OPTIMAL RESOURCE ALLOCATION TO MINIMIZE LAST MILE DELIVERY COSTS

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The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

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ABSTRACT

This study focusses on a decision making tool to assist an organization in planning for capacity needed for the Last Mile Delivery (LMD) services which is the most expensive part of the entire supply chain. Considering the use of Crowdsourcing for Logistics (CSL), the decision-making tool's objective is to provide an optimal combination of fulltime, seasonal and CSL resources that lead to minimum operational LMD costs and meet the variable demand.

To achieve this, a three phased approach is used, where in the first analytical phase an expected cost model is numerically validated. In the second stochastic program phase, the capacity and cost of the CSL resources are varied. Finally, in the third simulation phase, the approach is further extended to consider the daily employee attrition rate and unsatisfied demand being carried over to the next day. Lastly, the use of automation or newer technologies, such as robots, for LMD services is introduced in this simulation phase to show the benefits in terms of the operations costs.

The results from the analytical model described the optimal values of fulltime and seasonal considering the utilization of CSL and experienced some penalty costs. In this case, the parameters being fixed, does not capture the differences due to the variability of CSL availability or costs, which is addressed in the stochastic program phase. Though the output from the stochastic model is higher, it does consider the variability in the CSL capacities and costs, which is practically observed. The simulation section gives a further refined optimal combination of fulltime, seasonal and CSL that meets the demand considering the attrition rate of fulltime and seasonal, and rollover of the units by one day. Within this, the consideration of automated delivery systems like using a robot for LMD services leads to further cost savings opportunity.

Here, the fulltime delivery cost is benefited, with low utilization of seasonal and CSL limited for optimizing delivery strategy.

In conclusion a tool is provided for aggregate delivery capacity planning that would consider an optimal combination of fulltime, seasonal and CSL resources lowering the LMD costs and meeting the variable demand.

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DEDICATION

I would like to dedicate this work to my mother, my father, my teachers and god.

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LIST OF ABBREVIATIONS

SCM ....Supply Chain Management.

LMD..Last Mile Delivery.

CSL ....Crowdsourcing for Logistics.

B2B ....Business to Business.

B2C ....Business to Consumer.

UD...Uniform Distribution.

ND...Normal Distribution.

PDF ....Probability Density Function.

CDF...Cumulative Distribution Function.

TC ....Total Cost.

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1. INTRODUCTION

Within a Supply Chain Management (SCM) system, the logistics division (Ballou, 2004) focusses on movement of goods and services from a source to the end destination meeting the suppliers' and the customers' expectations. The key expectations here are to have the products moved in the shortest possible time and at the lowest possible cost. An SCM system with its key functional areas are shown in Figure 1.

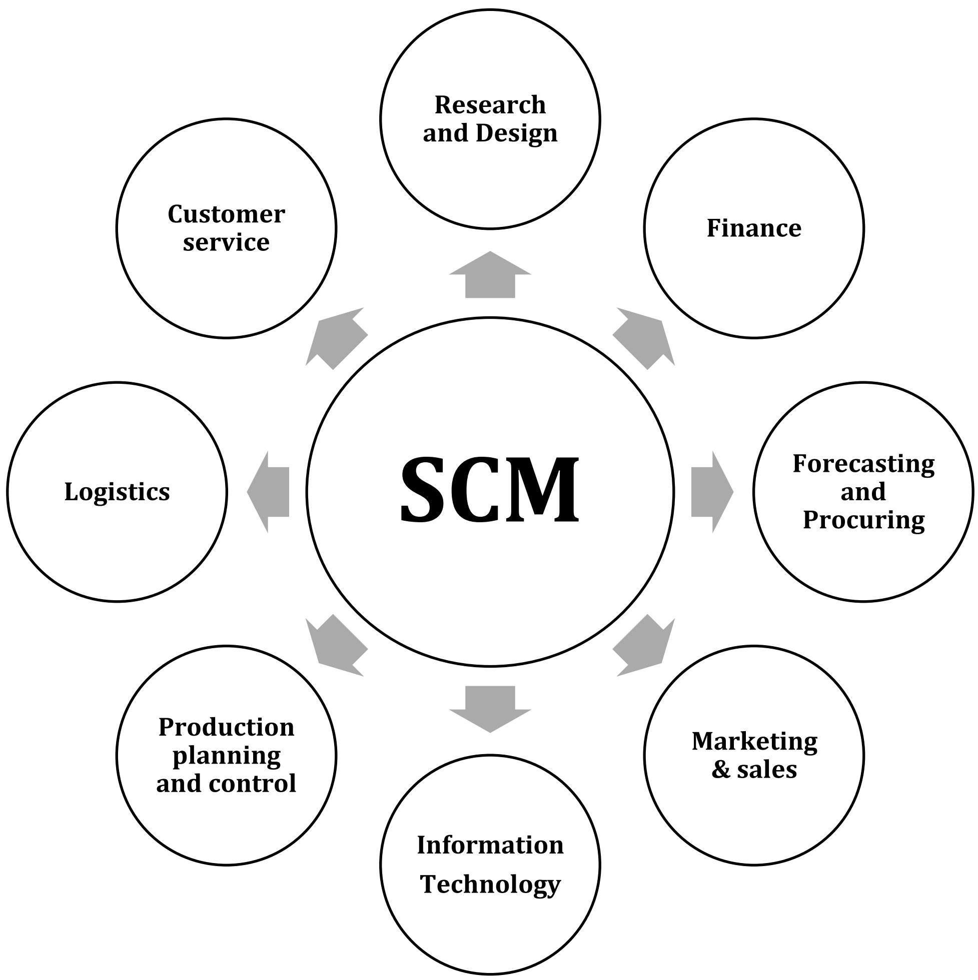


Figure 1. SCM and key functional areas.

The varying demand of the product, delay in procurement of raw materials, or any disruption in manufacturing, failing to provide output on time; stresses the logistics function to transport the output (mostly the finished goods) on time. Within these movements of the material from source to a destination, various activities are involved. These activities are coordinated by the functions within SCM to move the products optimally from one point i.e. the source to the second point, the destination. Figure 2 considers an example of a traditional flow, from raw materials being shipped to manufacturing plant and then the finished goods from the manufacturing plant to the end customer via the wholesalers and retailers. In this study, the portion of logistics dealing with the finished goods delivery with forward logistics is being considered, where the source will be the local warehouse/retailer site and the destination will be the end customer; a residential type for this scenario. Reverse logistics, dealing with the return of finished goods to the warehouse/retailer (for example warranty or returns) is not in the scope of this study.

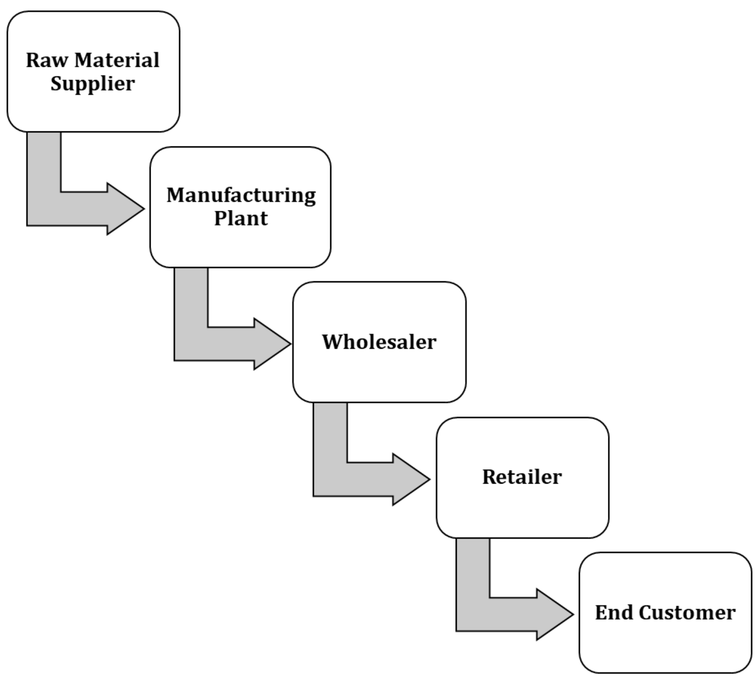


Figure 2. Material movement from source to destination.

The logistics of moving material or products from the warehouse/retailer to the end customer, can be further divided into two broad categories, i.e. if shipping to a business entity or an individual noncommercial customer. It is also termed as business to business (B2B) and business to consumer (B2C), respectively. The portion of logistics services of interest is the B2C scenario wherein the delivery of the goods is to the end customer or the end user, usually a noncommercial residential type. For example, an individual ordering an electronic device from an e-commerce company where the product is moved from the e-commerce company's local warehouse/retailer to the end customer's residence. Another example is an individual ordering groceries online from the convenience of their residence, and having it delivered from the local supermarket.

For the raw materials, the sources would be the suppliers and the destination would be the manufacturing plant. For finished goods, the source is the manufacturing plant and destination is the warehouse/retailer or the end noncommercial customer. Though it is a possible scenario that the goods (finished goods or service parts) can be shipped directly from the manufacturing plant to the end customer, for this case, the scope is limited considering the finished goods flow from the local warehouse/retailer to the end customer's residence.

In this movement of goods, the most expensive is the final leg, i.e. from the local warehouse/retailer to the end customer's residence. This logistic movement is popularly known as Last Mile Delivery (LMD). LMD is known to be the most expensive, challenging and least efficient (Perboli et al., 2021) when it comes to material movement. Research indicates that LMD accounts to anywhere between 13% and 75% of the overall supply chain costs (Gevaers et al., 2009).

1.1. Last Mile Delivery

LMD is the final leg of the product transportation for a logistics company (Wang et al., 2016). It is primarily from a local warehouse/retailer to the hands of the end customer. The importance of optimizing LMD services was primarily due to it being most expensive part of the supply chain system. Of recent, factors like an increase in e-commerce volumes, a push for sustainable transportation reducing carbon footprints, time constraints and an aging workforce are leading to the innovation in LMD services. Strategies like using an existing transportation pool, use of drones (Boysen et al., 2021), or use of storage points, have gained significant attention to address the expected boom in e-commerce with rapid urbanization.

Top logistics companies are constantly in pursuit of optimizing their LMD strategy. For example, a recent press release (FedEx, 2020) shows how the growth in the e-commerce business is leading to optimization efforts at the organizational level. This impact is much more profound in cities with higher population density as e-commerce grows and thus needs optimization of LMD (Viu-Roig & Alvarez-Palau, 2020). Walmart being a top supermarket across the globe has its own innovative approaches. Concepts like owning delivery vehicles or partnering with a delivery services company (Walmart, 2019) were established by Walmart in various parts of the world.

1.2. Optimizing LMD

Today, LMD has gained profound interest (Mangiaracina et al., 2019) with the sole objective to optimize the final leg of logistics delivery making a big impact to cost savings. In the current state, the cost of delivery constitutes the delivery vehicle cost, the human resource used and the travel route. Given that LMD is the most expensive part of the supply chain and the growth in e-commerce there is a need for more cost efficient strategies (Vakulenko et al., 2019). There has been active research in the field of optimizing travel routes, pick up points, altering the type of vehicle (electric powered), aerial vehicles, robots and the use of lockers. Parcel deliveries in an urban setting have also been studied comparing vehicles and bikes (Perboli & Rosano, 2019; Eliyan et al., 2021) to focus on sustainable benefits (McLeod et al., 2020). However, there is one arena that can use more research in terms of aligning human resources to capacity. Organizations have been long struggling to achieve a fine balance of required human resources for the variation in capacity. Strategy like using third party logistics services (Ponce et al., 2020) for operations is also a popular method to lower the supply chain costs. With intense competition in the retail sector, further cost reduction opportunities have evolved with the human resources openly available in the region, which leads us to utilization of crowd for logistics services in the LMD portion of the supply chain. This sourcing of logistics services from crowd is termed as Crowdsourcing for Logistics (CSL) in this study.

Among the mix of opportunities to optimize LMD, the use of CSL (Boysen et al., 2021; Cleary and McLarney, 2021; Mangiaracina et al., 2019) is one avenue that can help deliver product on time and achieve organizations' focus on sustainability (economic and environmental) by reducing overall logistics costs. This can be achieved by using just CSL services, or by combining it with the existing workforce within an organization. Usable CSL services with real time information flow between systems has been the motivating factor along with the emerging need of consumers (Kafle et al., 2017). Businesses and/or consumers today are empowered with tools and knowledge to constantly demand more choice and flexibility in delivery options using CSL services (Ermagun & Stathopoulos, 2018) and with the objective of obtaining lowest possible cost (Perboli et al., 2021). Along with this flexibility, service quality has to be ensured.

Crowdsourcing has always been in existence wherein an organization or a person can refer to the crowd for a solution, benefitting from the knowledge and wisdom of the crowd. Companies using crowd input for product feature designs or to test a new to be released software version (beta testing) has partly influenced the concept of using crowdsourcing for logistics services. With the available potential of the crowd and information technology support, this arena has picked up its pace in little more than a decade from ride sharing services to grocery deliveries (Alnaggar et al., 2021; Punel et al., 2018). Furthermore, the lockdowns (Rodríguez García et al., 2021) during the pandemic situation mostly during the year 2020, has led to an improved customer online shopping pattern, specifically for fresh produce and groceries (Kim and Wang, 2021).

1.3. Problem Statement

The advancement in the field of information technology (Marzanoa et al., 2019) and the ability to create mobile applications (commonly known as apps) linking the available crowd resources for a business has fostered CSL services in recent years. CSL services have witnessed strong growth with outright participation of businesses and local populations (Carbone et al., 2017) leading to a win-win situation. Doordash, Instacart, Shipt, and Ubereats are a few examples (Alnaggar et al., 2021) that have recently gained popularity with a promising outlook. There is a significant amount of research focusing on the employers' and crowd's willingness to participate in CSL for LMD (Le et al., 2019) and factors influencing the usage of CSL (Punel & Stathopoulos, 2017). The interest level between the two parties seems to be experiencing a positive trend, with strategies matching expectations of both the parties boosting the use of CSL. CSL provides an added price advantage over traditional logistics companies (Shen & Lin, 2020), which is a motivating factor. The same approach has been extended to grocery deliveries from a local retailer to the end customer. This strategy, has boosted the e-commerce sales or online ordering for groceries with all major retailers now offering this service (Wang & Zhou, 2015).

Costs for delivering one order can fall between $10 and $20 (Boyer et al., 2009), along with the costs of preparing an order. Competition advertising to provide free order delivery irrespective of order amount adds to the need for an efficient delivery strategy. A study that understands the effects of delivery strategies to customer needs and eventually how it impacts their expectations (Esper et al., 2003) shows that lower cost of delivery and higher speed impacts the online ordering preferences of customers. Consumer preference is heavily influenced by delivery speed and cost (Nguyen et al., 2019) and is now on the radar of top grocery chains and e-commerce organizations. This increase in online ordering for any organization, adds to the dilemma of utilizing existing full time staff, adding seasonal staff, or utilizing available CSL for LMD services while optimizing the operational costs ensuring timely and accurate deliveries.

1.4. Significance of the Study

The objective of this study is to propose a decision making tool for organizations when planning for capacity to meet LMD services for the given seasonal variation. It is of expectation that this kind of tool would assist managers in budgeting the resources by having chosen an optimal combination between fulltime, seasonal and CSL resources that would incur lowest expense while meeting the demand. In addition, the benefits of using an automated system such as a van-robot delivery is also explored, along with the change in the resource combinations that would assist an organization to keep their LMD operations costs lower.

The recent trend in increasing online sales has led to an increase in revenue but at a cost, since LMD is the most expensive portion of logistics (Gdowska et al., 2018). Companies today, are facing intense competition to gain market share in grocery deliveries (along with existing e-commerce business) with the likes of giant retailers like Walmart and Amazon. More and more grocery chains have joined in this concept of online ordering of groceries and having them delivered to residences. Thus, it is essential for an organization to provide utmost customer care by providing the right order at the right time.

CSL being a growing field (Le et al., 2019), still has its challenges to be implemented on a full scale and thus this approach to develop a decision making tool. The characteristics of the order profile like periodic variations, seasonal variations, fulltime and seasonal resources costs, delivery vehicle costs for fulltime and seasonal resources, costs of CSL services, availability of CSL services, fulltime and seasonal employee attrition rate, and rollovers of missed deliveries by one day; are all considered in this research to give an overview of resource needs at an aggregate capacity planning level and provide insights for managerial decision making.

2. LITERATURE REVIEW

A study by Gevaers et al. (2009) emphasizes how the growth in the e-commerce business and the e-grocery market has influenced the LMD services. This LMD part of the supply chain being the most expensive has led to various innovations over the last few decades. Improvements were in the areas such as improving delivery fleet by use of electric vehicles, autonomous applications such as drones or robots, vehicle route optimization, scheduling, delivery window considerations, staffing levels, outsourcing of logistics services and use of cargo bikes to name a few. Apart from the fact that the LMD is most expensive part of the supply chain, it also is linked to causing environmental impact due to pollution. As a significance growth in e-commerce is observed, so is the increase in traffic and congestion in a locality.

Allen et al. (2020) have highlighted the fact that the increase in the last mile deliveries with the online orders and expectations of same day delivery has led to the increased traffic in a region. This further, highlights the negative environmental impact these services cause and call for policy makers to act on this situation by providing a discussion on key issues. Arnold et al (2018) have also highlighted that growth in the e-commerce distributions have resulted in traffic congestions or emissions. To alleviate this issue, the authors use a simulation approach to evaluate if alternate modes such as using bikes for deliveries. A two-echelon model has been proposed by Caggiani et al. (2021), where using electronic cargo bikes and electronic vans were considered against the traditional vehicles. Concerns were travel costs, vehicle investment costs, wage related costs and depot costs resulting into the economic comparison between the use of electronic cargo bike and electronic van. In this pursuit, a methodology is also proposed by Comi & Savchenko (2021) to choose the most sustainable option of using a bicycle or traveling by foot when fulfilling a delivery of small parcels in an urban setting. Similarly, approaches from sustainable aspect to optimize LMD costs was studied by Gatta et al. (2019), where usage of lockers was considered inside or near public transit systems. Their summary concludes that CSL has good potential both ways, i.e. economically and environmentally.

At the same time, a survey by Nogueira et al. (2021) has shown the customers preference in terms of contributing to environmental sustainability, where delivery speed was the top priority and concluded with the fact that this choice would be product dependent. Secondly, to educate the customers how they can contribute to sustainability aspect while choosing delivery options when ordering goods. On the same note, McLeod et al. (2020) have discussed about the benefits of using porters or cycle couriers for LMD services. Benefits here pertain to both the objectives of having lower operational costs and avoid negative environmental impact. As seen in the study by Perboli and Rosano (2019) where the authors highlight the need for making the LMD services more sustainable. The objective can be achieved by optimizing the traditional delivery flow by considering inclusion of contemporary practices such as cargo bikes among others, built into the parcel distributions.

Boysen et al. (2020) in their paper have also highlighted the impact of the growth in the e-commerce and specifically how the LMD leads to traffic congestion and pollution. To address this have surveyed the novel approaches in LMD. Among the approaches reviewed by the author, the utilization of crowd for transportation also garnered interests with the evolution of digital platforms for taxi services or food delivery apps. Alnaggar et al. (2021) in their review paper have described an overview of evolution of the CSL delivery platforms, also discuss about their scheduling, matching and compensation schemes. In parallel to this, the authors also have described the research efforts that continued through the same timeline. The authors view point leads to numerous research agendas encompassing managerial decision making with scheduling, matching, compensation and routing considering the current industry trends and how it can be optimized further. Behrend and Meisel (2018) discuss about integrating and item sharing and crowd shipping for small parcel deliveries. Here they have investigated three different modes of transfer of parcels. The results show that the integration of item sharing and crowdsourcing, and utilization of three modes of delivery leads to highest profits and service levels.

Carbone et al. (2017) have studied the utilization of crowd for logistics services considering various initiatives around the world. It is intriguing to know that this type of service creates value and thus has a possibility of creating newer methods of delivery disrupting the traditional business models. Castillo et al. (2021) explore the impact on cost and service level by considering the hybrid fleet of vehicles with crowdsourcing. A stochastic simulation integrating the discrete event, agent based methodologies lead to an understanding of the crowd based logistics services rates would impact the overall costs. The crowdsourcing rate at a median pay and a mix of hybrid vehicles were found be optimal in case of operational costs and meeting the service levels. Shen and Lin (2020) have also studied this innovative logistics service and have shown the price advantage for same day service in their analysis.

Similarly, with Autry's (2021) review paper has highlighted the very fact that with dynamically changing environment calls for innovative methodologies for logistics activities and CSL can be one good fit. The key question related to this study is the fact that how much CSL services would be needed when considering with existing resources. Several other studies like Cleary and McLarney (2021) and Mangiaracina et al. (2019) have also highlighted the use of CSL to be critical in optimizing LMD costs. Furthermore, Seghezzi and Mangiaracina (2021) explore the multi-parcel option. Asserting that CSL is a promising solution for lowering LMD costs, the authors also explore the option of one CSL resource delivering multiple parcels in a given route.

A study by Huang & Ardiansyah (2019) has also shown that a well-planned integration of CSL into LMD services can give the advantage of being flexible and save costs. The rate at which e-commerce is growing today and the need for parcel deliveries as mentioned by Guo et al. (2019) has led to the need effective last mile solutions. Pina-Pardo et al. (2022) have highlighted the fact that there has been a huge spike in retail sales and as a result, the LMD services will be a prominent area where cost effective solutions are the need. The authors used a two-stage stochastic program to design a two-echelon LMD network and provided managerial insights into the transportation modes, facility location, and benefits of outsourcing deliveries. Perboli et al. (2021) consider a satellite depot system and solving to provide the optimal cost. The authors use a mixed integer program and heuristics to solve the problem. Nieto-Isaza et al. (2022) have proposed a model considering mini-depots for LMD. Here the authors used a benders decomposition approach. Lu et al. (2020) have mentioned about a similar concept with driver helpers for LMD services. Their study was inspired by the challenges faced by logistics companies during peak seasons and with an objective of keeping operational costs low.

As seen so far, CSL does seem to be a favorable option among others to lower the LMD related costs. However, it is advisable to be mindful of the capacity availability and pricing structures of the CSL resources. Boysen et al. (2022) have studied an aspect where the employees of the retailers or distribution centers opt for delivering shipments on the way back from work to their residence. The success is attributed to the availability of resources for crowd based shipping. A study by Castillo et al. (2018) also evaluates the use of CSL and its performance in terms of logistics effectiveness. To achieve this, the authors here have used a simulation approach to deliver goods from a warehouse to customers within a city highlighting the strategic benefits of the use of CSL with more deliveries done but might impact service level. With this advantage of utilizing the CSL, there is always a concern with level of resources to use and meet the demand. One approach that complements the resource utilization is where Le et al. (2021) highlight that the pricing must be determined for CSL models. Le et al. (2019) in their research have reviewed the current state of the use of CSL considering the supply, demand, and operations and management. The authors focus lies more on the current state considering the various components interacting with each other, the challenges and benefits when shipping a package. Nevertheless, the authors do highlight the fact that CSL has a promising outlook and is at its early stages needing further research. Le et al. (2019), also analyze the willingness of CSL services, and specifically in terms of pay and distance travelled. This will definitely be a critical factor deciding the availability of CSL. Similarly, Le and Ukkusuri (2019) and Pourrahmani and Jaller (2021) have reviewed the factors and operational challenges and discussed research opportunities with the use of CSL.

