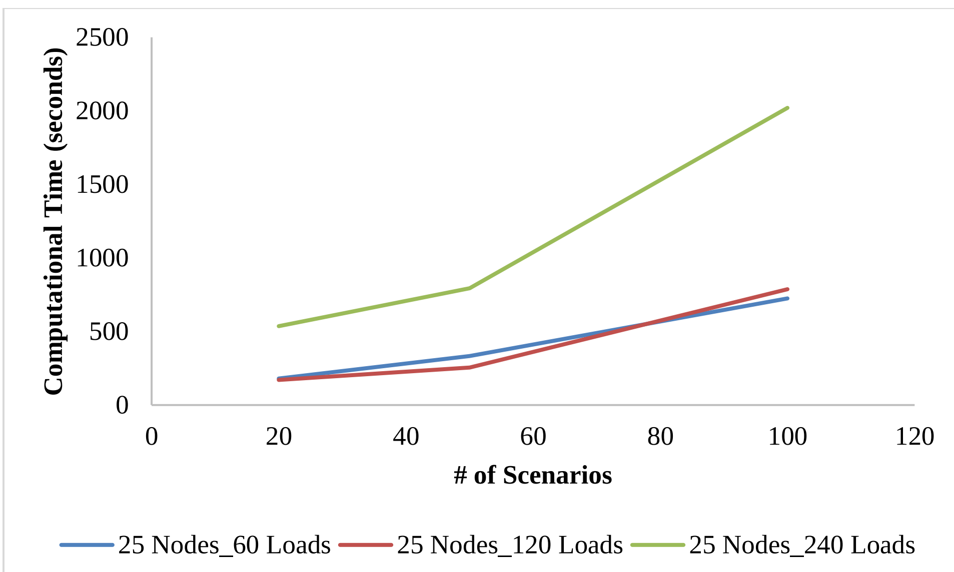

Figure 27: Total CPU time for 25-Node Instances with Different Values of *S* (10 Units of Demand Fluctuation).

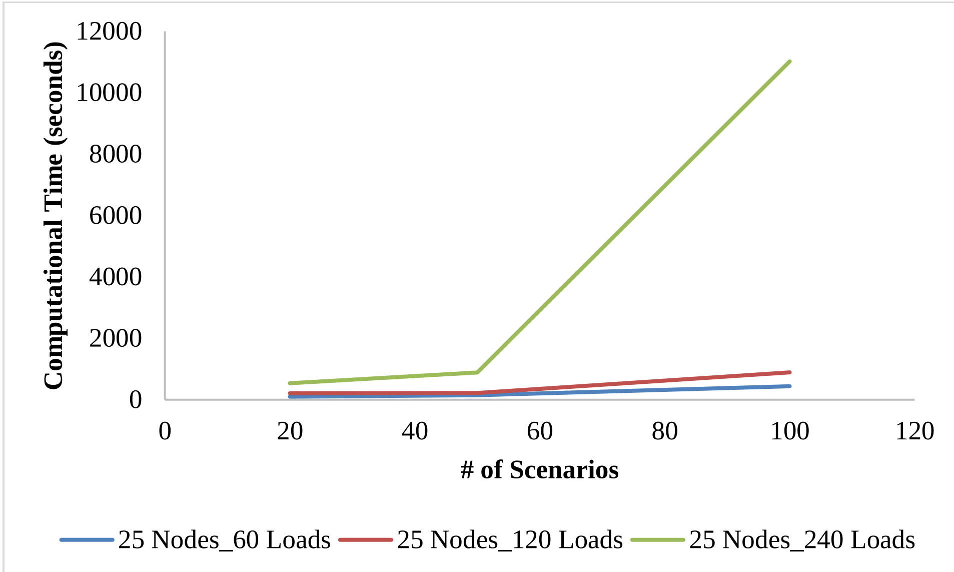

Figure 28: Total CPU time for 25-Node Instances with Different Values of *S* (30 units of fluctuation).