One approach of an analytical model observed in a literature was for e-commerce deliveries for B2C scenario was by Seghezzi & Mangiaracina (2021) for LMD. The authors here have highlighted the fact that the availability of economic analysis of the use of CSL in LMD is limited. Ermagun and Stathopoulos (2018) have reviewed the probability of receiving a bid and the counts of bid. This aspect is very critical when planning to make us of the CSL services. Furthermore, Ermagun et al. (2019) have studied the performance of CSL services from two years of data. This level of data assists in determining the effectiveness of CSL services when lowering LMD costs. Gdowska et al. (2018) discuss about the implications of a CSL service declining orders. This will become essential aspect for an organization to ensure service levels at peak period are maintained and providing insights for managerial decision making, in this study. Punel et al. (2018) in their study have highlighted the growing trend of the CSL services. At the same time, considering the disadvantages listed by the authors in their study, service level is one aspect that is incorporated in this study, as it needs to be thoroughly evaluated when committing to CSL for LMD delivery services by any organization.

LMD being the most expensive portion within the entire supply chain has been studied extensively to optimize operational costs, various strategies have been highlighted ranging from use of cost efficient equipment, optimized routes, optimal location of depots, automation such as drones or robots, and utilization of CSL for logistics services. Thus here is an approach targeting to lower the labor costs by incorporating CSL services, and at the same time reduce environmental pollution by making use of the existing traffic (owned and operated by CSL resources) in the neighborhood.

The one avenue that is scarce on research is with the aggregate planning for capacity considering the use of seasonal and CSL resources in conjunction with existing fulltime staff for a logistics provider. This leads to the question of having optimal capacity for the LMD services while meeting the variable demand, and yielding the benefits the CSL services can provide benefits in both ways, economically and less environmental impact. Yildiz & Savelsbergh (2019) studied the capacity model but were limited to short term capacity only and not at an aggregate level. A capacity planning model has been proposed by Dai & Liu (2020) where a combination of part time crowdsource, fulltime crowdsource and in house drivers are considered. Their approach specifically focusses more on the use of crowdsourced resource to fulfill order requirements. Ulmer and Savelsbergh (2020) have shown a similar approach of using CSL services but with the workforce shift scheduling. Their aim being to reduce the impact of on service level due to any uncertainties in the availability of CSL.

Considering the risks associated with the uncertainties in the capacity and cost efficient availability of CSL resources, the service level and the operational expenses are at stake. Moreover, during peak season as order volumes increases and with multiple businesses in the locality wanting to use the same pool of CSL capacity, challenges the timely sales of the businesses. Thus, it will be worthwhile to look at the resource distributions at an aggregate level and gain insights for long term capacity planning purposes, which is currently not available in literature.

Thus, in this study, a long term strategic capacity planning tool is proposed, which determines the optimal combination of fulltime, seasonal and CSL resources to meet the seasonal demand. The objective here is to contribute to the efforts of lowering the LMD services related costs by creating providing an aggregate capacity planning tool, that would empower organization to make decisions with the need for resources like fulltime, seasonal and CSL when comparing to the periodic and seasonal variation. Finally, exceeding the customer service levels at the lowest LMD costs.

3. ANALYTICAL MODEL

3.1. Analytical Model Objective

The objective of the analytical model is to determine the lowest expected capacity cost for LMD services. This is achieved by using a combination of fulltime, seasonal and CSL resources to meet the demand which is seasonal in nature. This stylized model with random demand is numerically run considering uniform and normal distribution of demand. The results from this numerical analysis show the impact on the capacity levels, orders fulfilled and orders missed. Any missed orders are subject to a penalty cost, which eventually gets added to the total operational costs.

In a way, the objective of determining optimal capacities for fulltime, seasonal and CSL resources when the actual demand is not yet known or continuously varies, is similar to a newsvendor model (Qin, et al., 2011). However, whereas in a newsvendor model the tradeoff is between having too much or too little inventory, for this model the tradeoff is between having too much or too little delivery capacity. With this in consideration, the model description is presented in the next subsection.

3.2. Assumptions Used for Analytical Model

The model described here is derived from an expected cost for a logistics company to provide LMD services on a daily basis or per period as used in this model. It is assumed that the logistics company faces a random demand for each period and by seasons. The distribution of demand for each period in the respective seasons follow a PDF $g_j(x)$ and a CDF $G_j(x)$.

At the beginning of every fiscal year, it is assumed that the logistics company considers to employ a steady count of fulltime resources ensuring a certain section of capacity is fixed.

Depending upon the random orders per period and season, the company wants to employ seasonal resources to meet the variation in demand.

Furthermore, the company also wants to explore the option of using CSL resources to optimize LMD costs and service levels. As this capacity of CSL is also highly variable, it is of importance to understand the risks and have the knowledge for an informed decision making.

3.3. Analytical Model Description

The notations used in the model formulation are as below:

T = Fulltime capacity.

T_j = Seasonal capacity for season j.

T_j^*= Optimal seasonal capacity in season j in number of deliveries.

T^*= Optimal value of T (minimizing expected costs) in number of deliveries.

$H_j(T)$ = Derivative of cost for seasonal capacity in season j.

E_F = Expected error cost of one unit of demand being satisfied by fulltime capacity in USD.

F = Per period cost of full-time capacity to satisfy one unit of demand in USD.

S = Per period cost of seasonal (part-time) capacity to satisfy one unit of demand in USD.

E_S = Expected error cost of one unit of demand being satisfied by seasonal capacity in USD.

U = Per unit cost of CSL to satisfy demand which includes E_U, in USD.

E_U = Expected error cost of one unit of demand being satisfied by CSL capacity in USD.

O = Cost per unit of unsatisfied demand in USD.

n = Number of seasons.

n_j = Number of periods in season j.

$G_j(x)$ = CDF of demand for one period in season j.

$g_j(x)$ = PDF of demand for one period in season j.

UD = Uniform distribution.

ND = Normal distribution.

C= CSL capacity.

For the numerical analysis, three scenarios are considered based on the costs of CSL deliveries U. The three scenarios are:

Scenario 1 - Assuming $U > S + E_S \; and > F + E_F$

In Scenario 1, T_j is obtained by solving equation 1 and $H_j(T)$ is as in equations 2 and 3. Corresponding equations are provided for T_j and $H_j(T)$ with Scenarios 2 and 3 in equations 4-9.

$$S + (E_S - U) * (1 - G_j(T_j)) + (U - O) * \left(1 - G_j(T_j + C)\right) = 0 \quad (1)$$

$$H_j(T) = F + (E_F - U) * \left(1 - G_j(T)\right) + (U - O) * (1 - G_j(T + C) \; if \; T \geq T_j \quad (2)$$

$$H_j(T) = (F - S) - (E_F - E_S) * \left(1 - G_j(T)\right) \; if \; T < T_j \quad (3)$$

Scenario 2 - Assuming $S + E_S \geq U > F + E_F$

$$T_j = G_j^{-1}\left(\frac{O - S - E_S}{O - E_S}\right) \quad (4)$$

$$H_j(T) = F + (E_F - U) * \left(1 - G_j(T)\right) + (U - O) * (1 - G_j(T + C) \; if \; T + C \geq T_j \quad (5)$$

$$H_j(T) = (F - S) + (E_F - U) * \left(1 - G_j(T)\right) + (U - E_S) * \left(1 - G_j(T + C)\right) \; if \; T + C < T_j \quad (6)$$

Scenario 3 - Assuming $U < \; F + E_F \; and < S + E_S$

$$T_j = G_j^{-1}\left(\frac{O - S - E_S}{O - E_S}\right) \quad (7)$$

$$H_j(T) = F - (O - E_F) * \left(1 - G_j(T + C)\right) if \; T + C \geq T_j \quad (8)$$

$$H_j(T) = F - S - (E_F - E_S) * \left(1 - G_j(T + C)\right) if \; T + C < T_j \quad (9)$$

To obtain T^*, equation 10 is solved in Excel solver as a function of T.

$$\sum_{j=1}^{n} n_j H_j(T^*) = 0 \quad (10)$$

Once T^* is known, T_j^* is solved for using equation 11.

$$T_j^* = \left(T_j - T^*\right)^+ \quad (11)$$

A detailed proof for scenario 1 is provided in Appendix A. Scenario 2 and 3 follow similarly. The scenario 1 expected cost model considers that demand will first be satisfied by fulltime capacity and once fulltime delivery capacity is used up, additional demand will be satisfied by seasonal capacity, followed by CSL capacity and finally a penalty is applied for each unit when demand exceeds the total capacity of fulltime, seasonal, and CSL. This reflects the fact that fulltime capacity and seasonal capacity are paid for whether or not they are used and it is expected that fulltime deliveries to have a lower expected error cost than seasonal which should in turn have a lower expected error cost than CSL.

The parameter values for this numerical experiments are determined from multiple sources. The per period demand and seasonal demand was referenced from a postal company's annual performance reports (USPS, 2021). Assuming it to meet town type setting, the volumes were scaled down. Wage rates were assumed to be competitive along the lines of industry trends considering a standard 8-hour work period and 5 periods per week assuming a total of 264 periods per year. Resource capacity and vehicle depreciation costs were referenced from Boyer at al. (2009). In the case of full time and seasonal capacities, the operational cost of using a vehicle such as delivery is added into the cost of fulltime and seasonal capacities respectively. Appendix B and C summarizes the input values used for the analysis along with the assumptions used. The numerical analysis of this model including sensitivity analysis was performed in Microsoft Excel.

3.4. Results From the Numerical Experiments

To understand the influence of the variables, numerical experiments were performed using scenarios 1, 2 and 3, where in scenario 1 the cost of CSL is greater than fulltime and seasonal, in scenario 2 it is between fulltime and seasonal and in scenario 3 it is less than fulltime and seasonal. The three scenarios are evaluated with demand following a uniform distribution (UD) and then repeated for demand following a normal distribution (ND) with the mean and standard deviation calculated from minimum and maximum when with UD and listed in Table 1. All numerical experiments use two seasons for determining the distribution of demand. The capacity for CSL is based on the maximum demand possible with UD and experiments used capacities of 0%, 25%, 50%, 75%, and 100% of the maximum demand value. These same CSL capacities were used with ND. After evaluating baseline cases, a sensitivity analysis is performed by varying the minimum and maximum demand (VAR and LEVEL cases), and varying the length of the seasonality (SPIKE case). Table 1 gives the demand values for each case of UD and ND calculated using formula in Appendix D.

Table 1. Minimum maximum values for UD, mean and standard deviation for ND.

Case		Uniform Distribution		Normal Distribution	
		Minimum	Maximum	Mean	Standard Deviation
BASE	Season 1	109	1032	570.50	266.45
	Season 2	97	459	278.00	104.50
VAR	Season 1	309	1232	770.50	266.45
	Season 2	47	409	228.00	104.50
LEVEL	Season 1	59	982	520.50	266.45
	Season 2	297	659	478.00	104.50

3.4.1. BASE case with demand following UD

Under UD, the demand is characterized by the minimum and maximum values possible for any given period. These bounds for each of the two seasons in each of the three scenarios are:

Scenario 1 with $U > S + E_S \, and \, F + E_F$. Season 1 109-1032, Season 2 97 - 459.

Scenario 2 with $S + E_S \geq U > F + E_F$. Season 1 109-1032, Season 2 97 - 459.

Scenario 3 with $U < \, F + E_F \, and \, S + E_S$. Season 1 109-1032, Season 2 97 - 459.

Figure 3 shows the optimal capacity for fulltime (T) and seasonal (T_j^*) deliveries by the capacity for CSL (C) deliveries. Note that the optimal seasonal capacity for season 2 is always 0 since demand is lower in season 2 compared to season 1. From Figure 3, it can be seen that both T and T_j^* reduce with an increase in C. In scenario 3, it is observed that T is reduced to 0 when the availability of C is greater than or equal to 50% of maximum demand whereas T_j^* remains high compared to scenarios 1 and 2 so that demand can be met in season 1.

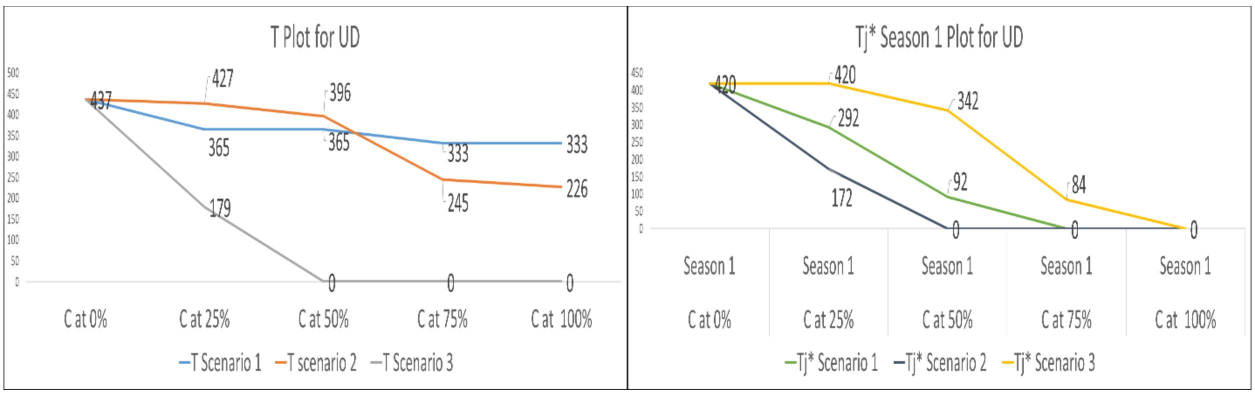


Figure 3. T and T_j^* for various capacities of C in BASE case with demand following a UD.

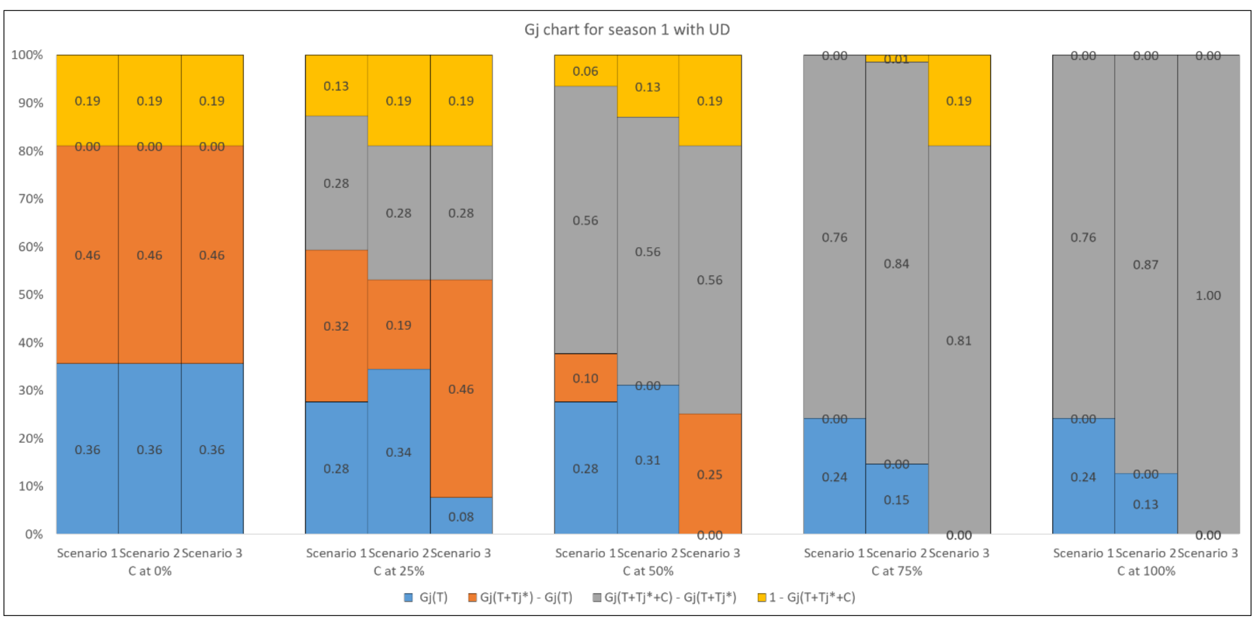


Figure 4. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in BASE case with demand following a UD in season 1.

Figures 4 and 5, show the percentage of deliveries being fulfilled by each type of capacity and the percent overcapacity for seasons 1 and 2, respectively. Figure 4 suggests that in season 1, the fulltime capacity is used for a lower percentage of deliveries, with use of seasonal and CSL leading to lower costs, whereas in season 2, based on Figure 5, fulltime capacity is used to perform a significant percentage of deliveries except in scenario 3, where after the capacity of CSL, $C \geq 25\%$, deliveries are dominated by CSL services.

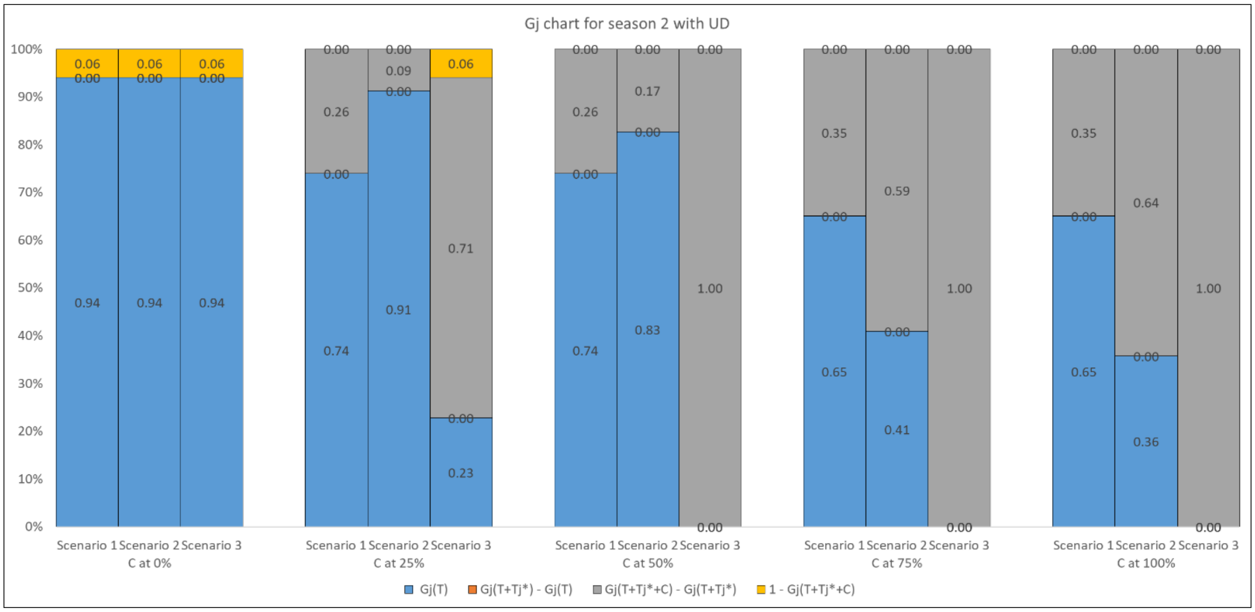


Figure 5. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in BASE case with demand following a UD in season 2.

Across the three scenarios, when comparing T, T_j^* and C, it is observed that as C increases, T_j^* i.e., the seasonal employees are reduced at a faster rate and eventually not needed when capacity of C is sufficiently large. With scenario 3, as the cost of the CSL resource is lower than the fulltime resource, the reliance on fulltime resources decreases more than the seasonal resources.

3.4.2. Base case under ND

For the model with ND, the same experiments were performed by calculating the mean and standard deviation using the minimum and maximum values used in UD, as listed in Table 1.

Scenario 1 with $U > S + E_S \; and > F + E_F$. Season 1 mean 570.5 and standard deviation 266.45, Season 2 mean 278 and standard deviation 104.50.

Scenario 2 with $S + E_S \geq U > F + E_F$. Season 1 mean 570.5 and standard deviation 266.45, Season 2 mean 278 and standard deviation 104.50.

Scenario 3 with $U < \; F + E_F \; and < S + E_S$. Season 1 mean 570.5 and standard deviation 266.45, Season 2 mean 278 and standard deviation 104.50.

Figure 6 shows the optimal capacity for fulltime (T) and seasonal (T_j^*) deliveries by the capacity for CSL (C) deliveries. Note that the optimal seasonal capacity for season 2 is always 0 since demand is lower in season 2 compared to season 1. As with the UD, both T and T_j^* reduce with an increase in C, but with exceptions, T increases when C is at 25% for scenario 2 and then decreases with increase in C. In scenario 3, it is observed that T is reduced to 0 when the availability of C is greater than or equal to 50% of maximum demand whereas T_j^* remains high compared to scenarios 1 and 2 so that demand can be met in season 1.

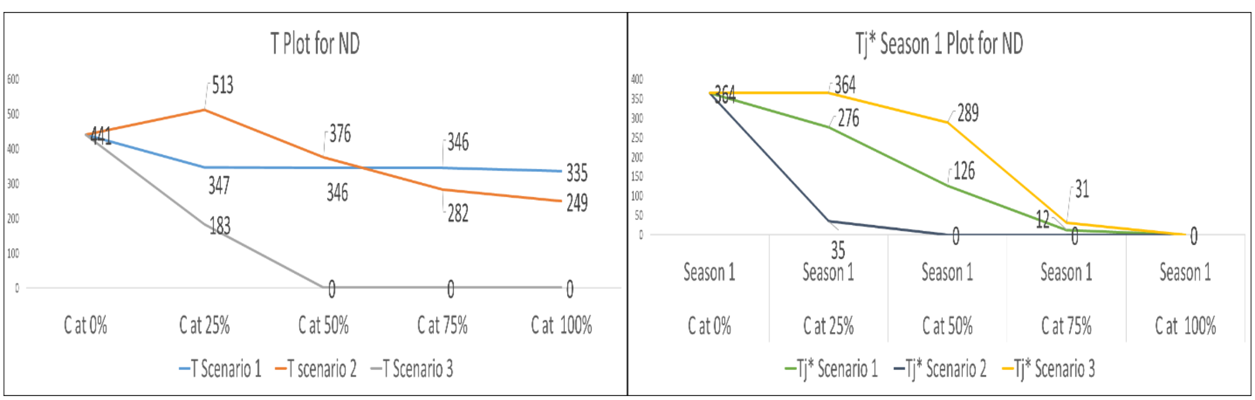


Figure 6. T and T_j^* for various capacities of C in BASE case with demand following a ND.