In addition to evaluating the performance of the integrated framework, we present numerical results corresponding to a deterministic expected value problem (EVP) and the SAA problem to study the impact of the proposed framework on the quality of the solutions as well as design of the networks. The EVP is the deterministic capacitated TLRND-MD problem presented in Section 5.4. of Chapter 5. Table 12 shows the solution values obtained by the EVP and the best solutions obtained by SAA algorithm (i.e. the candidate solution with lowest objective function value) for different network densities and sample sizes of Γ realizations. The sample size of 1 represents the deterministic scenario (i.e., EVP). According to Table 12, the proposed framework integrating robust and stochastic optimization to model uncertainty yields larger solution values compared to the EVP. This observation can be justified by the additional load demand in the network considered in the robust approach to handle demand uncertainty. A similar trend is observed in the last column presenting the number of RPs in the network. We observe that the proposed framework selects more nodes to serve as RPs to be able to address demand uncertainty. Furthermore, Table

12 also shows the % optimality gap and the error intervals for the SAA gap at $2^*\sigma_{gap}$. The optimality gaps are below 0.65% and the upper bounds of the error intervals are below 47.05 providing small % gap with respect to the magnitude of the objective value. Therefore, the results confirm the efficiency of the SAA algorithm in providing high quality solutions while incorporating uncertainty.

Table 12: Comparison of Results Obtained for Deterministic and Uncertain 25-Node Instances (10 Units of Demand Fluctuation)

# of O-D Pairs	Sample Size	Objective Value		Optimality % Gap	Error Intervals for Gap at ± $2^*\sigma_{gap}$	# of RPs Open
		EVP	SAA			
60	1	905.51	-	-	-	11.3
	20	-	1215.52	0.28	(-23.92, 30.91)	13.1
	50	-	1217.35	0.19	(-22.79, 27.52)	12.8
	100	-	1217.59	0.23	(-23.08, 28.08)	12.9
120	1	1936.3	-	-	-	16.2
	20	-	2585.36	0.42	(-27.23, 33.38)	18.1
	50	-	2584.11	0.26	(-21.84, 35.47)	17.4
	100	-	2585.95	0.12	(-23.37, 30.59)	17.5
240	1	2926.87	-	-	-	17.5
	20	-	3985.05	0.65	(-20.59, 47.05)	18.9
	50	-	3987.41	0.32	(-22.55, 39.28)	18.9
	100	-	4002.46	0.37	(-21.92, 35.75)	18.75

When completing the experiments for 50-node network instances, we observed that the computational complexity was dramatically affected by the sample size. Therefore, we limited the computation time to three hours for the large sample size settings. The results presented in Table 13 show the estimated % gap, standard deviation for the gap and total computational time. For the instances in which we obtained solutions within the limit of three hours, we observed that the optimality gap decreases when increasing the sample size from 20 to 50. The same trend was observed for the standard deviation of the optimality gap. Moreover, the last column in Table 13 shows the dramatic increase in the computational time for sample size of 50. The values presented in Table 13 are the average of results for 5 different network instances.

Table 13: Computational Results Obtained for Uncertain 50-Node Instances (10 Units of Demand Fluctuation)

# of O-D Pairs	Sample Size	Estimated % Gap	Standard Deviation for Gap	CPU Time (seconds)
	20	0.29	19.72	604.11
245	50	0.07	16.72	5532.08
	100	-	-	-
	20	0.37	22.32	2323.71
490	50	0.04	14.45	11292.89
	100	-	-	-
	20	0.25	31.12	6159.35
980	50	-	-	-
	100	-	-	-

Table 14 shows numerical results comparing the solutions obtained for deterministic and uncertain problems (i.e., EVP and SAA, respectively). We observed that incorporating uncertainty via the proposed framework results in higher solution value and in most cases selecting more nodes to serve as RPs in the network. However, for the problems 490 O-D pairs, we observed that the number of RPs for the uncertain scenario is smaller than for the deterministic scenario. According to Table 14, the optimality % gaps and the upper bounds of the error intervals were below 0.37% and 90.11, respectively. Considering the magnitude of the objective value, 90.11 yields reasonably small % gap.