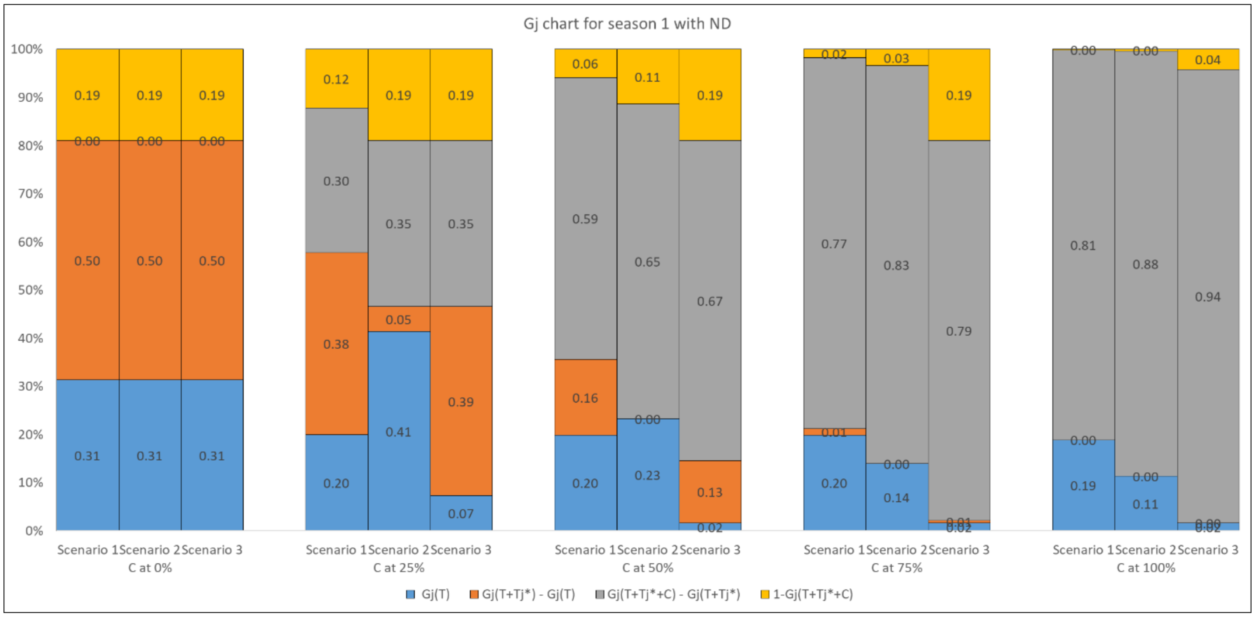


Figure 7. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in BASE case with demand following a ND in season 1.

Figures 7 and 8, show the percentage of deliveries being fulfilled by each type of capacity and the percent overcapacity for seasons 1 and 2, respectively. Figure 7 suggests that in season 1, the fulltime capacity is used for a lower percentage of deliveries, with use of seasonal and CSL leading to lower costs, whereas in season 2, based on Figure 8, fulltime capacity is used to perform a significant percentage of deliveries except in scenario 3, where after $C \geq 25\%$ deliveries are dominated by CSL.

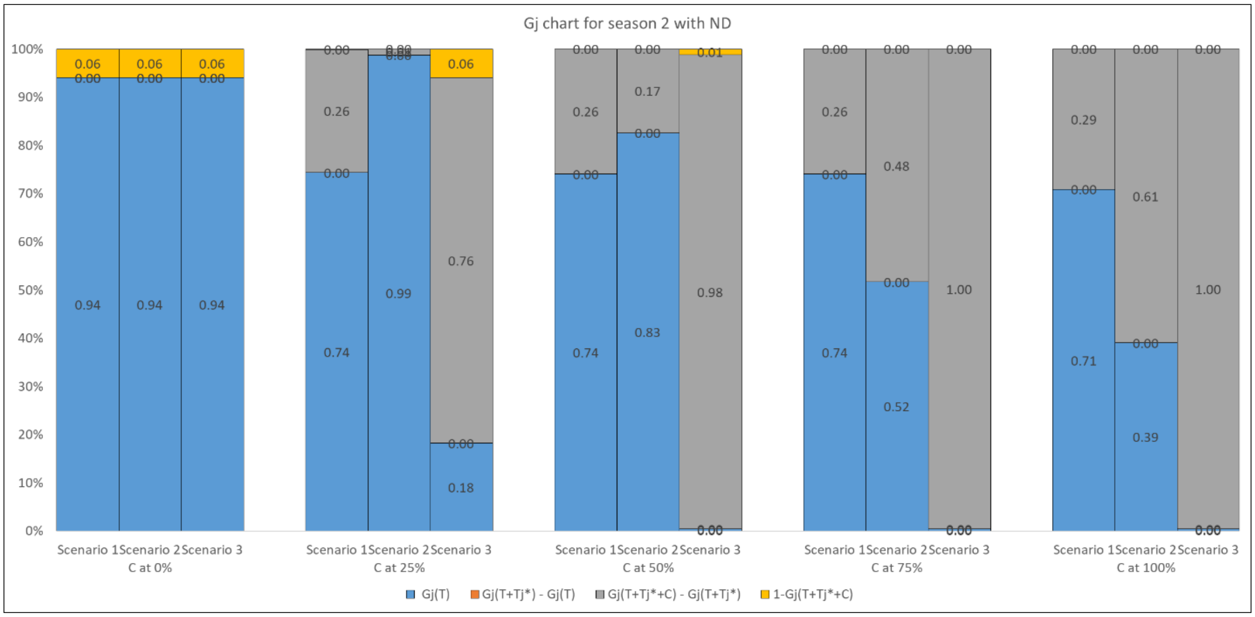


Figure 8. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in BASE case with demand following a ND in season 2.

Across the three scenarios, when comparing T, T_j^* and C, it is observed that as C increases, T_j^* i.e., the seasonal employees are reduced at a faster rate with the exception of scenario 3 and eventually not needed when C is sufficiently large. With scenario 3, as the cost of the CSL resource is lower than the fulltime resource, the reliance on fulltime resources decreases more than the seasonal resources.

3.4.3. Sensitivity analysis in UD

The sensitivity analysis is performed by varying the minimum and maximum value of the demand considering uniform distribution (VAR case and LEVEL case), and reducing the peak period (SPIKE case).

3.4.3.1. VAR case

The first minimum maximum change experiment is done by increasing the values of per period demand for the season 1 and reducing for season 2 as listed below.

Scenario 1 with $U > S + E_S$ $and > F + E_F$. Season 1 309-1232, Season 2 47 - 409.

Scenario 2 with $S + E_S \geq U > F + E_F$. Season 1 309-1232, Season 2 47 - 409.

Scenario 3 with $U < \ F + E_F \ and < S + E_S$. Season 1 309-1232, Season 2 47 - 409.

Figure 9 shows the resources needed in case of fulltime employees (T) and seasonal employees (T_j^*) needed for respective seasons. These two needs are based on the availability of CSL (C), which is projected at C for 0%, 25%, 50%, 75% and 100% of maximum demand of the peak period. Both, T and T_j^* reduces with each case of increase in C, but with exceptions, T increases when C is at 25% and 50% for scenario 2, and being steady when $C \geq 25\%$ for scenario 1. In case of scenario 3, it is observed that T is reduced to 0 when the availability of C tends to be greater than or equal to 50% of demand whereas T_j^* is utilized at a higher number (C at 25% and 50%) than scenarios 1 and 2, for season 1 to meet the demand.

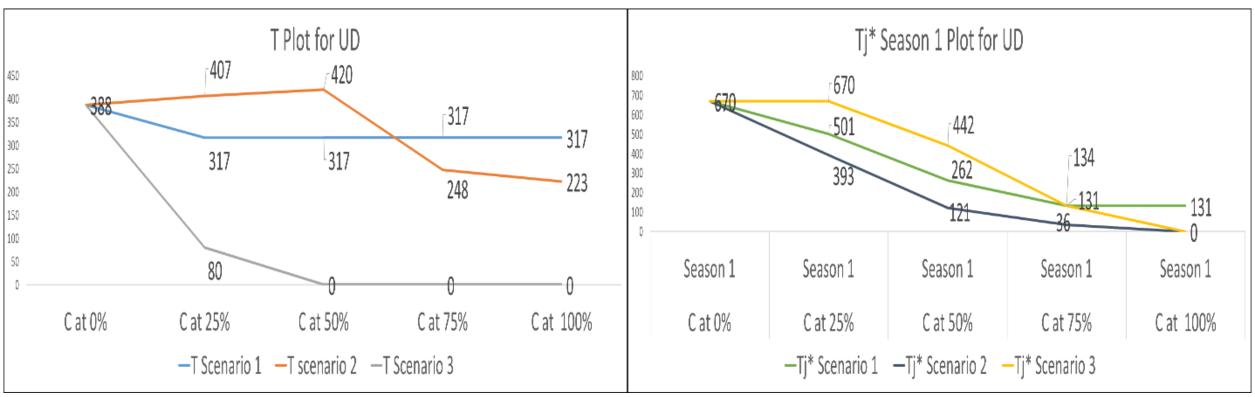


Figure 9. T and T_j^* for various capacities of C in VAR case with demand following a UD.

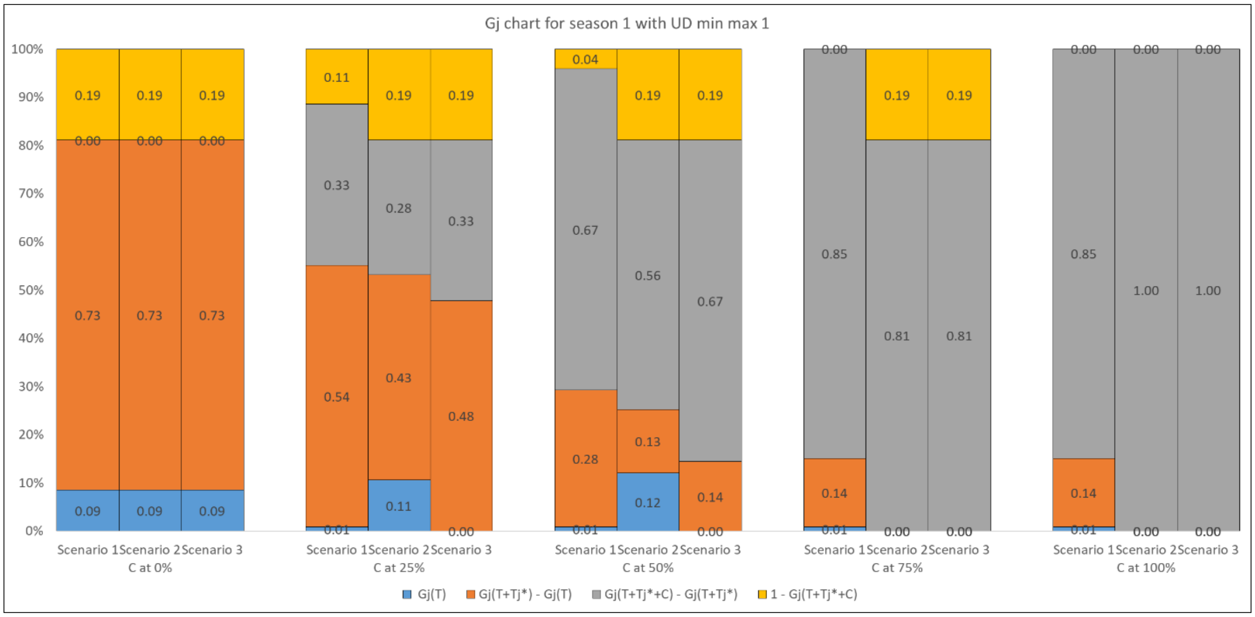


Figure 10. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in VAR case with demand following a UD in season 1.

Figures 10 and 11, gives the percentage of orders being fulfilled by each type of resources and if any overcapacity penalty experienced for seasons 1 and 2 respectively. Figure 10 suggests that in season 1, the fulltime capacity has a lower involvement, with use of seasonal and CSL leading to lower costs, whereas in season 2 per Figure 11, fulltime resources have a significant rate of order fulfillment except for scenario 3, where after $C \geq 25\%$ is dominated by the resource type C.

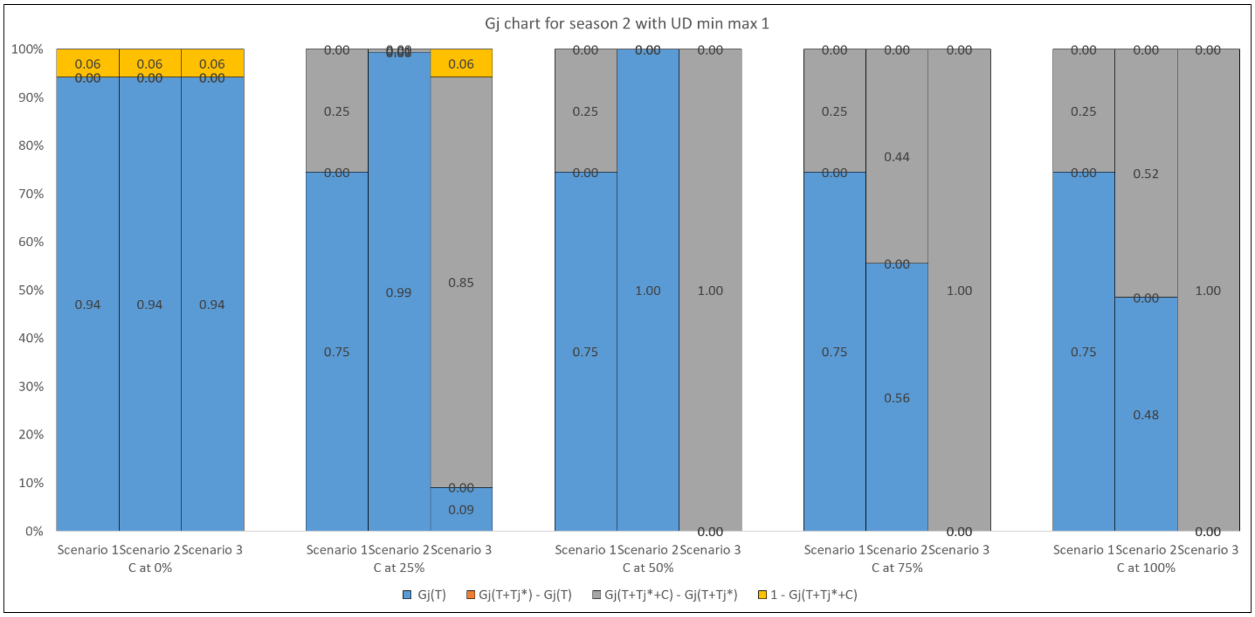


Figure 11. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in VAR case with demand following a UD in season 2.

3.4.3.2. LEVEL case

The second minimum maximum change experiment is done by decreasing the values of per period demand for the season 1 and increasing for season 2 as listed below.

Scenario 1 with $U > S + E_S$ $and > F + E_F$. Season 1 59-982, Season 2 297 – 659.

Scenario 2 with $S + E_S \geq U > F + E_F$. Season 1 59-982, Season 2 297 – 659.

Scenario 3 with $U < F + E_F$ $and < S + E_S$. Season 1 59-982, Season 2 297 – 659.

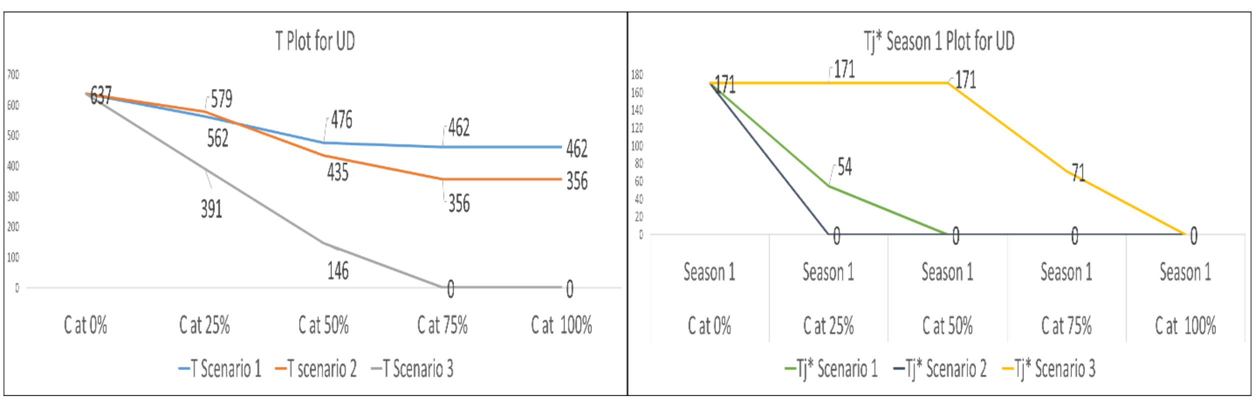


Figure 12. T and T_j^* for various capacities of C in LEVEL case with demand following a UD.

Figure 12 shows the resources needed in case of fulltime employees (T) and seasonal employees (T_j^*) needed for respective seasons. These two needs are based on the availability of CSL (C), which is projected at C for 0%, 25%, 50%, 75% and 100% of maximum demand of the peak period. Both, T and T_j^* reduces with each case of increase in C. In case of scenario 3, it is observed that T is reduced to 0 when the availability of C tends to be greater than or equal to 75% of demand whereas T_j^* is utilized at a higher number than scenarios 1 and 2, for season 1 to meet the demand. It is interesting to note that when compared to the first minimum maximum change as in the VAR case, T is very much preferred than utilization of seasonal.

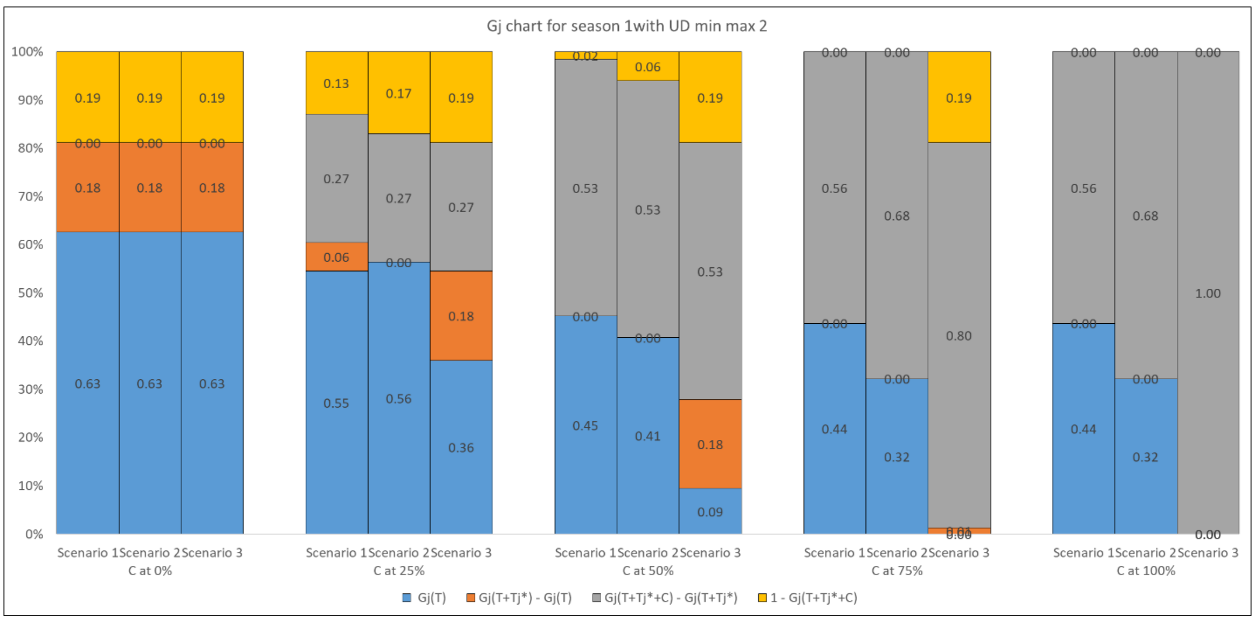


Figure 13. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in LEVEL case with demand following a UD in season 1.

Figures 13 and 14, gives the percentage of orders being fulfilled by each type of resources and if any overcapacity penalty experienced for seasons 1 and 2 respectively. Figure 13 suggests that in season 1, the fulltime capacity involvement reduces with increase in CSL capacity. Except for scenario 3, where after $C \geq 75\%$ is dominated by the resource type C. Whereas in season 2, per Figure 14, fulltime resources have a significant rate of order fulfillment but keep reducing with increase in C, except for scenario 3, where after $C \geq 25\%$ is dominated by the resource type C.

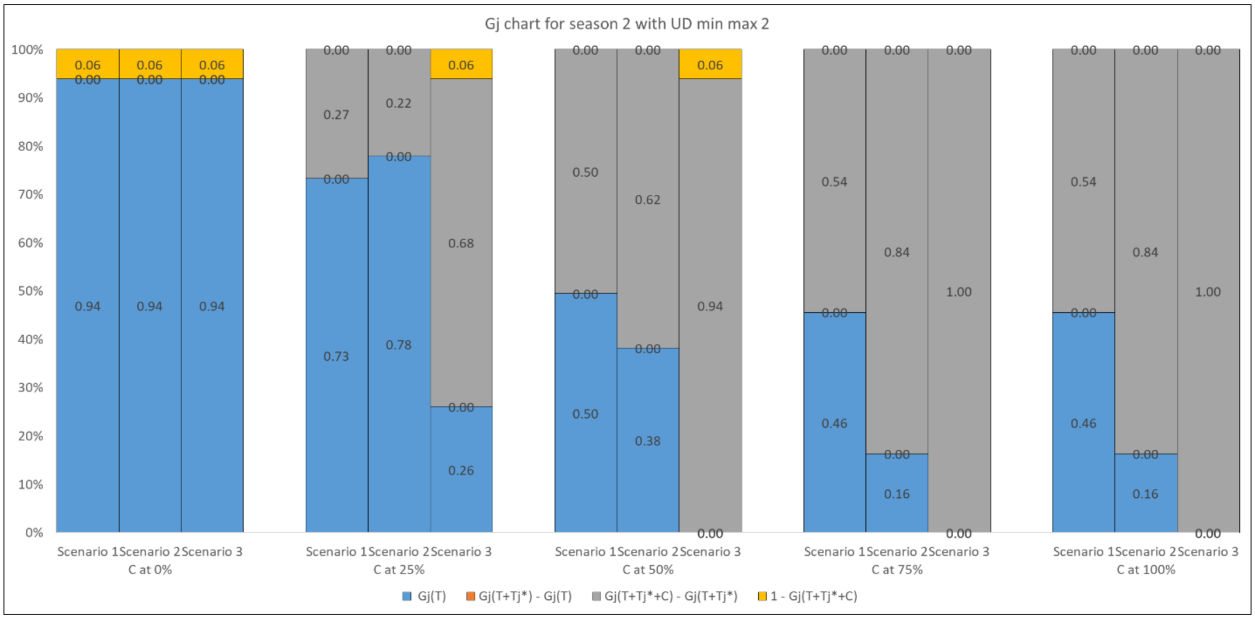


Figure 14. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in LEVEL case with demand following a UD in season 2.

3.4.3.3. SPIKE case

In this case, the peak period i.e., season 1 is shortened and season 2 is extended as below.

Scenario 1 with $U > S + E_S$ *and* $> F + E_F$. Season 1 66 days, Season 2 198 days.

Scenario 2 with $S + E_S \geq U > F + E_F$. Season 1 66 days, Season 2 198 days.

Scenario 3 with $U < F + E_F$ *and* $< S + E_S$. Season 1 66 days, Season 2 198 days.

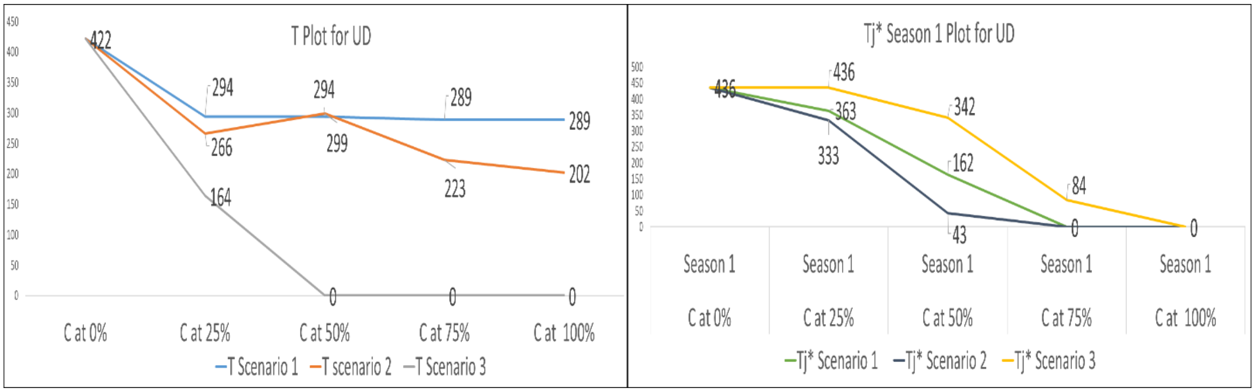


Figure 15. T and T_j^* for various capacities of C in SPIKE case with demand following a UD.

Figure 15 shows the resources needed in case of fulltime employees (T) and seasonal employees (T_j^*) needed for respective seasons. These two needs are based on the availability of CSL (C), which is projected at C for 0%, 25%, 50%, 75% and 100% of maximum demand of the peak period. Both, T and T_j^* reduces with each case of increase in C with an exception for scenario 2, an increase in T is observed when C is at 50%. In case of scenario 3, it is observed that T is reduced to 0 when the availability of C tends to be greater than or equal to 50% of demand whereas T_j^* is utilized at a higher number than scenarios 1 and 2, for season 1 to meet the demand

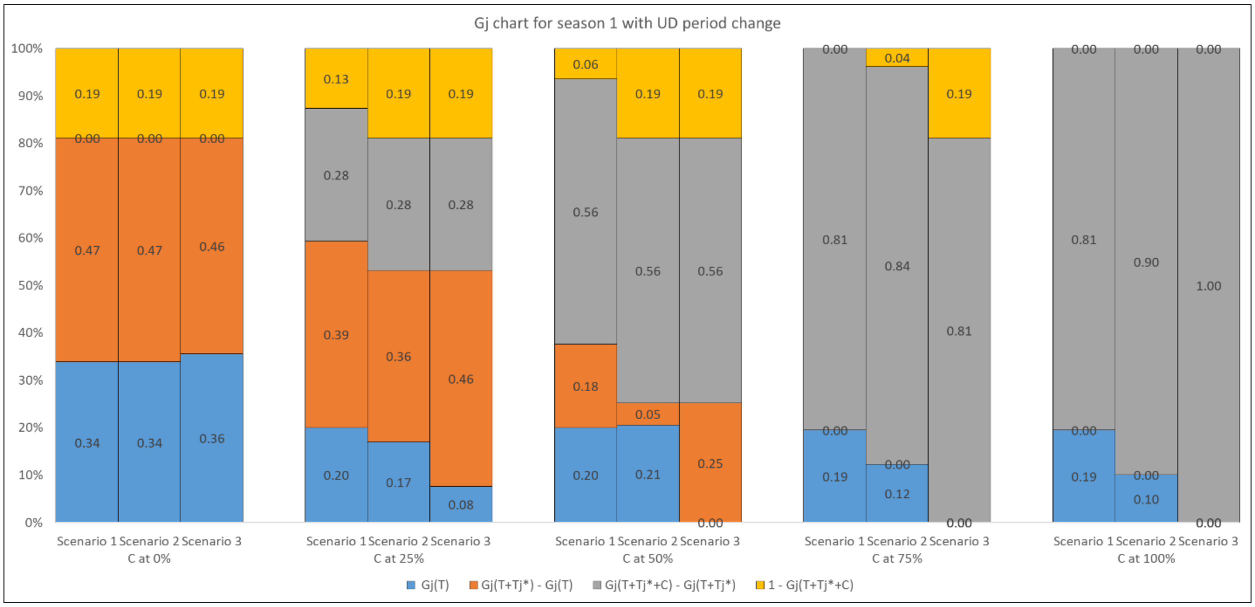


Figure 16. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in SPIKE case with demand following a UD in season 1.

Figures 16 and 17, gives the percentage of orders being fulfilled by each type of resources and if any overcapacity penalty experienced for seasons 1 and 2 respectively. Figure 16 suggests that in season 1, the fulltime capacity has a lower involvement, with use of seasonal and CSL leading to lower costs, whereas in season 2, per Figure 17, fulltime resources have a significant rate of order fulfillment except for scenario 3, where after $C \geq 25\%$ is dominated by the resource type C.

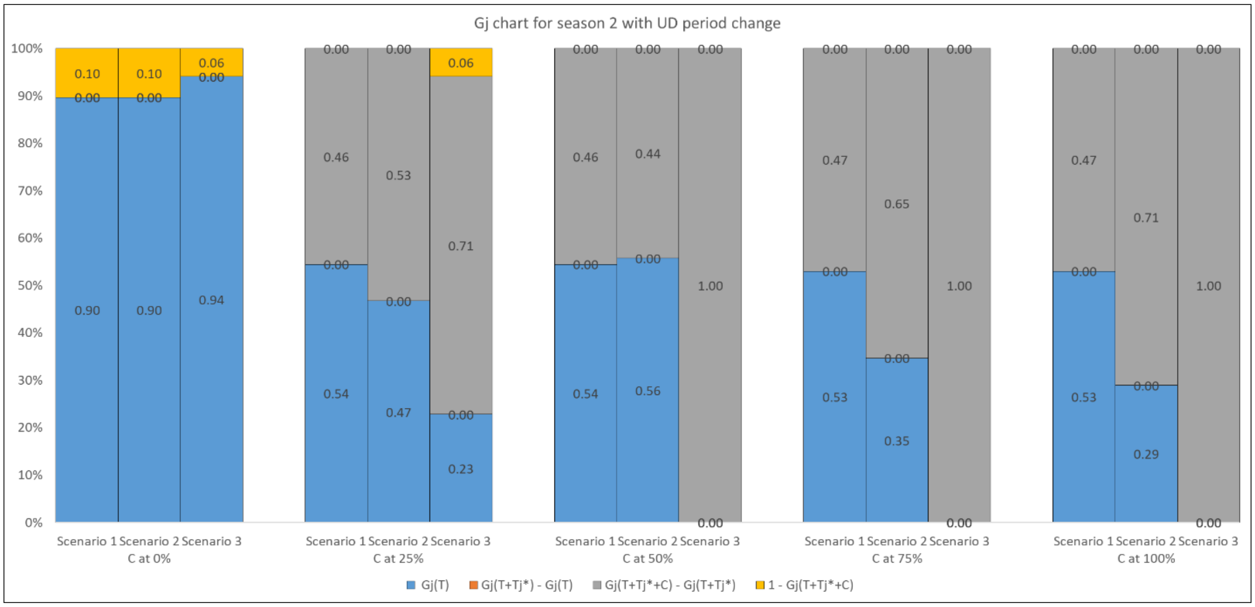


Figure 17. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in SPIKE case with demand following a UD in season 2.

3.4.4. Sensitivity analysis in ND

For the model with ND, the same experiments were performed by calculating the mean and standard deviation using the minimum and maximum values used in UD, as listed in Table 1. The sensitivity analysis is performed by varying the demand considering normal distribution (VAR case and LEVEL case) and reducing the peak period (SPIKE case).

3.4.4.1. VAR case

The first minimum maximum change experiment is done by increasing the values of per period demand for the season 1 and reducing for season 2 as listed below.

Scenario 1 with $U > S + E_S \; and > F + E_F$. Season 1 mean 770.5 and standard deviation 266.45, Season 2 mean 228 and standard deviation 104.50.

Scenario 2 with $S + E_S \geq U > F + E_F$. Season 1 mean 770.5 and standard deviation 266.45, Season 2 mean 228 and standard deviation 104.50.

Scenario 3 with $U < F + E_F$ $and < S + E_S$. Season 1 mean 770.5 and standard deviation 266.45, Season 2 mean 228 and standard deviation 104.50.

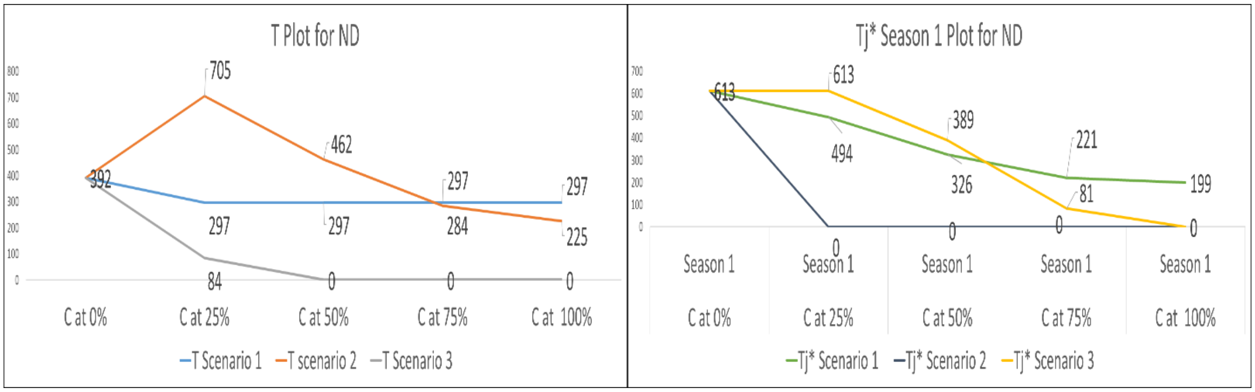


Figure 18. T and T_j^* for various capacities of C in VAR case with demand following a ND.

Figure 18 shows the resources needed in case of fulltime employees (T) and seasonal employees (T_j^*) needed for respective seasons. These two needs are based on the availability of CSL (C), which is projected at C for 0%, 25%, 50%, 75% and 100% of maximum demand of the peak period. Both, T and T_j^* reduces with each case of increase in C except for, T in scenario 1 which is steady for C greater than 25%, T in scenario 2 which increases when C is at 25% and then reduces. In case of scenario 3, it is observed that T is reduced to 0 when the availability of C tends to be near 50% of demand whereas T_j^* is utilized at a higher number than scenarios 1 and 2, for season 1 to meet the demand.

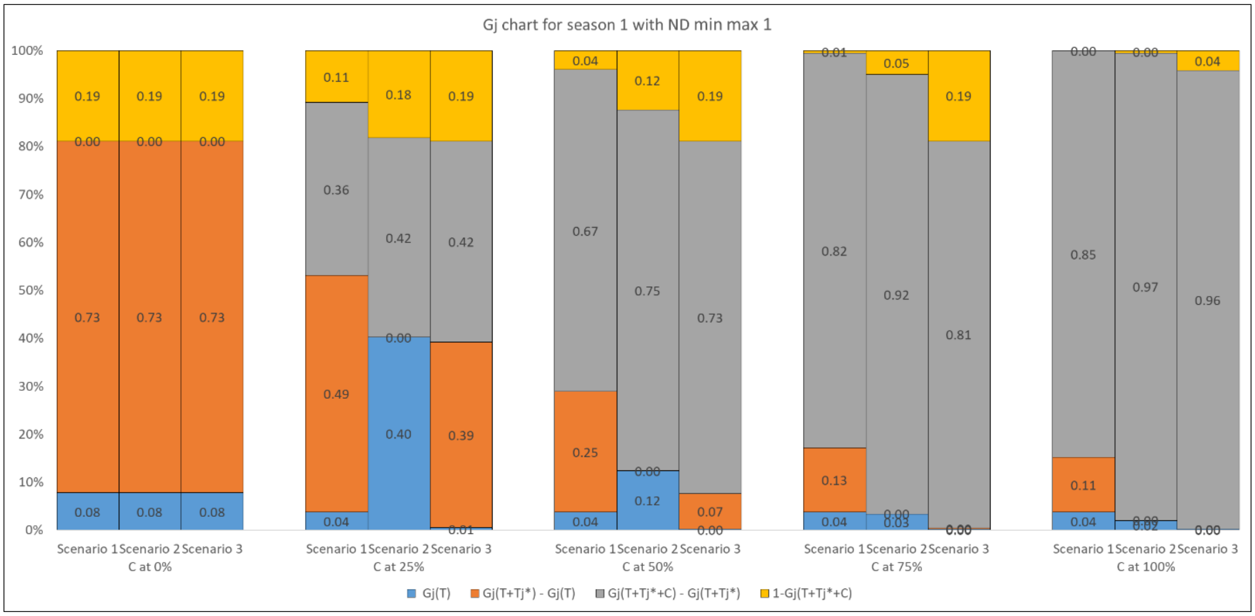


Figure 19. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in VAR case with demand following a ND in season 1.

Figures 19 and 20, gives the percentage of orders being fulfilled by each type of resources and if any overcapacity penalty experienced for seasons 1 and 2 respectively. Figure 19 suggests that in season 1, the fulltime capacity has a lower involvement, with use of seasonal and CSL leading to lower costs, whereas in season 2, per Figure 20, fulltime resources have a significant rate of order fulfillment except for scenario 3, where after $C \geq 25\%$ is dominated by the resource type C.

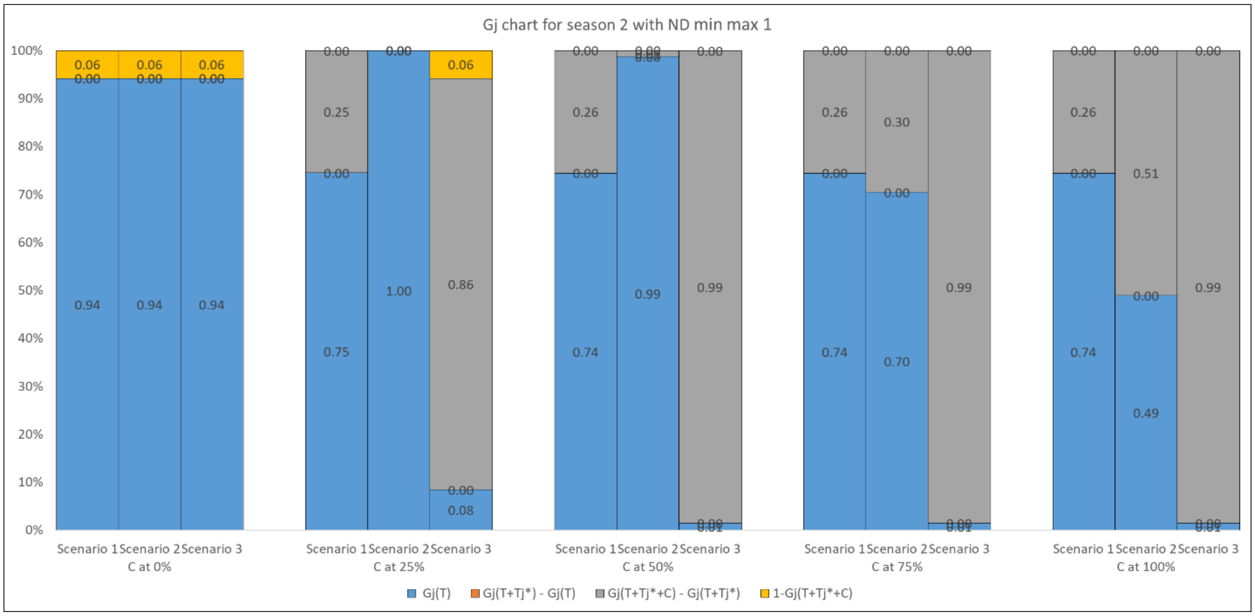


Figure 20. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in VAR case with demand following a ND in season 2.

3.4.4.2. LEVEL case

The second minimum maximum change experiment is done by reducing the values of per period demand for the season 1 and increasing for season 2 as listed below.

Scenario 1 with $U > S + E_S \; and > F + E_F$. Season 1 mean 520.5 and standard deviation 266.45, Season 2 mean 478 and standard deviation 104.50.

Scenario 2 with $S + E_S \geq U > F + E_F$. Season 1 mean 520.5 and standard deviation 266.45, Season 2 mean 478 and standard deviation 104.50.

Scenario 3 with $U < \; F + E_F \; and < S + E_S$. Season 1 mean 520.5 and standard deviation 266.45, Season 2 mean 478 and standard deviation 104.50.

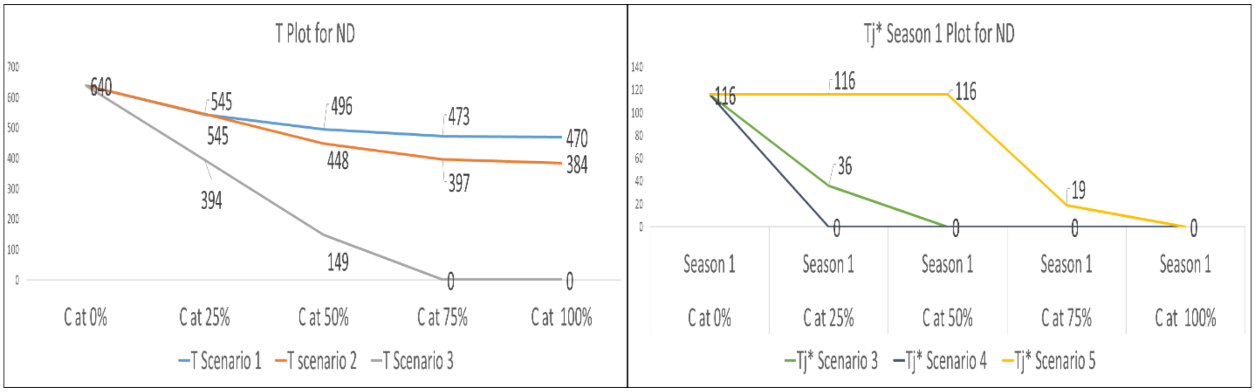


Figure 21. T and T_j^* for various capacities of C in LEVEL case with demand following a ND.

Figure 21 shows the resources needed in case of fulltime employees (T) and seasonal employees (T_j^*) needed for respective seasons. These two needs are based on the availability of CSL (C), which is projected at C for 0%, 25%, 50%, 75% and 100% of maximum demand of the peak period. Both, T and T_j^* reduces with each case of increase in C. In case of scenario 3, it is observed that T is reduced to 0 when the availability of C tends to be near 75% of demand whereas T_j^* is utilized at a higher number than scenarios 1 and 2, for season 1 to meet the demand.

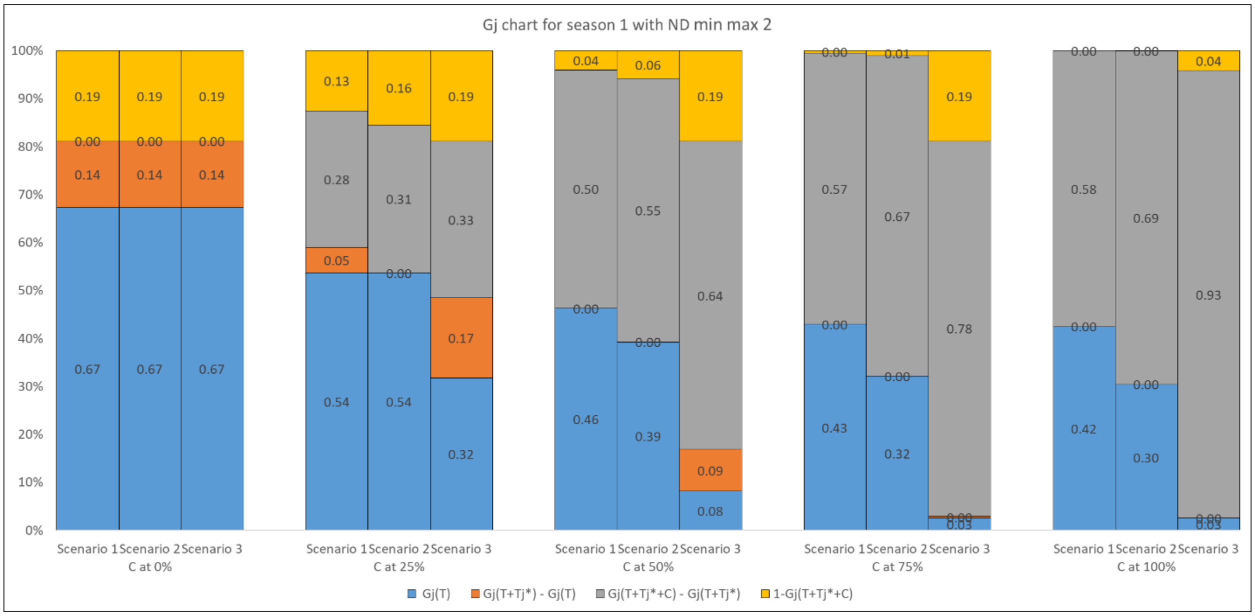


Figure 22. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in LEVEL case with demand following a ND in season 1.

Figures 22 and 23, gives the percentage of orders being fulfilled by each type of resources and if any overcapacity penalty experienced for seasons 1 and 2 respectively. Figure 22 suggests that in season 1, the fulltime capacity has a considerable involvement, with use of seasonal and CSL leading to lower costs, whereas in season 2, per Figure 23, fulltime resources have a significant rate of order fulfillment when compared to season 1, except for scenario 3, where after $C \geq 25\%$ is dominated by the resource type C. In both the cases, the decrease in fulltime is observed as C increases.