An interesting observation in terms of the design of the relay network was that most of the nodes serving as relay points in the deterministic solution remained open in the

SAA solutions. In most cases, the SAA solutions had a few more relay points than the deterministic solutions to handle the additional load shipments that the robust optimization approach assumes exist in the network. Moreover, we observed that considering capacity at the relay points affects the solutions and requires opening additional relay points near the relay points that handle a large amount of load shipment traffic in the network. Therefore, once the capacity of those relay points that were open in the deterministic solution is fully utilized, the additional relay points are able to handle the dispatching of loads considered in the robust case scenario.

Table 14: Comparison of Results Obtained for Deterministic and Uncertain 50-Node Instances (10 Units of Demand Fluctuation)

# of O-D Pairs	Sample Size	Objective Value EVP	Objective Value SAA	Optimality % Gap	Error Intervals for Gap at $\pm$ 2*σ_{gap}	# of RPs Open
245	1	2734.37	-	-	-	26
	20	-	3659.11	0.29	(-28.78, 50.10)	26.2
	50	-	3665.43	0.07	(-31.20, 35.67)	26.3
	100	-	-	-	-	-
490	1	5095.11	-	-	-	33.3
	20	-	6791.29	0.37	(-22.79, 66.49)	31.7
	50	-	6778.2	0.04	(-26.28, 31.52)	31.5
	100	-	-	-	-	-
980	1	9459.42	-	-	-	35.3
	20	-	12800.91	0.25	(-34.37, 90.11)	37
	50	-	-	-	-	-
	100	-	-	-	-	-

6.6 Conclusions and Future Research

In this paper, we have proposed a framework to model uncertainty in truckload relay network design problem. We presented the robust counterpart formulation for capacitated TLRND-MD problem under demand uncertainty. Then, regarding that the choice of value for the variability parameter to control the level of conservatism introduced by robust optimization is challenging, we proposed to treat this parameter as a random variable. Therefore, we extended the robust counterpart formulation to a two-stage stochastic program addressing stochastic variability parameter. This model that combines aspects of robust optimization and stochastic optimization enables us to incorporate a large number of scenarios for the variability parameter of the robust counterpart formulation. Within this framework, we aim to analyze and optimize the expected worst case transportation cost with regard to possible realizations of the variability parameter. We developed a Monte-Carlo simulation based algorithm known as SAA to alleviate the complexity of optimizing the expectation term in the objective function. Using SAA, we approximated the expected transportation cost by averaging the worst case transportation cost obtained by choosing different levels of conservatism.

The computational results indicated that the proposed framework, in most cases, yields larger solution values and requires more RPs to address additional load demand in the network compared to deterministic solutions. Moreover, we obtained high quality optimality gaps below 0.65% and 0.37% for 25-node and 50-node network instances, respectively. By increasing the sample size of the variability parameter realizations we obtained smaller optimality gaps and therefore better estimations of the true objective function.

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7 Conclusions and Future Work

7.1 Concluding Remarks

Since the environment in which TL transportation systems operate can be highly uncertain, decision makers must account for the impact of uncertainty on the solutions they obtain when planning for the strategic design of the transportation network. Two common approaches to explicitly incorporate uncertainty in decision problems are: (a) Stochastic Optimization (SO) that treats randomness probabilistically; and (b) Robust Optimization (RO) that treats randomness deterministically. In SO, we assume that knowledge about the distribution of the uncertain parameter is available. In this case, we observe realizations of the uncertain parameter following a specific distribution and SO optimizes the expected behavior of the system over realizations of the parameter. On the other hand, RO is used when no such precise knowledge to model uncertainty is available. In this case, which is more likely to happen in practice in the context of TL transportation planning, uncertainty is described using uncertainty sets and robust optimization attempts to optimize the system against the worst case scenario of the uncertain parameter.