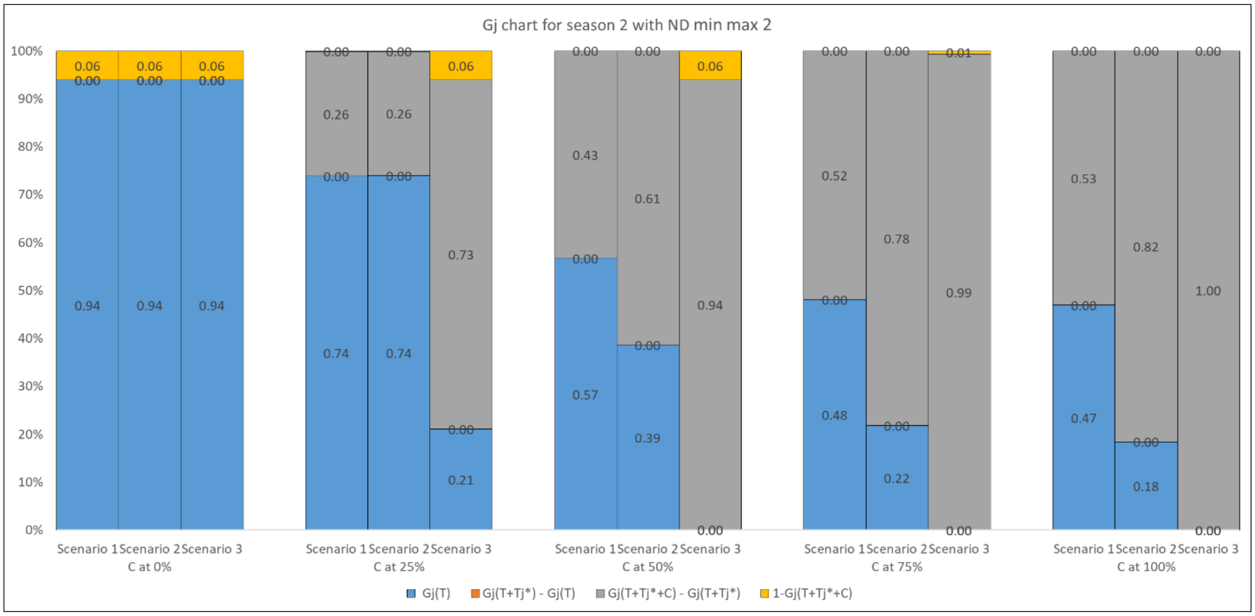


Figure 23. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in LEVEL case with demand following a ND in season 2.

3.4.4.3. SPIKE case

In this case, the peak period i.e., season 1 is shortened and season 2 is extended as below.

Scenario 1 with $U > S + E_S$ *and* $> F + E_F$. Season 1 66 days, Season 2 198 days.

Scenario 2 with $S + E_S \geq U > F + E_F$. Season 1 66 days, Season 2 198 days.

Scenario 3 with $U < F + E_F$ *and* $< S + E_S$. Season 1 66 days, Season 2 198 days.

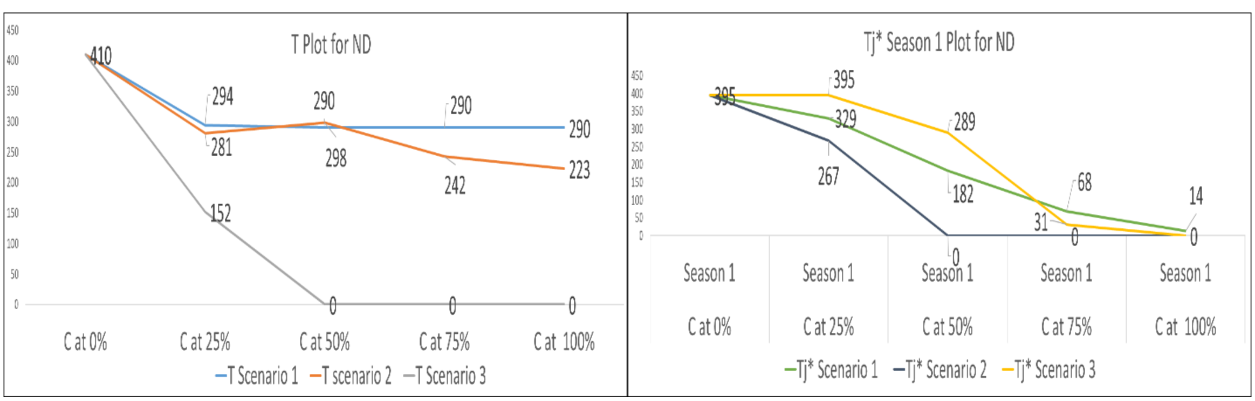


Figure 24. T and T_j^* for various capacities of C in SPIKE case with demand following a ND.

Figure 24 shows the resources needed in case of fulltime employees (T) and seasonal employees (T_j^*) needed for respective seasons. These two needs are based on the availability of CSL (C), which is projected at C for 0%, 25%, 50%, 75% and 100% of maximum demand of the peak period. Both, T and T_j^* reduces with each case of increase in C except, for T in scenario 1 showing to be steady after $C \geq 50\%$ and for T in scenario 2 showing and increase when C is at 50%. In case of scenario 3, it is observed that T is reduced to 0 when the availability of C tends to be greater than or equal to 50% of demand whereas T_j^* is utilized at a higher number than scenarios 1 and 2, for season 1 to meet the demand.

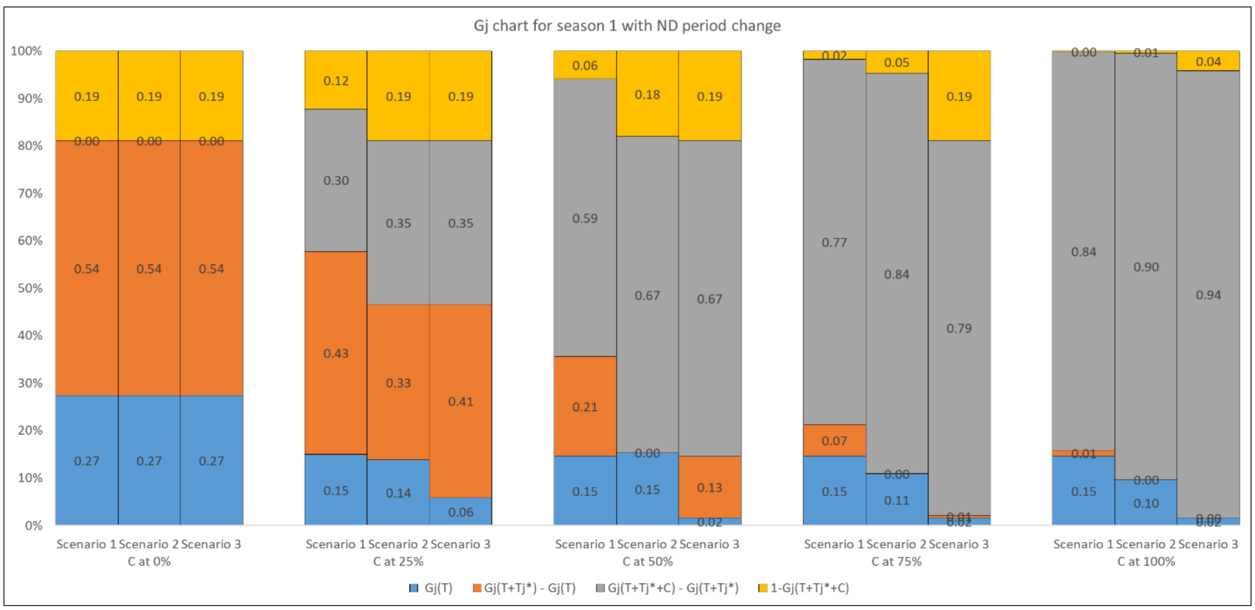


Figure 25. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in SPIKE case with demand following a ND in season 1.

Figures 25 and 26, gives the percentage of orders being fulfilled by each type of resources and if any overcapacity penalty experienced for seasons 1 and 2 respectively. Figure 26 suggests that in season 1, the fulltime capacity has a lower involvement, with use of seasonal involvement, whereas in season 2, from Figure 26, fulltime resources have a significant rate of order fulfillment except for scenario 3, where after $C \geq 25\%$ is dominated by the resource type C.

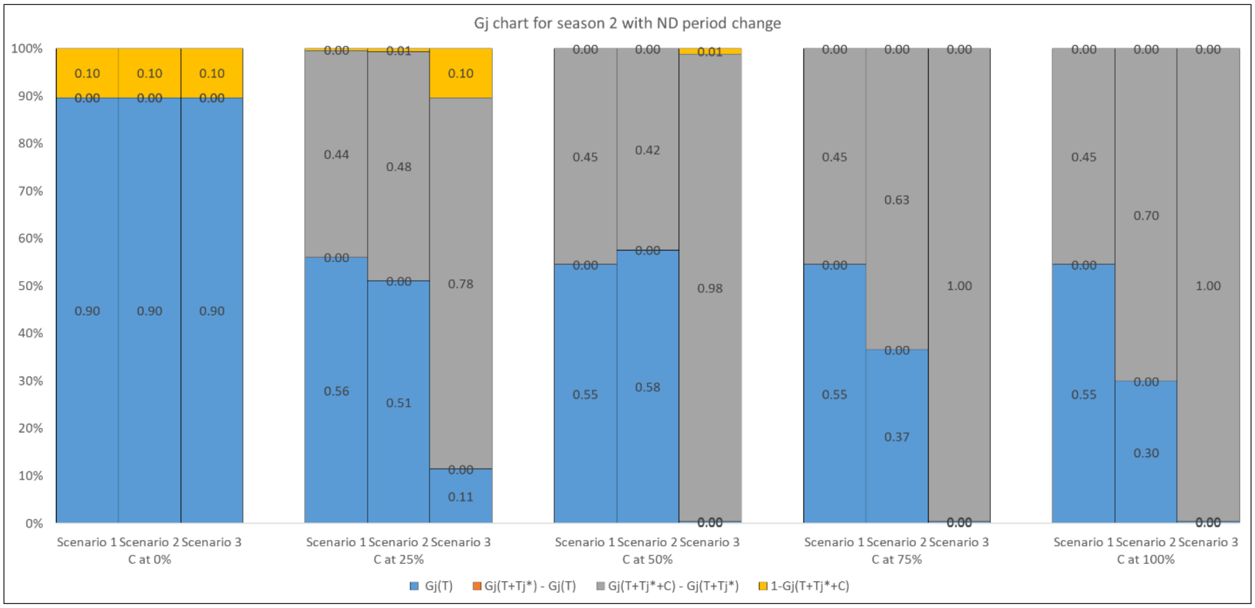


Figure 26. Percentages of orders fulfilled using T, T_j^* and C, and percentage of orders missed for various capacities of C in SPIKE case with demand following a ND in season 2.

Within this sensitivity analysis exercise, it was observed that the change in the minimum and maximum values, reducing the peak period duration and considering the costs of CSL resource (the three scenarios; greater than fulltime and seasonal, between fulltime and seasonal and less than fulltime and seasonal) with uniform and normal distribution of demand data lead to a similar change in all the cases. Though the trend followed the same in uniform and normal with a few exceptions, the count of resources and percentages of orders fulfilled by respective resources varied as shown in the above graphs and charts in subsection 3.4. As the cost of the CSL services dropped and their capacity increases, the order fulfillment rate was observed to be improving with the optimal combination of resources for all three scenarios, with scenario 3 leading to the lowest operational cost with high utilization of CSL resources.

3.5. Discussion of Results

The results of the numerical experiments performed, give an overview of the total operational cost considering the variation in the capacities and costs of the CSL resources. As observed in the base case results, as the capacity of CSL increases, the fulltime and seasonal resource count reduces. Along with this, the order fulfillment rate also improves. Comparing the seasons 1 and 2, the season 2 has the highest order fulfillment probability with the use of fulltime and CSL resources. In case of scenario 1 where the cost of CSL was greater than the fulltime and seasonal, the usage of CSL resource was still observed. This was primarily due to the fact that this CSL resource is only utilized when needed and not committed for the entire year like fulltime. This CSL resource also, alleviated some costs that would be incurred by the seasonal resources for season 1, but to keep the costs lower the seasonal utilization can be varied as observed for seasonal trend with each increase of CSL capacity.

As observed in the sensitivity analysis, when the peak season 1 demand increased and season 2 demand was decreased, the increase in seasonal resources was observed in both the distribution types. When this demand change was switched with season 1 decreased and season 2 increased, the reliance on seasonal dropped with steady consideration of fulltime resources to even the operational costs. In either of the distributions considered, the CSL capacity had prominent impact with maximum benefit observed in scenario 3. Though scenario 3 provides the lowest overall cost since it has the lowest per delivery CSL cost, it is worth noting that it does not provide the highest service level in season 1 where in fact it provides the lowest service level with the highest percentage of demand exceeding overall capacity or undelivered units. Between fulltime and CSL resources, a CSL resource is more prone to delivery errors impacting the quality of service and profit margins. The advantage of CSL resource is that it only incurs a cost if it is used, which assists in lowering the cost. Thus, the capacity and cost of the CSL resources becomes a prominent aspect to be considered when planning capacity for LMD services in a given region.

Overall, it appears that when a small amount of CSL capacity is added to the model, it primarily substitutes for seasonal capacity, even when seasonal capacity is cheaper per delivery in case of scenario 1. For scenarios 1 and 2, as CSL capacity increases, it replaces all of seasonal capacity before beginning to reduce fulltime capacity. In contrast, in scenario 3 when a CSL delivery is cheaper than a fulltime delivery, CSL first reduces fulltime capacity and then seasonal capacity, despite fulltime capacity being cheaper per delivery. These price-capacity anomalies are likely driven by the fact that CSL capacity, like fulltime capacity, is available all year long while seasonal capacity is only available for one season.

To summarize, in the model provides the optimal levels of fulltime, seasonal, and CSL capacities to minimize the expected cost of deliveries. However, this being an analytical model, many complexities have been left out of the model to facilitate analysis. Thus, this study in continued further by investigate the use of stochastic program to capture the complexities around the cost and capacity of CSL deliveries, as in practice both the costs and capacity of CSL deliveries are random variables rather than deterministic in nature.

4. STOCHASTIC PROGRAMMING SECTION

In the last section, an analytical model was used to determine the minimum cost for LMD services by using a combination of resources between fulltime, seasonal and CSL to fulfill the seasonal demand. Based on the results, it was concluded that CSL can be utilized to reduce overall costs but service levels must be monitored to meet customer expectations. In addition, the CSL cost and capacity were considered known values at fixed slabs. However, in reality the cost and capacity will be random variables.

Thus, to address the impact on operating costs due to the random nature of the CSL capacity and costs; in this section the problem is solved using a stochastic program. The stochastic program considers the randomness in the availability of CSL services and the costs to determine the optimal combination of resources to minimize LMD costs.

4.1. Stochastic Program Objective

In this portion of the study, stochastic programming is used to better understand the situation with certain uncertainties involved, primarily with the capacity and cost of CSL. The objective here is to minimize the costs of deliveries by considering the variable capacities and costs of CSL. Considering the analytical modeling section, and the utilization of stochastic programming for cost optimization in LMD services, in this section a refined optimal resource strategy is determined for aggregate capacity planning.

Continuing the study from the analytical model in the previous section, the randomness in the CSL capacities and costs are considered in the stochastic program, in this section. The objective of this model is to capture the minimum cost considering that the demand in a given day of a season is satisfied with either fulltime capacity, seasonal capacity or CSL with varying capacities and costs of CSL services. Any demand that was not fulfilled would initiate a penalty cost.

4.2. Assumptions Used for Stochastic Programming

The assumptions used in the analytical phase are still valid and continued for the stochastic program as well, with the exception of the capacity and cost for CSL becoming random variables. Also, continuing with the parameters and notation used in the analytical phase, in this phase additional aspects considered are as below.

P = Percentage variation in the CSL costs for scenario 1, scenario 2 and scenario 3.

I = Number of price points for CSL costs.

The stochastic program is run using the BASE case of the analytical model. The costs and capacities for CSL are generated each day as follows. First, I price points are randomly generated from a UD over the interval $[PUci,(1+P)Uci]$ where Uci is the cost of CSL used in Scenario i in the analytical model for i = 1, 2, and 3. Next, for each price point the corresponding capacity is randomly generated using a Poisson distribution with mean Ca/I where Ca is the CSL capacity used in the analytical experiments. The demand per day is generated using a UD with the BASE case minimum and maximum values for seasons 1 and 2 respectively.

4.3. Stochastic Program Description

In this subsection, the stochastic program is described with the objective to minimize the total operational costs. The model will consider the fulltime cost per unit, fulltime error cost, seasonal cost per unit, seasonal error cost, number of periods, seasons, number of scenarios, demand for each scenario, and, varying CSL capacities (Ca) and CSL costs (Scenario 1, Scenario 2 and Scenario 3). The CSL costs considered here includes the error cost caused by the CSL resource. The periods per season and the demand per season used in stochastic program are the same as the BASE case in the analytical model. For the stochastic model formulation, parameters from the analytical section will be used. In addition, some newly defined parameters appear in table 2.

Table 2. Additional parameters for stochastic program.

Parameter	Definition
J	Number of periods in planning horizon
K	Number of seasons in planning horizon
I	Number of intervals in piecewise linear CSL cost
$\sigma(j)$	Season in which day j occurs
H	Number of scenarios

In addition to the parameters in Table 2, there are random parameters defined to induce the variable nature of the CSL capacities and costs. Table 3, gives the random parameters and definitions that are used in this modeling section.

Table 3. Random parameters for stochastic program.

Random Parameter	Definition
D_{jh}	Demand on day j for scenario h
C_{ijh}	Cost per unit of demand (including expected error cost) satisfied by CSL on day j in interval I in scenario h
b_{ijh}	Available capacity at cost C_{ijh}

The decision variables to be used for this model are defined in Table 4.

Table 4. Decision variables for stochastic program.

Decision Variable	Definition
T	Fulltime capacity
T_k	Seasonal capacity in season k
X_{ijh}	Units of demand satisfied at cost C_{ijh}
U_{jh}	Unsatisfied demand on day j in scenario h
f_{jh}	Units of demand satisfied by fulltime capacity on day j in scenario h
S_{jh}	Units of demand satisfied by seasonal capacity on day j scenario h

The objective of the stochastic program is to minimize operations cost for LMD services by using an optimal combination of resources to address demand in each season. Equation 12. gives the objective function for the stochastic program. Utilizing the available information, the stochastic model is run in SAS 9.4 for 72 different combinations of scenarios, P, Ca, and I. Appendix E gives one portion of the SAS stochastic program as an example. Two different percentage variations of mean costs are considered in this run, first it is varied by 25% and second 50% for each of the three scenarios with the cost of CSL. The capacities evaluated were at four levels, and three price points were considered for the SAS program run.

$$\text{Min cost} = \sum_{h=1}^{H} \sum_{j=1}^{J} (\boldsymbol{FT} + \boldsymbol{ST}_{\sigma\,(j)} + \sum_{i=1}^{I} \boldsymbol{C}_{ijh} * \boldsymbol{X}_{ijh} + \boldsymbol{E}_f * \boldsymbol{f}_{jh} + \boldsymbol{E}_s * \boldsymbol{S}_{jh} + \boldsymbol{OU}_{jh}) \qquad (12)$$

The constraints identified for the stochastic program are:

$f_{jh} \leq T$

$S_{jh} \leq T_{\sigma(j)} \ \forall \ \ j, h$

$X_{ijh} \leq b_{ijh} \ \forall \ \ i, j, h$

$f_{jh} + \ S_{jh} + \sum_{i=1}^{I} Xijh + U_{js} \geq D_{js} \ \ \forall \, j, h$

Non-negativity for all variables.

4.4. Results From the Stochastic Program

The results obtained from the SAS program are displayed in the table in Appendix F. The table gives the optimal combination of resources to be used considering fulltime T , seasonal T_k, and CSL x. The notation T will be implying that the fulltime resource is for the entire year, whereas for T_k, x and U, there will be a suffix “1” or “2” for seasons 1 and 2 respectively. Where T_k [1] is the season 1 seasonal resource, x1 and x2 are the number of CSL deliveries in season 1 and season 2 respectively, and U1 and U2 are the undelivered units for season 1 and season 2 respectively. The results obtained are average values for each scenario considering the cost variation percentage P, capacity of CSL Ca, and the number of cost intervals I for each of the cost categories per scenario 1, scenario 2 and scenario 3. The Appendix Figures, Figure G1 to Figure G12 shows the charts for these results observed for various combinations of scenario 1, scenario 2, scenario 3, P, Ca and I.

To summarize, with an increase in the capacity of CSL, there is an increase in the utilization of CSL as well, for each case of scenario 1, scenario 2 and scenario 3. With the increase in utilization of the CSL capacity the seasonal capacity, T_k first starts to reduce and finally the fulltime capacity is reduced. The number of price points does help in lowering the total cost which is dependent on the expected CSL capacity and the variation in the price points. The higher the variation in random CSL price points, the lower the expected operational cost.

Figure 27 and Figure 28 give the trend of the optimal values of T and T_k when P = 0.25 and 0.5 respectively. It is interesting to note that as CSL capacity increases, the reliance on seasonal reduces to zero, as in the case when Ca = 5, I = 3 in scenario 1 for P = 0.25 and Ca = 5, I = 3 and 5 for P = 0.5 for scenario 1 and for both cases of P, when Ca = 5, I = 1, 3 and 5 for scenario 2 and scenario 3.

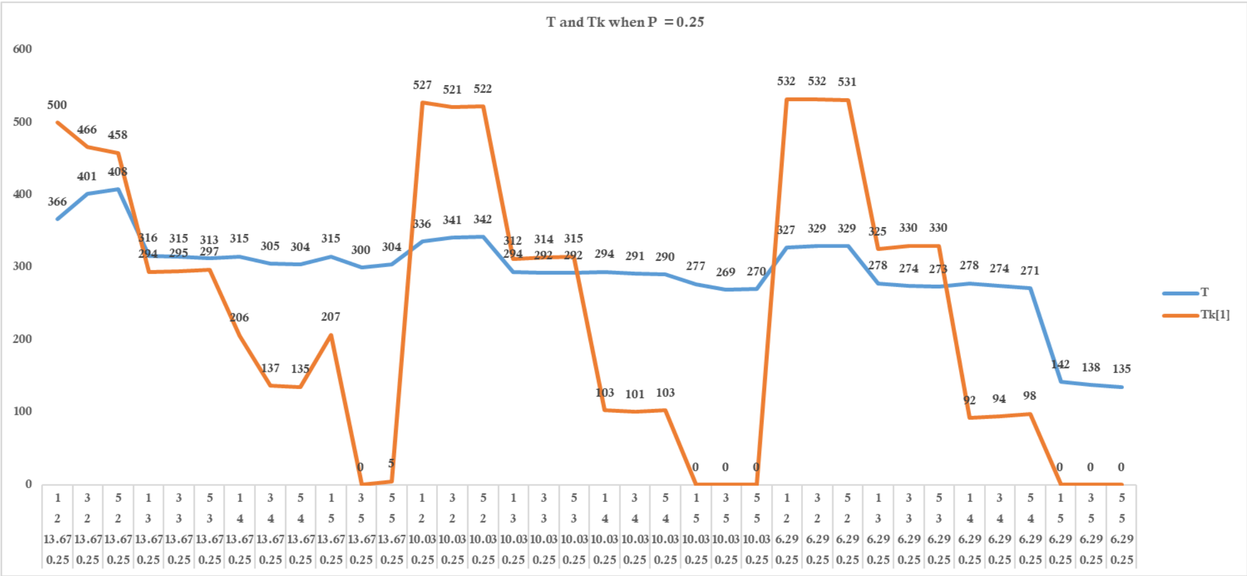


Figure 27. Optimal T and T_k trend when P = 0.25, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

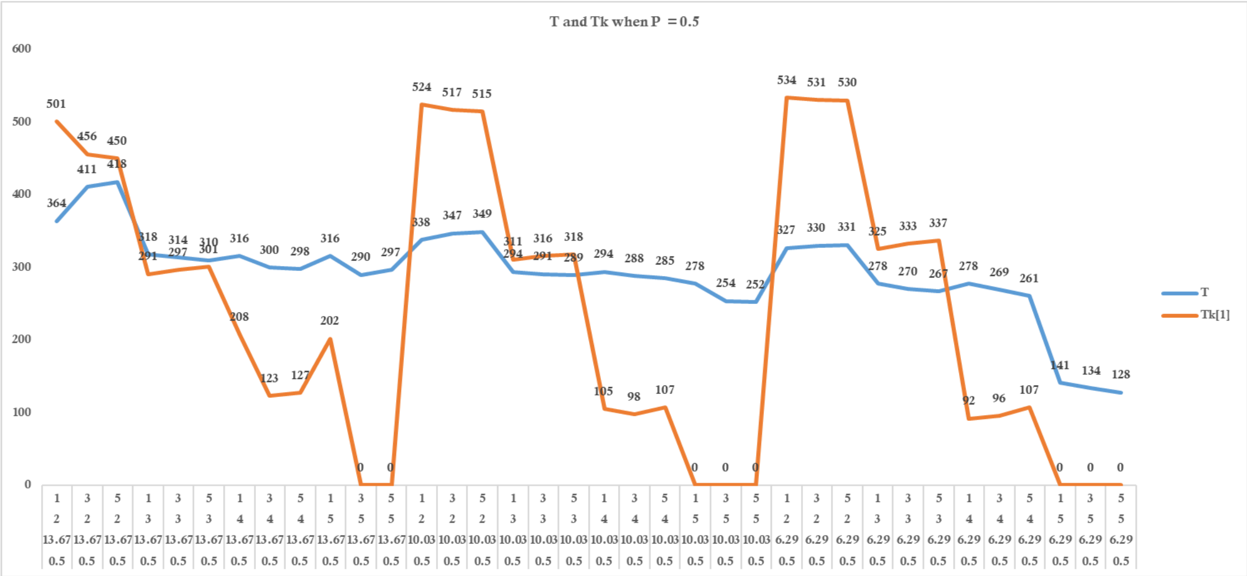


Figure 28. Optimal T and T_k trend when P = 0.5, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

As with increase in capacity, and the variation in cost of the CSL resource, it is observed that with the reduction in T, the utilization of x is also considerable in season 2 and increases where reduction in T is observed, especially in cases where capacity is at maximum and the cost of CSL is lowest per scenario 3, which is less than fulltime and seasonal as shown in the Figures 29 and 30.

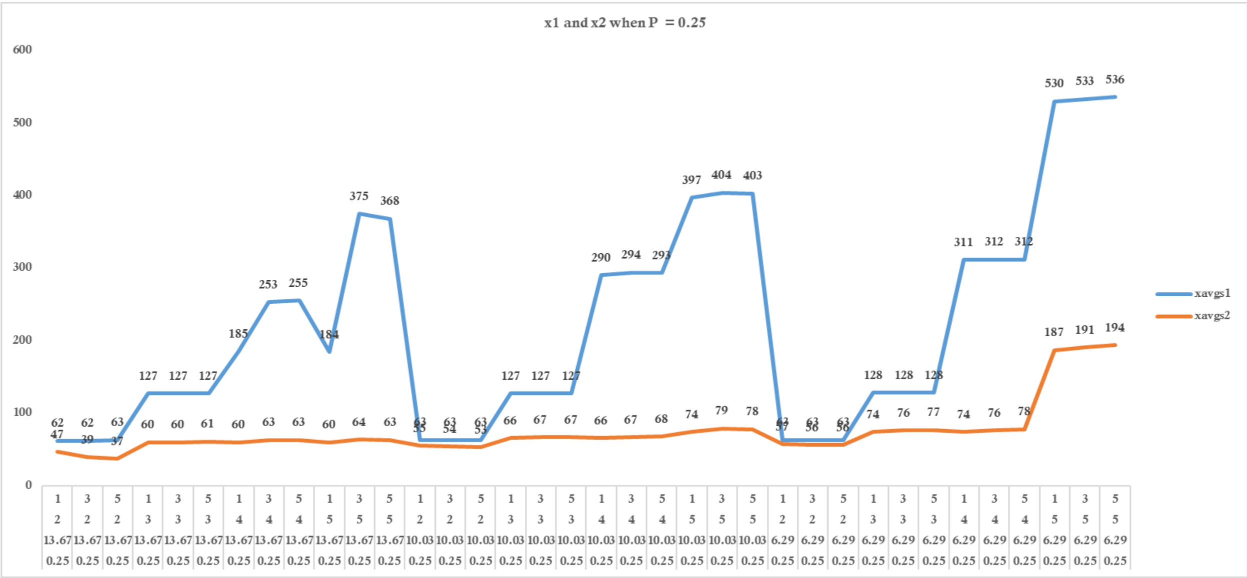


Figure 29. Optimal x1 and x2 trend when P = 0.25, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

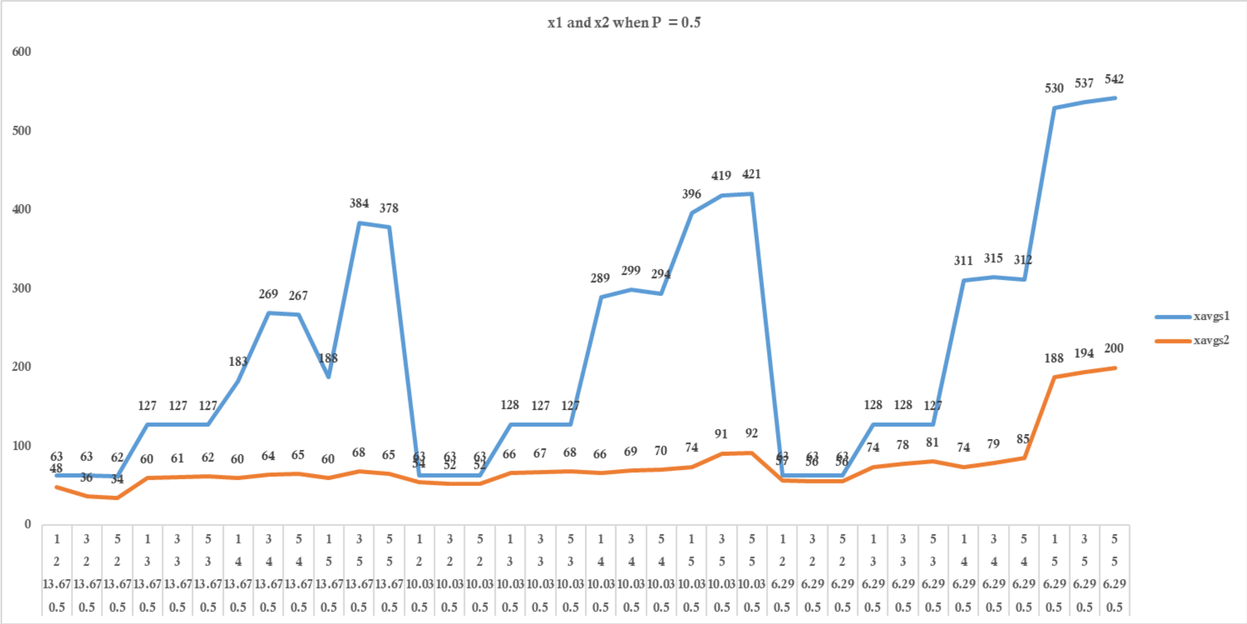


Figure 30. Optimal x1 and x2 trend when P = 0.5, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

The demand being seasonal in nature, where season 2 experiences lower volume, it is observed that the seasonal resources, T_k are only utilized in season 1, and in season 2 fulltime resources and CSL are utilized. Another aspect to note is that as the utilization of x increases, the units that cause penalty also reduce, when comparing the two seasons, as shown in Figures 31 and 32.

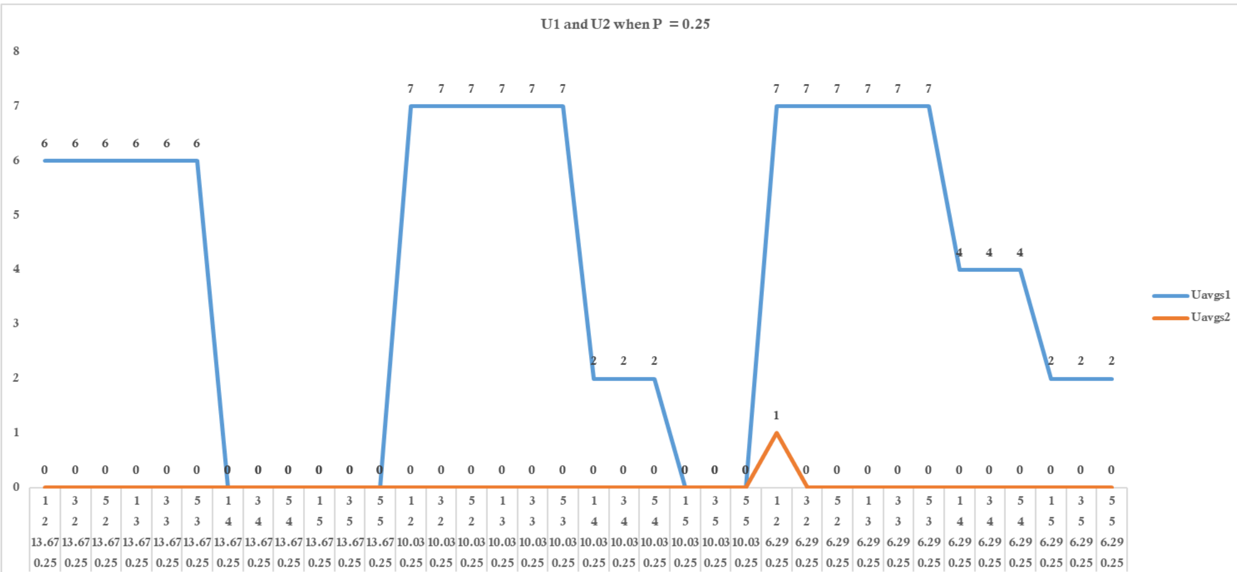


Figure 31. Optimal U1 and U2 trend when P = 0.25, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

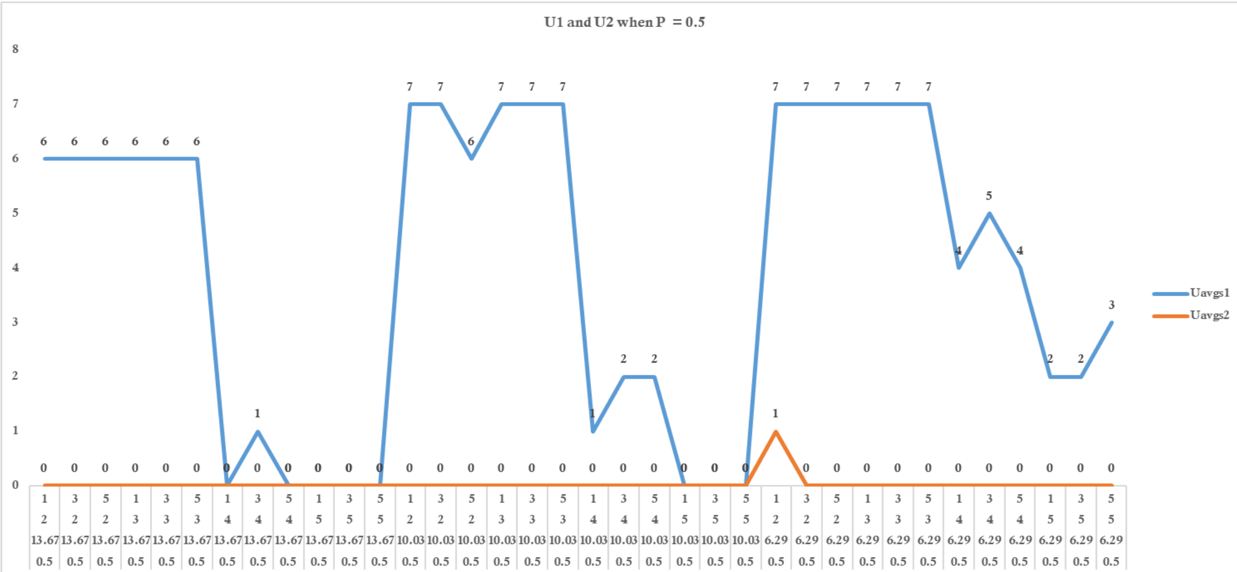


Figure 32. Optimal U1 and U2 trend when P = 0.5, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

4.5. Discussion of Results

The results from the stochastic program generated an optimal combination of fulltime, seasonal and CSL resources that would lower the operational costs for LMD services and at the highest fulfillment rate. This combination was considering for each scenario, percentage variations, number of price points for CSL costs and various capacities of CSL. Within, each scenario, as the capacity of the CSL increases and being variable, the utilization of fulltime and seasonal reduces. Between fulltime and seasonal, the seasonal decrease is drastically observed whereas the fulltime utilization is steady minor rate of decrease observed. With this drastic decrease of seasonal, the utilization of CSL resource is observed to increase, implying that the drop in the utilization of seasonal resource is being compensated by this CSL resource and in all three scenarios. The resource count also accounts in the variability of the price points that would be practically observed as not all CSL resource would accept the same delivery fee. This further enables the model to predict the output replicating the expectations of a CSL resource.

From the stochastic program output is was observed that with the variation in CSL capacities and costs an optimal combination of resource combination would exists for each price point interval I. This model gives us a refined result when compared to the analytical model with added variabilities. However, this method does have some limitations in terms of considering the attrition rate observed with fulltime and seasonal resources and units that were missed due to this shortage of resources. Stochastic programming has some limitation in terms of capturing these nuances of daily operations. To refine it further, it would need an alternate solution methodology such as simulation approach, to capture the impact of employee attrition or missed/rollover orders being fulfilled the next day.

5. SIMULATION MODELING

In the previous section, a stochastic program was used to understand the optimal combination of resources by inducing some variability in capacities and costs of CSL resources. One aspect that could not be considered was the attrition rate of the fulltime and seasonal employees. Thus in this section, a simulation is used to capture the impact of the orders having the possibility of getting missed due to fulltime or seasonal employees leaving. Simulating a process provides us with an explanation of the system and how they work in the real world where there are factors varying on a continual basis.

Simulation will be used to further investigate the impact of CSL in LMD considering additional aspects of the last-minute variations that will take place. Variations with regards to employee attrition rate, missed deliveries and roll overs by one day will be accounted for in this simulation. How these additional variations will impact the daily delivery performance and the operating costs of the organization, will be investigated through the simulation. Simulation, being one of the most sought after decision making tools with its ability to add in real time variations, will assist us in complementing the analysis from the stochastic program.

A simulation approach exploring how same day delivery services can be improved using the crowd sourcing approach considering the time window and daily demand was performed by Castillo et al. (2018), where OTD and total number of deliveries were taken into consideration for the simulation model. In one research by Guo et al. (2019), the authors explored how CSL (considering the e-commerce need, trust and technology) would help last mile delivery lower operational costs. To achieve this, the authors performed a simulation considering the inputs of population size, online vs supermarkets, deliverers, order arrival, delivery time, and associated costs. They concluded with the fact that, though the CSL shows significant savings, a hybrid delivery network will maintain the balance for challenges faced by each approach. Thus, this leads us to add the concept of service reliability, for which it is expected to see an optimum mix of fulltime, seasonal, and CSL resources.

5.1. Simulation Modeling Objective

Simulation modeling will be done in SAS software. Variations with employee attrition rate will be applied and simulated in each of the scenarios to study the impact on the costs to meet daily demand. Figure 33, gives us the basic simulation model flowchart where the impacts of the employee attrition rate will be added and the orders missed on the current day will be fulfilled the next day.

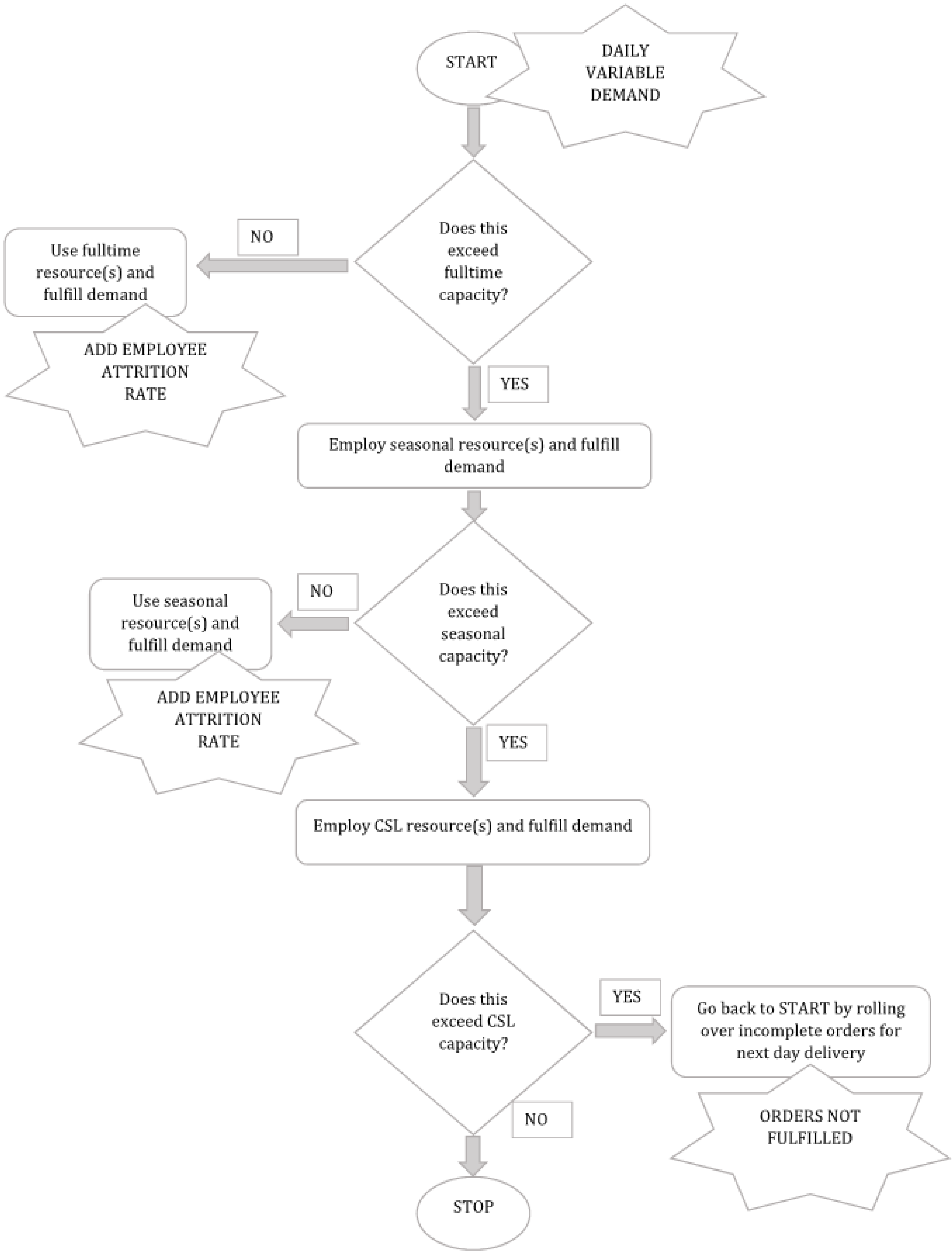


Figure 33. Basic simulation flowchart.

5.2. Assumptions for Simulation Model

The formulation of the simulation model is comprised of the parameters and variables accounted for in the analytical and stochastic programming sections. The outputs from the stochastic programming section, specifically the T and T_k will be used as input values for the simulation. To determine the lowest possible operating cost, various combinations of T and T_k will be simulated in this section. To that end, the combinations of T and T_k will vary within the ranges of $T - 50\ to\ T + 50$ for T and $T_k - 50\ to\ T_k + 50$ for T_k. If the lower value of T_k is less than zero, then it will be limited to 0. For each of the T and T_k, an attrition rate will be applied and the model will calculate the impact of this attrition rate on the demand to be fulfilled and if any missed deliveries for the current day will be rolled over and added to the next day's demand. Following that, the model will calculate the current day's metric in terms of CSL used and any missed deliveries that might have resulted. Based on this, the simulation model will calculate the total cost for each case of scenario 1, scenario 2, scenario 3, P, Ca and I. From this total cost, it will have the lowest possible cost for each case of I, giving the optimal combination of resources considering the attrition rate of employees. This model will be a more refined solution when compared to the analytical results and the stochastic programming results.

5.3. Simulation Model Formulation

The data for the simulation model will be the same as used in the analytical and the stochastic programming sections. An 10% annual attrition rate is assumed for the fulltime and seasonal resources. It is also assumed that there is a hiring cost involved for the absent resource for a period of one day. Utilizing the available information, the simulation model is built and run in SAS 9.4 for 72 different combinations of scenarios, P, Ca, and I. Appendix H gives one portion of the SAS simulation as an example. Two different percentage variations of mean costs are considered in this run, first it is varied by 25% and second 50% for each of the three scenarios with the cost of CSL. The capacities evaluated were at four levels, and three price points were considered for the SAS program run.

5.4. Results From the Simulation Runs

The results obtained from the SAS program simulation runs are displayed in the Appendix Table I1. The table gives the optimal combination of resources to be used considering fulltime T, seasonal T_k, and CSL x. For T_k, x and U, there will be a suffix "1" or "2" for seasons 1 and 2 respectively. Where $T_k[1]$ is the season 1 resource, x1 and x2 are the number of CSL deliveries in season 1 and season 2 respectively, and U1 and U2 are the undelivered units for season 1 and season 2 respectively. The results obtained are average values for each scenario considering the cost variation percentage P, capacity of CSL Ca, and the number of cost intervals I for each of the cost categories per scenario 1, scenario 2 and scenario 3. The Appendix Figures, Figure J1 to Figure J12 shows the charts for these results for various combinations of scenario 1, scenario 2 scenario 3, P, Ca and I. Appendix Table I2 gives the 95% confidence intervals of the results obtained from the simulation runs.

To summarize, with an increase in the expected capacity of CSL, there is an increase in the utilization of CSL as well, for each case of scenario 1, scenario 2 and scenario 3. With the increase in utilization of the CSL capacity the seasonal capacity, T_k first starts to reduce and finally the fulltime capacity is reduced. The number of price points does help in lowering the total cost which is dependent on the expected CSL capacity and the variation in the price points. The higher the variation in random CSL price points, the lower the expected operational cost.

Figures 34 and 35 gives the trend of the optimal values of T and $T_k$when P = 0.25 and 0.5 respectively. It is interesting to note that as CSL capacity increases, the reliance on seasonal reduces to zero, as in the case when Ca = 5, I = 5 for scenario 2 and when Ca = 5, I = 1 and 3 for scenario 3 when P is varied by 50% of the mean.