In this dissertation, we studied the strategic problem of truckload relay network design with mixed-fleet dispatching (TLRND-MD) under uncertainty. First, we developed a robust counterpart formulation associated with the uncapacitated TLRND-MD problem. We modeled demand uncertainty via a symmetric uncertainty set and controlled its size via a variability parameter. The variability parameter directly affects the level of conservatism of the robust model. We took advantage of the tractability of RO and obtained solutions for several combinations of network design and RO factors in the computational experiments. We completed a comprehensive computational experiment, and according to the computational results the solutions obtained by the RO program required opening more RPs to manage the additional loads in the network as well as higher total cost for the network. As we increased the problem size and the level of uncertainty, we observed an increasing trend in the number of RPs required in robust solutions. However, the tractability of the robust counterpart formulation resulted in computational times that were not significantly affected by uncertainty. We also investigated the nodes serving as RPs in deterministic and robust solutions and observed that most of the nodes serving as RPs in deterministic solutions remained open in the robust solutions as well. This was also the case for the traffic at the RPs and we observed that it remained almost the same in both scenarios. We also made another interesting observation about deadhead movements. These movements that are planned to balance the equipment at the nodes were eliminated in the robust solution and were replaced with loaded movements due to the additional freight loads in the network.

Then, we extended the TLRND-MD problem to develop a capacitated TLRND-MD mathematical formulation and applied stochastic optimization to incorporate demand uncertainty. We were invested in investigating how treating demand as a random variable following a probability distribution would impact the solutions. We developed a two-stage stochastic program that allowed us to generate a large number of scenarios of demand following a uniform distribution. In this model, we treated the facility location decisions as first-stage decisions that will be made regardless of realizations of demand, while transportation decisions were second-stage decisions that are closely dependent on the demand realizations. Therefore, we were interested in minimizing RP location costs and expected transportation costs over demand realizations. We utilized a sampling scheme based on Monte-Carlo simulation known as the sample average approximation (SAA) algorithm to be able to approximate and optimize the expected behavior of the system. In our computational results, we obtained sufficiently small optimality gaps for up to 50-node network instances (i.e., below 0.82%). In particular, we observed a decreasing trend in the optimality gaps as we increased the sample size resulting in more accurate approximations of the true objective value. We also observed that as the sample size increases, the corresponding standard deviation for the optimality gap is considerably reduced providing less variation of the gap with regard to the samples drawn for demand realizations. Moreover, since the SAA algorithm has a trade-off between optimality and computational burden, we observed that the computational times for solving the SAA problems increased dramatically for large sample sizes. To overcome this challenge, we developed an accelerated Benders decomposition algorithm to solve large SAA problems, but we observed a very slow convergence behavior of this algorithm in our application. The reason for the failure of Benders decomposition in this application was the large number of binary variables in the master problem. We presented error intervals for the optimality gaps indicating robustness of the SAA solution approach. Moreover, we showed that the solutions obtained by the SAA algorithm outperform those of the deterministic expected value problem. This observation confirms that not accounting for uncertainty will result in sub-optimal solutions.

Comparing the results obtained with RO and SO, we conclude that RO provides more conservative solutions when compared to SO. However, RO results in a more tractable formulation, while in SO problem sizes become computationally intractable for larger sample sizes.