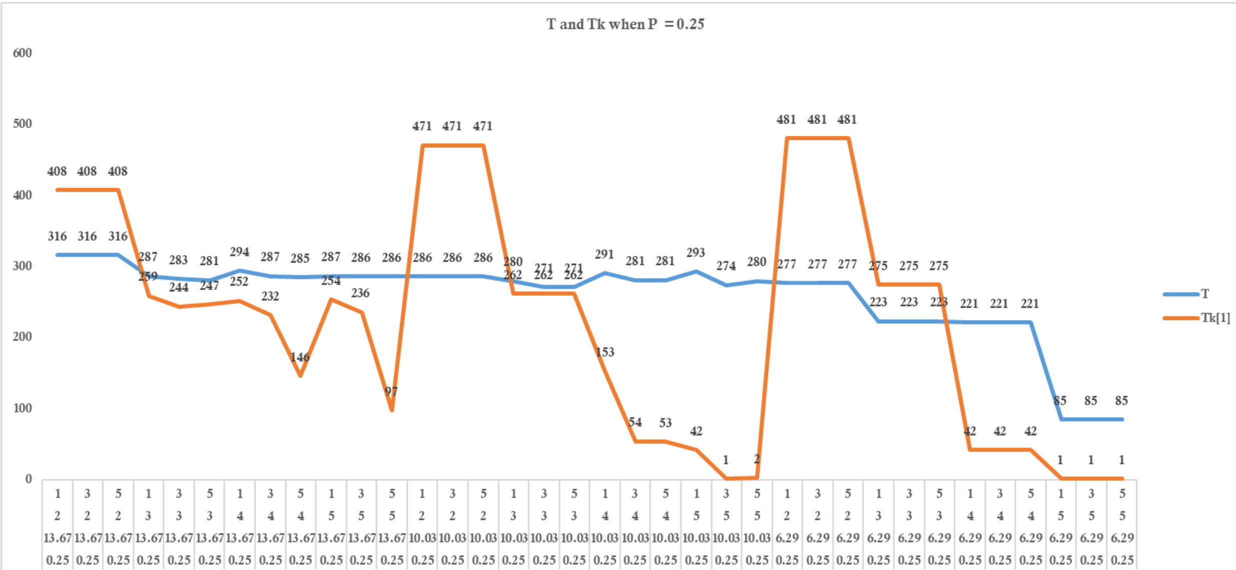


Figure 34. Optimal T and T_k trend when P = 0.25, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

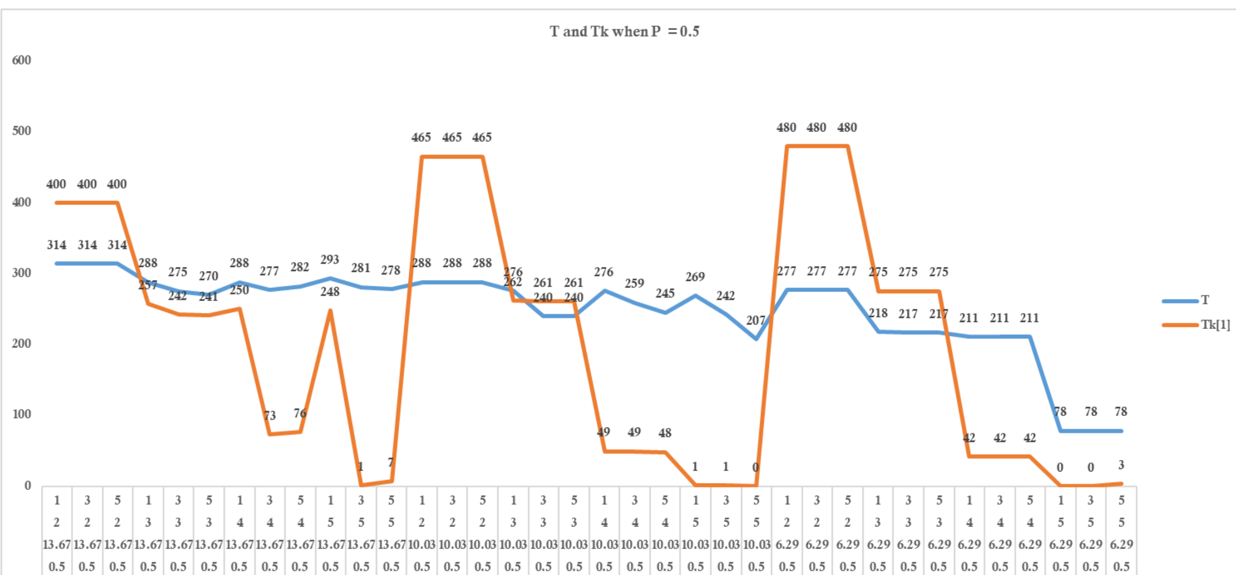


Figure 35. Optimal T and T_k trend when P = 0.5, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

As with an increase in capacity, and the variation in cost of the CSL resource, it is observed that with the reduction in T, the utilization of x increases where reduction in T is observed, especially in cases where capacity is at maximum and the cost of CSL is per scenario 3, which is less than full time and seasonal as shown in the Figures 36 and 37.

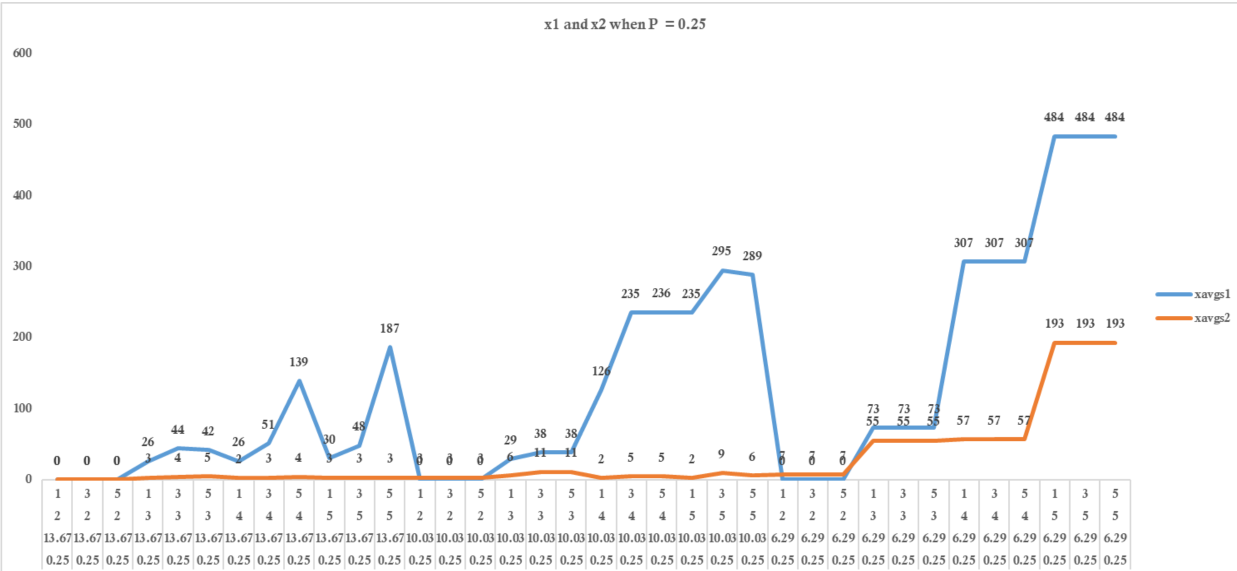


Figure 36. Optimal x1 and x2 trend when P = 0.25, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

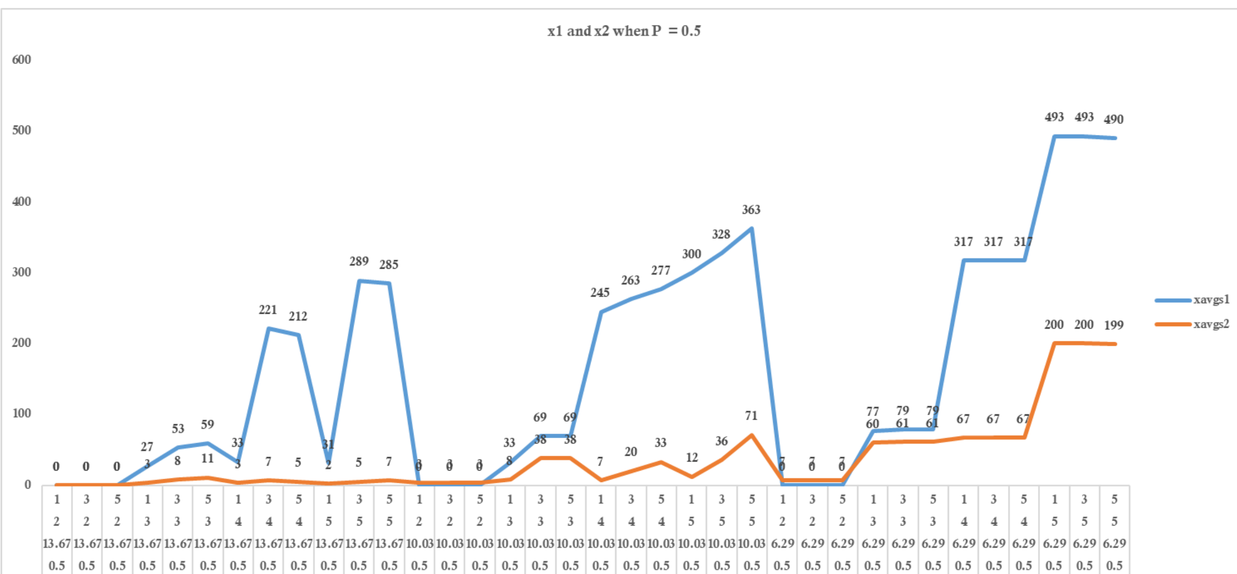


Figure 37. Optimal x1 and x2 trend when P = 0.5, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

The demand being seasonal in nature, where season 2 experiences lower expected demand, it is observed that the seasonal resources, T_k are only utilized in season 1, and in season

2 fulltime resources and CSL are utilized. Another aspect to note is that as the utilization of x increases, the undelivered units also reduce to 0 per Figures 38 and 39.

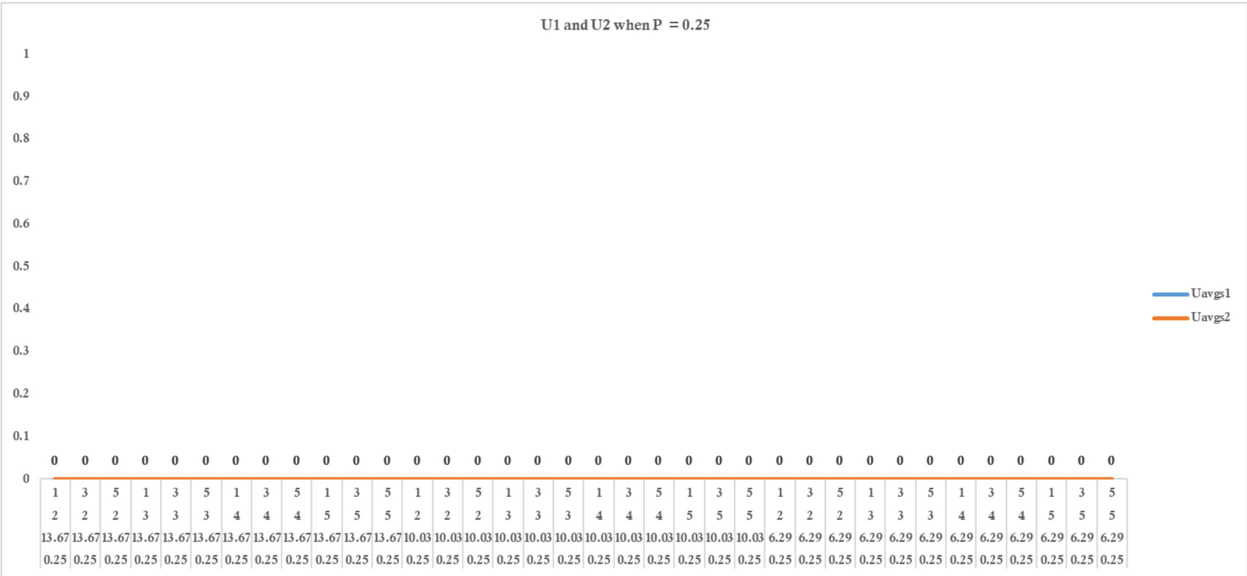


Figure 38. Optimal U1 and U2 trend when P = 0.25, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

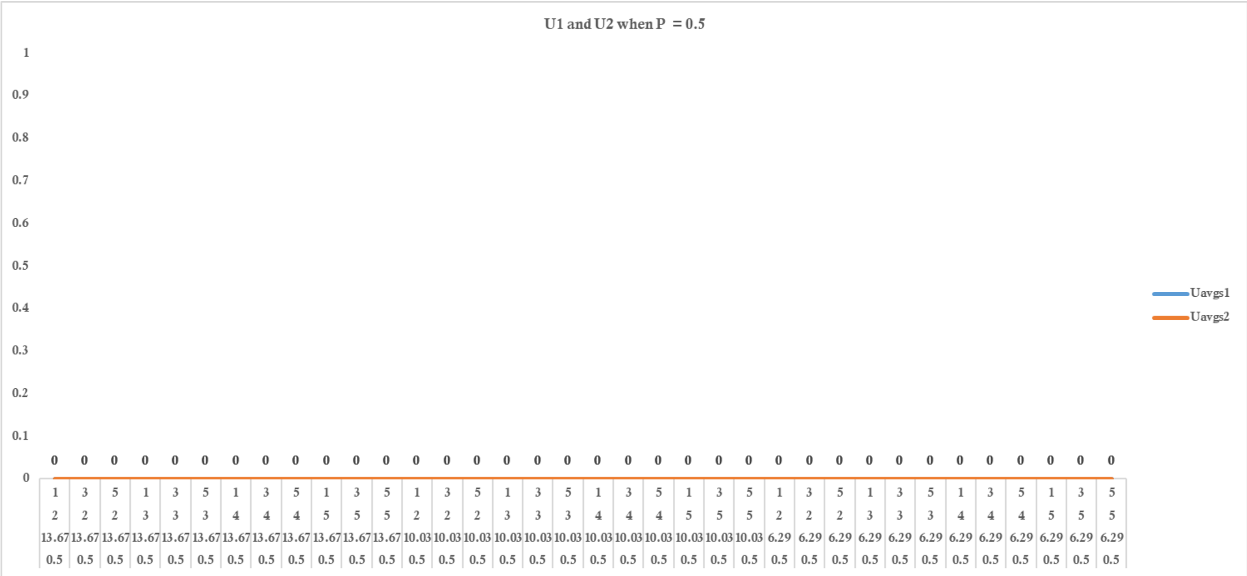


Figure 39. Optimal U1 and U2 trend when P = 0.5, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

The impact of full-time capacity on cost is not the only concern when determining workforce size. Specifically, if the optimal full-time capacity is less than the current workforce size, reducing capacity to match the model recommendations would require firing workers. As firing workers comes with many negative effects beyond just costs, we wanted to explore how sensitive the cost was to deviations from the optimal full-time capacity. To that end, we explored how the cost changes if a full-time capacity 10% greater than the optimal full-time capacity was used. Figures 40 and 41 show the percentage difference in the costs when the cost with the optimal full-time capacity is compared to the cost with 10% more full-time capacity. Figures 40 and 41 show that as CSL capacity increases the percentage change in the cost decreases with full-time capacity. Hence, in environments with high levels of CSL capacity it may be advantageous to tradeoff levels of full-time capacity which are higher than suggested by the model with firing fewer current employees.

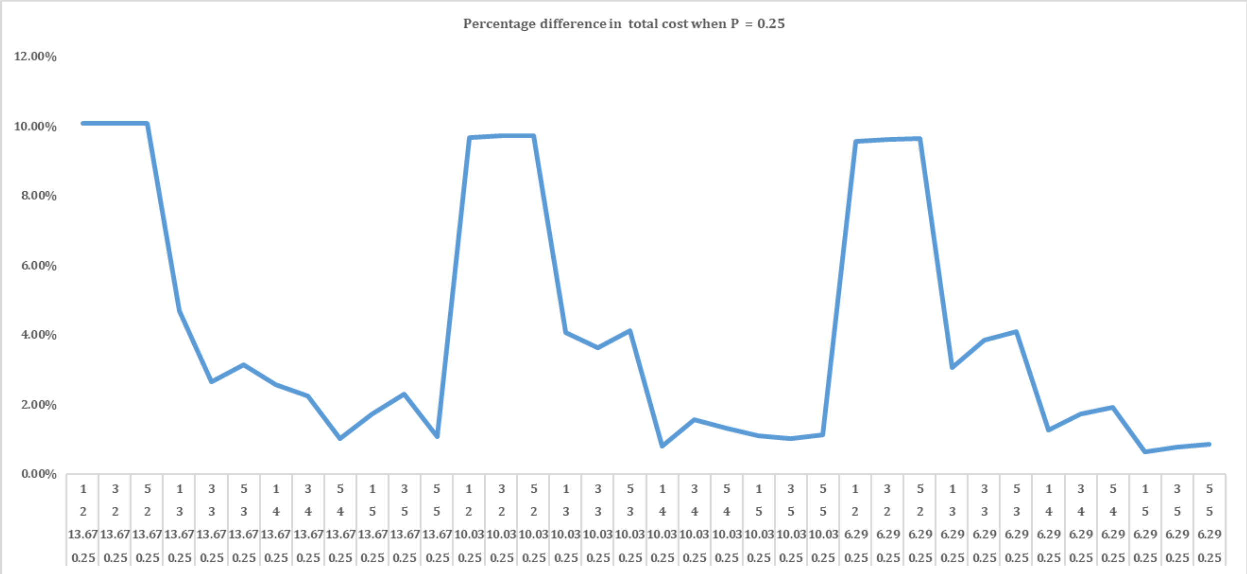


Figure 40. Percentage difference in total cost when P = 0.25, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

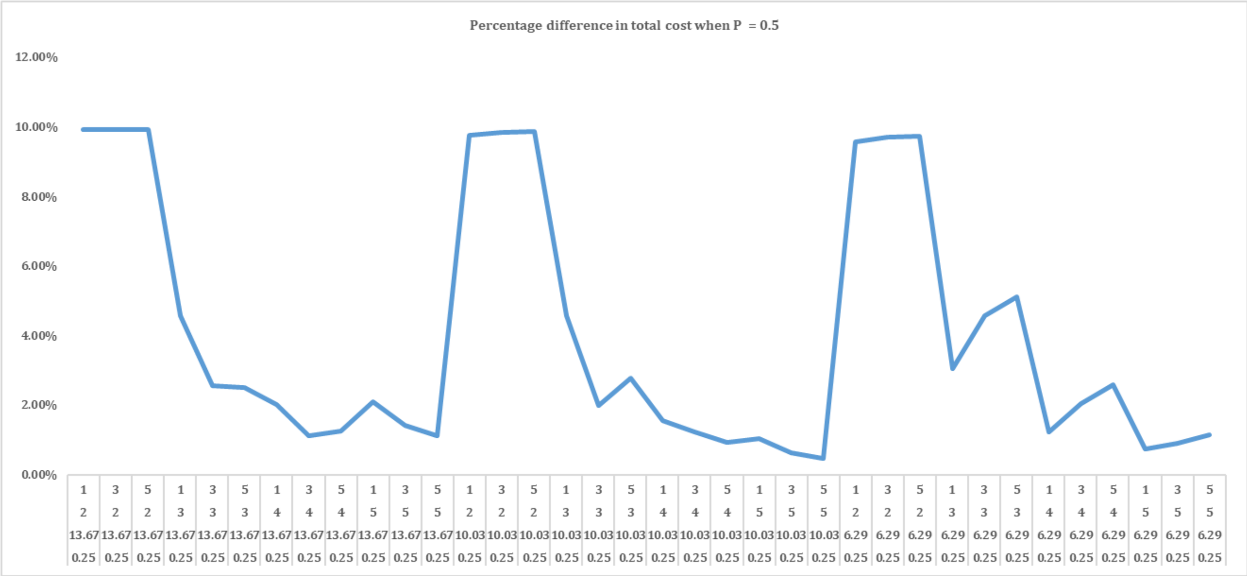


Figure 41. Percentage difference in total cost when P = 0.5, Scenario 1 = 13.67, Scenario 2 = 10.03, Scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

5.5. Discussion of Results

The results from the simulation generated an optimal combination of fulltime, seasonal and CSL resources that would lower the operational costs from LMD services and at the highest fulfillment rate. This combination was considering for each scenario of costs, percentage variations, number of price points for CSL costs, various capacities of CSL and considering an 10% attrition rate for fulltime and seasonal resources. Within, each scenario, as the capacity of the CSL increases and being variable, the utilization of fulltime and seasonal reduces. Between fulltime and seasonal, the seasonal decrease is drastically observed whereas the fulltime utilization is steady minor rate of decrease observed. With this drastic decrease of seasonal, the utilization of CSL resource is observed to increase, implying that the drop in the utilization of seasonal resource is being compensated by this CSL resource and in all three scenarios. The optimal resource combination is an extension of the output of the stochastic program, simulated for various combinations of fulltime and seasonal resource and considering attrition rate of these resources. This further enables the model to predict the output replicating the daily operations.

5.6. Simulation Considering the Use of Robots for LMD

In this section, the impact of automation is evaluated for the case of LMD. Over recent years, incorporation of automation technologies, such a robot or drone (Aurambout, 2019; Yu et al., 2022; Swanson, 2019), has interested e-commerce companies to help reduce their overall LMD costs. In this section, a combination van-robot delivery is assumed where a person is allocated to operate a set of robots.

Pani et al. (2020) in their research have documented how consumer shopping preferences have been influencing the adaptation of autonomous delivery vehicles. The class of shoppers who use e-commerce extensively, omnichannel customers and consumers making decisions due to the pandemic situation tend to be the largest supporters of autonomous delivery concepts. Hesitancy in adopting this approach lies in the fact that companies doing so would have to bear the cost of such automation technologies. Similarly, Kapser and Abdelrahman (2020) supports the fact that the price of such services would be the top most determining factor for mass adoption. In contrast, Jennings and Figliozzi (2019), Reed et al. (2020), Patella et al. 2020, Simoni et al. (2020) and Lemardele et al. (2021) in their research have shown cost benefits when using autonomous delivery systems when compared to a traditional approach.

The advancements in technology do lead to lower cost of ownership for robots with applications to certain portions of LMD activities. One such robot that has been experimented with across todays markets are the Starship robot (Starship, n.d.). The application of these robots is currently limited to packages matching their specifications. This is assumed to be in line with the cases described here in the earlier stochastic and simulation sections. For this simulation, robot with similar characteristics and pricing referenced from the literature is used to calculate the improved fulltime costs as shown in Appendix K. The assumption is that, this operation will involve a van or a truck with a person operating it, navigating to a scheduled staging location from where the robots will be dispatched to deliver orders in the neighborhood. Heimfarth et al. (2022), Alfandari et al. (2022), Ostermeir et al (2022), Boysen at al. (2018) and Yu at al. (2022) have all shown a similar concept to be cost effective. Thus, a similar concept is assumed here, where there is a van-robot set up fulfilling daily demand and thus leading to improved fulltime costs. Using this as input, the stochastic program is ran to determine the new optimal combination of T and T_k. Following which the simulation program is run to determine the lowest cost combination for the T and T_k and corresponding count of CSL services used and calculating any undelivered units.