Finally, we proposed a framework that integrates the two approaches (i.e., RO and SO) to benefit from the modeling power of SO for treating the uncertain parameter as a random variable with the tractability power of RO. First, we developed a robust counterpart with controllable level of conservatism for the capacitated TLRND-MD problem under demand uncertainty. Then, motivated by the fact that considering a deterministic variability parameter in the RO formulation might not reflect its practical behavior and capturing the choice of its value would be a major challenge, we proposed to consider this parameter to be subject to uncertainty. Therefore, in our proposed framework, we treated the variability parameter of RO as a random variable following a distribution which allowed us to study the expected worst case behavior of the system by averaging over the worst case transportation costs when choosing different levels of conservatism. We extended the robust counterpart formulation and built a two-stage stochastic program in order to incorporate the stochastic nature of the variability parameter. We generated large samples of realizations of the variability parameter, and used the SAA algorithm to approximate the expected worst case transportation cost over the possible realizations. We obtained computational results for sample sizes of up to 100 scenarios for 25-node network instances and sample sizes of up to 50 scenarios for 50-node network instances. The SAA optimality gaps were inferior to 0.65% and 0.37% for 25-node and 50-node network instances, respectively. Moreover, the optimality gaps and their standard deviations tend to decrease by increasing the sample size. Overall, we observed larger solution values and more open RPs in the network for uncertain scenarios compared to deterministic solutions to address the additional load demand in the network considered by the worst case optimization approach.

This dissertation (a) extends the mathematical formulation for the TLRND-MD problem developed by Vergara and Root (2013) by limiting the capacity at RPs; (b) presents a robust counterpart to the TLRND-MD problem using the RO approach introduced in Bertsimas and Sim (2003) in which the level of conservatism is controllable; (c) presents a two-stage SO model for the capacitated TLRND-MD problem and obtains solutions using the SAA algorithm; (d) bridges SO and RO approaches to propose a framework to approximate and optimize the average worst case performance of the system for the capacitated TLRND-MD problem; and (e) conducts a comprehensive analysis on how uncertainty affects different characteristics of the solutions obtained.

7.2 Future Research

Future research extending this study includes investigating more complex uncertainty sets in robust optimization. Since the tractability of the RO model depends on the choice of the uncertainty set (Ben-Tal and Nemirovski 1998), examining the impacts of more complex uncertainty sets in the TLRND-MD problem under demand uncertainty is an interesting area for future research. Similarly, in the stochastic optimization approach, describing the uncertain parameter using other probability distributions is another interesting extension to our work. More precisely, one can extend this work to carry out a *distributionally robust optimization* of the TLRND-MD problem. In this scheme, the uncertain problem data is governed by a probability distribution that itself is subject to uncertainty. Therefore, the distribution is assumed to belong to an ambiguity set consisting of all distributions that are compatible with the decision maker's prior information (Wiesemann et al. 2014).

We also note that a challenge in stochastic optimization was solving large size instances and we observed that the accelerated Bender decomposition approach failed in assisting us to overcome this challenge. Therefore, developing a solution approach that enables us to solve the SAA problem for large instances needs to be addressed in future studies. In general, an immediate avenue of future work under both RO and SO is investigating the modeling and solution of problems in which uncertainty is assumed for multiple parameters. Several potential sources of uncertainty in the TL transportation environment are discussed in Chapter 2. Among the other possible sources of uncertainty, travel time uncertainty could be coupled with demand uncertainty in order to obtain realistic solutions. Since, in general, operational level decisions focus on detailed scheduling of the truckloads, in order to address travel time uncertainty, we would need to extend the TLRND-MD and capacitated TLRND-MD problems to entail operational decisions as well. In addition, one could implement a sensitivity analysis over the different parameters considered in the design of the system to discover uncertainty in which parameter seems to have a more significant effect on the network design.

Finally, considering that the instances tested in the computational experiment in this dissertation were randomly generated, the applicability of this research can be increased by validating the models and solutions approaches using real data sets. In particular, real data would help us to obtain a better understanding of the behavior of uncertain demand and consequently to make the best choice of the uncertainty modeling approach. In addition, a comparison of the methods used in this research based on a set of numerical benchmark problems would be useful. The goal would be to examine whether one of the tested methods outperforms all others on a majority of the benchmark problems.

Furthermore, during this research I had the opportunity to learn several operations research techniques that can be applied to large-scale optimization problems. I am interested in learning cutting-edge techniques and applications of operations research methods in solving more applied large-scale problems.

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