5.7. Assumptions for the Simulation Model With Robot Delivery

The assumptions used in the previous sections are valid and continued into this section with additional considerations as listed in Appendix K. The concept being that, a person would drive the van to a designated spot from where it would dispatch the allocated set of robots to deliver goods to the residential customers. The parameter values have been referenced from Ostermeier et al. (2022) where the authors have used a similar set up of delivery van and robots. The specifications of robots were referenced from a robot manufacturer's website (Starship, n.d.) to determine the improved fulltime costs per unit. The Appendix K shows the calculations for deriving the new fulltime costs which is applied in the simulation.

Using this new fulltime unit delivery cost, the stochastic program is run again in SAS to determine the optimal combination of T and T_k. Once the output from the stochastic program is obtained, the T and T_k will be used as input values for the simulation. To determine the lowest possible operations cost, various combinations of T and T_k will be simulated. As in the earlier simulation section, the combinations will vary over ranges of $T - 50 \; to \; T + 50$ for T and $T_k -$

$50\ to\ T_k + 50$ for T_k. If the lower value of T_k is less than zero, then it will be limited to 0. For each combination of the T and T_k. the attrition rate (only for fulltime and seasonal) will be applied and the model will calculate the impact of this attrition rate on the demand to be fulfilled and if any missed deliveries for the current day will be rolled over and added to the next day demand. Following that, the model will calculate the current day's metrics in terms of CSL used and any missed deliveries that might have resulted. Based on this the simulation model will calculate the total cost for each case of scenario 1, scenario 2, scenario 3, P, Ca and I. Form this total cost, it will have the lowest possible cost for each case of I, given the optimal combination of resources considering the attrition rate of employees. This solution will be based on the consideration of robots for LMD.

5.8. Simulation Model Formulation With Robot Delivery

The data for the simulation model will be the same as for the analytical and the stochastic programming sections. A 10% annual attrition rate is assumed only for the fulltime and seasonal resources. It is also assumed that there is a hiring cost involved for the absent resource for a period of one day. Utilizing the available information, the simulation model is built and run in SAS 9.4 for 72 different combinations of scenarios, P, Ca, and I. Two different percentage variations of mean costs are considered in this run, first it is varied by 25% and second 50% for each of the three scenarios with the cost of CSL. The capacities evaluated were at four levels, and three price points were considered for the SAS program run. The costs associated with the quantity of robots, amortized over time are all incorporated into the model to determine the cost and are incorporated in the simulation model mentioned in section 5.3.

5.9. Results From Simulation Runs for Robot Delivery

The results obtained from the SAS program simulation runs are displayed in the Appendix Table L1. The table gives the optimal combination of resources to be used considering full time T , seasonal T_k, and CSL x. For T_k, x and any unsatisfied demand U, there will be a suffix “1” or “2” for seasons 1 and 2 respectively. Where $T_k[1]$ is the season 1 resource, x1 and x2 are the number of CSL deliveries in season 1 and season 2 respectively, and U1 and U2 are the undelivered units for season 1 and season 2 respectively. The results obtained are average values for each scenario considering the cost variation percentage P, capacity of CSL Ca, and the number of cost intervals I for each of the cost categories scenario 1, scenario 2 and scenario 3. The Appendix Figures M1 to M12 show the charts for these results observed for various combinations of scenario 1, scenario 2, scenario 3, P, Ca and I. Appendix Table L2 gives the 95% confidence intervals of the results obtained from the simulation runs.

Regarding an increase in the expected capacity of CSL, there are different trends in the utilization of CSL for each of the three scenarios when compared with the simulation model in the previous section. The utilization of T_k is significantly reduced when compared to the traditional simulation model. The number of price points does help in lowering the total cost which is dependent on the availability of CSL capacity and variation in the CSL price points. The higher the variation in random CSL cost, the lower the operational cost.

Figures 42 and 43 give the trend in the optimal values of T and $T_k$when P = 0.25 and 0.5 respectively. It is interesting to note that as cost per unit of fulltime dropped below CSL costs when in scenario 3, the utilization of seasonal capacity is high when at capacity levels 2 and 3 for each price points.

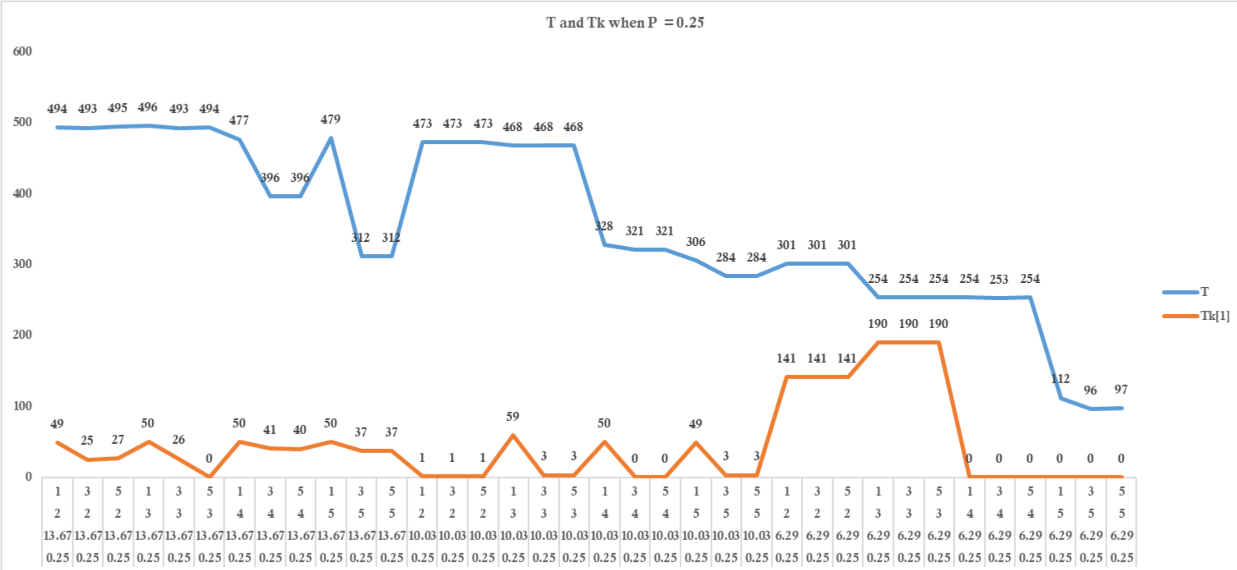


Figure 42. Optimal T and T_k trend when P = 0.25, scenario 1 = 13.67, scenario 2 = 10.03, scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

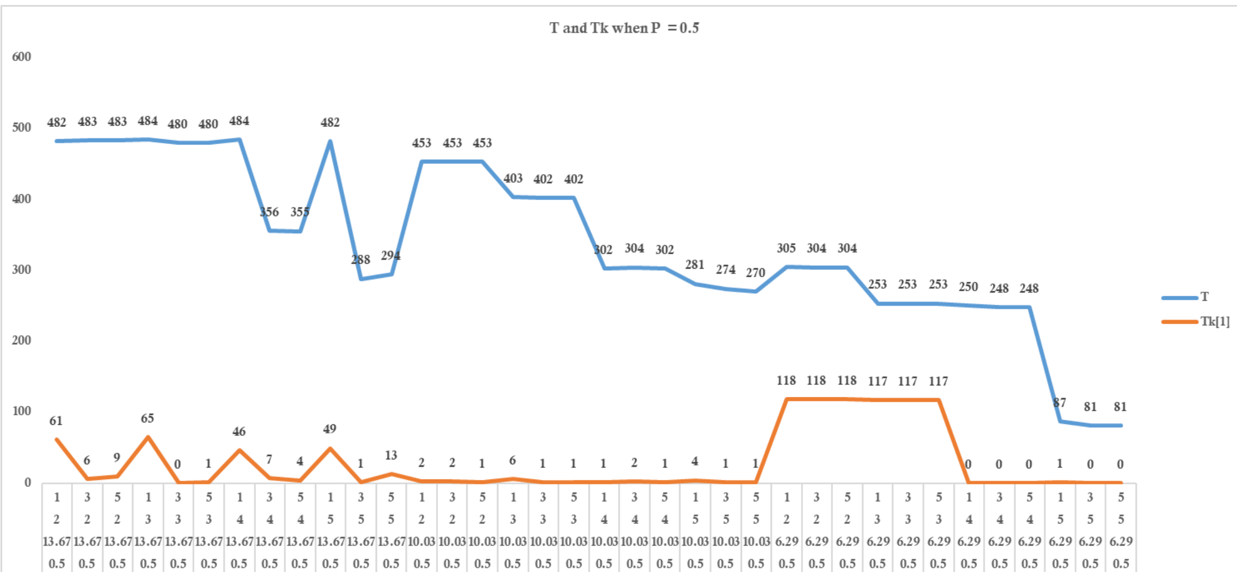


Figure 43. Optimal T and T_k trend when P = 0.5, scenario 1 = 13.67, scenario 2 = 10.03, scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

As with the increase in capacity, and the variation in cost of the CSL resource, it is observed that with the reduction in T, the utilization of x in season 2 is not so favored as T is observed to be dominating through seasons and meet the demand. Except for cases where capacity is at maximum and the cost of CSL is per scenario 3, as shown in Figures 44 and 45, the utilization of x is observed in season 2.

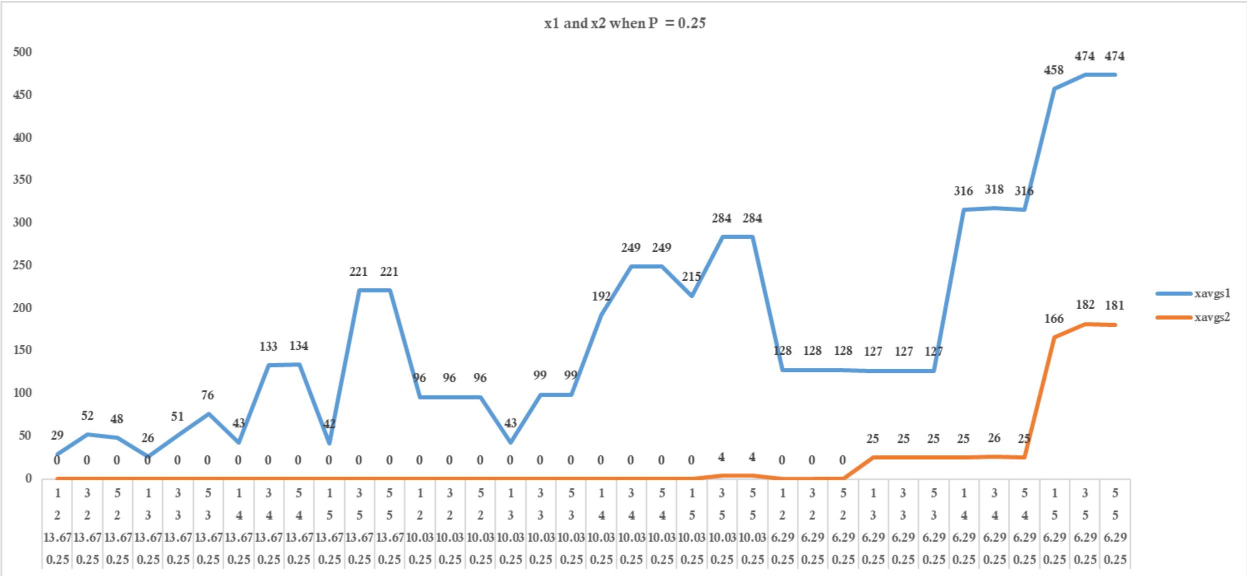


Figure 44. Optimal x1 and x2 trend when P = 0.25, scenario 1 = 13.67, scenario 2 = 10.03, scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

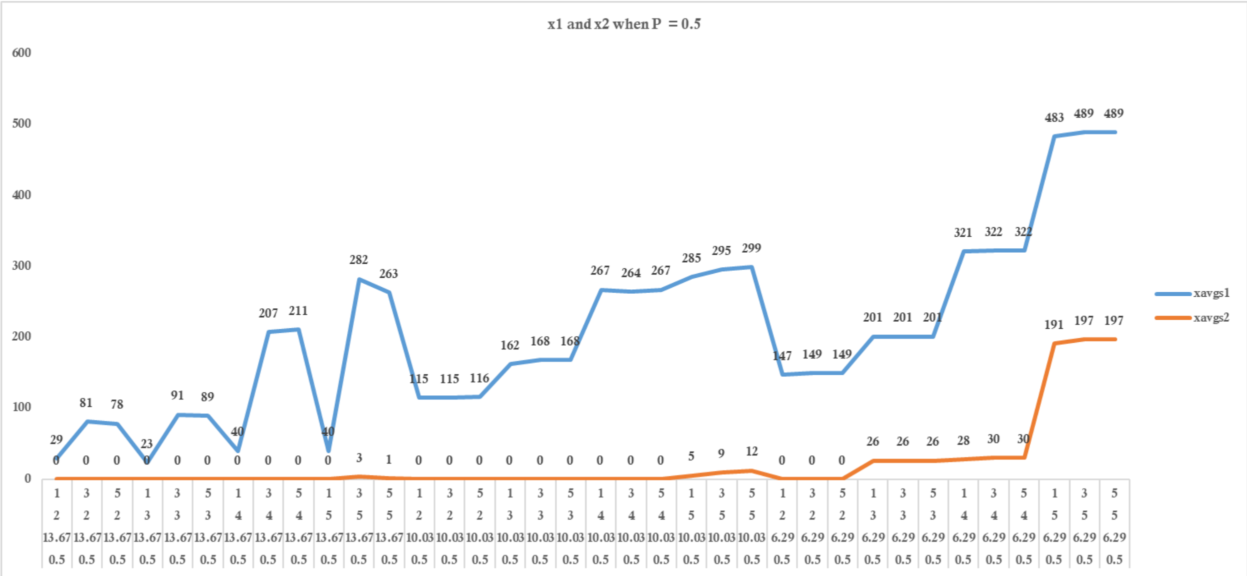


Figure 45. Optimal x1 and x2 trend when P = 0.5, scenario 1 = 13.67, scenario 2 = 10.03, scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

The demand being seasonal in nature, where season two experiences lower demand, it is observed that the seasonal resources, T_k are only utilized in season 1, and in season 2 fulltime resources and CSL have limited use. Another aspect to note is that as the utilization of T is favorable and x utilized on need basis, the units that cause penalty also reduce to 0 per Figures 46 and 47.

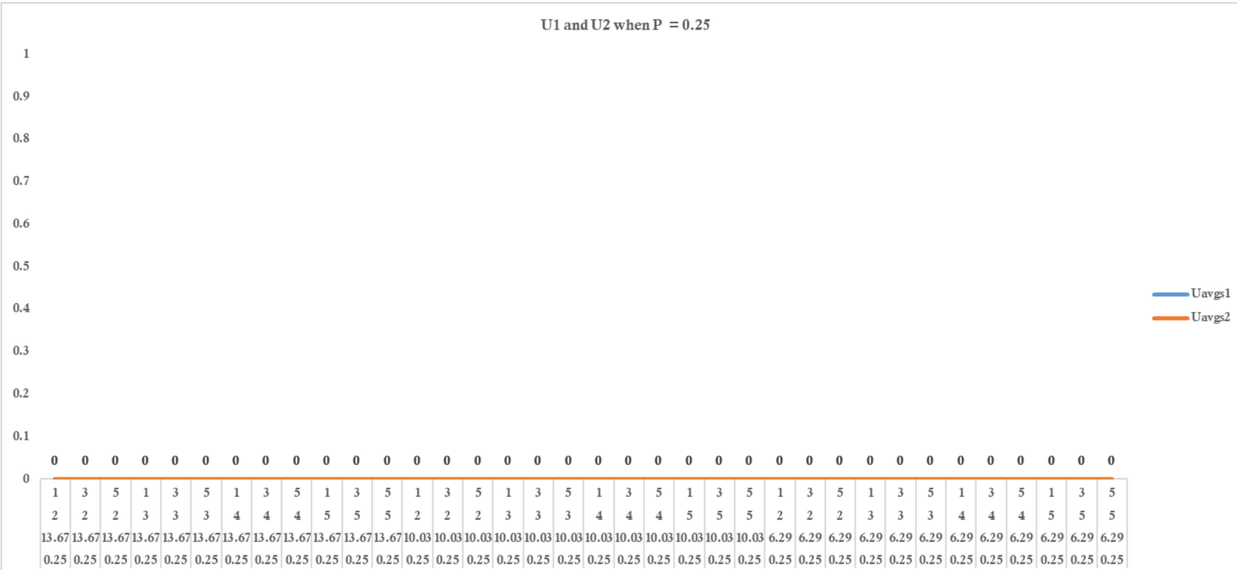


Figure 46. Optimal U1 and U2 trend when P = 0.25, scenario 1 = 13.67, scenario 2 = 10.03, scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

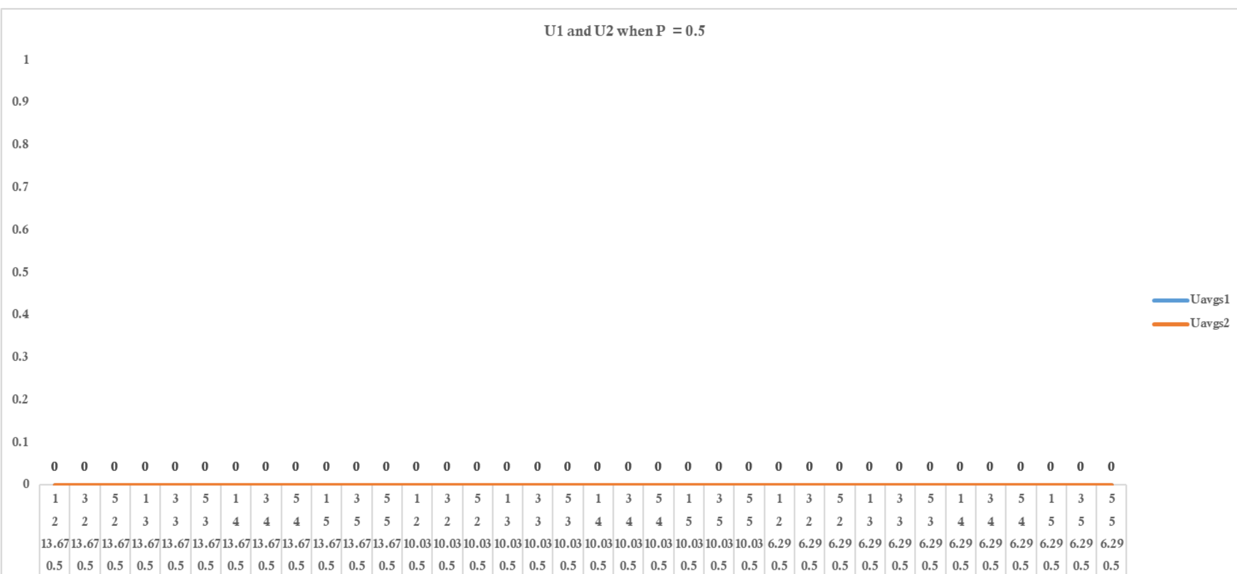


Figure 47. Optimal U1 and U2 trend when P = 0.5, scenario 1 = 13.67, scenario 2 = 10.03, scenario 3 = 6.29, Ca = 2 to 5 and I = 1,3 and 5.

5.10. Discussion of Results

The results from the simulation run with robots generated an optimal combination of fulltime, seasonal and CSL resources that would lower the operational costs from LMD services and at the highest fulfillment rate. This combination was considering for each scenario, percentage variations, number of price points for CSL costs, various capacities of CSL and considering an 10% attrition rate for fulltime and seasonal resources and utilizing an automated technology such as van-robot delivery. Within, each scenario, as the capacity of the CSL increases and being variable, the utilization of fulltime and seasonal reduces. Between fulltime and seasonal, the seasonal utilization is very less compared to the traditional simulation model. With this drastic decrease of seasonal, and that fulltime resource cost is now optimized, the utilization of CSL resource is also limited. This can be due to the fact that fulltime now costs less than CSL and that CSL is only utilized to address any spike in demand and on need basis. The optimal resource combination is an extension of the output of the stochastic program, simulated for various combinations of fulltime and seasonal resource and considering attrition rate of these resources with use of automated systems. This section highlights the benefits of considering contemporary methods while optimizing the LMD services.

6. CONCLUSION AND FUTURE RESEARCH

In this study, a resource modeling tool was detailed for aggregate capacity planning for LMD services. Based on the inputs, the capacity allocations for fulltime and seasonal deliveries were determined to minimize cost of LMD operations to meet random demand under seasonality. Specifically, the model was used to explore how a CSL option impacted the aggregate plan. As an extension to the simulation exercise, the use of automated technology, such as a robot, was applied to see the impact on costs and the aggregate plan.

6.1. Conclusion

To better understand the need, the study involved three different solution methodologies, each refining the results of the previous one. An analytical model was done first, followed by a stochastic program where the cost and capacity of CSL were variable, and finally a simulation where the daily turnover of fulltime and seasonal employees was considered along with rolling over unmet deliveries to the next day and getting fulfilled.

The results from the analytical section, which being a basic model without any complexities involved when compared to stochastic or simulation versions has a very basic output in terms or resource need and costs. One key aspect to note is that, in the scenario 3, when the cost of CSL is lower than fulltime and seasonal it takes into account 100 % use of CSL resources. This, might be a biggest risk in the event of the demand exceeding CSL capacity and negatively impacting the organization. This is when the stochastic version has an assumption to consider the variable CSL capacity and cost and to maintain a minimum service level. Table 5 gives a comparison of costs between analytical and stochastic for scenarios 1 to 3 and capacities 2 to 5.

Table 5. Comparison of costs between analytical and stochastic for scenarios 1 to 3 and capacities 2 to 5.

Scenario	Ca	Total Cost AM	Total Cost SP
Scenario 3	2	$ 1,380,292.20	$ 1,756,161.44
Scenario 3	3	$ 1,229,764.93	$ 1,476,159.96
Scenario 3	5	$ 1,186,312.95	$ 1,397,116.38
Scenario 3	5	$ 1,186,312.95	$ 1,397,635.14
Scenario 4	2	$ 1,362,618.58	$ 1,701,425.88
Scenario 4	3	$ 1,143,559.56	$ 1,385,756.24
Scenario 4	5	$ 1,021,594.33	$ 1,236,354.90
Scenario 4	5	$ 1,020,128.26	$ 1,183,948.48
Scenario 5	2	$ 1,296,218.18	$ 1,639,990.00
Scenario 5	3	$ 1,045,303.48	$ 1,285,204.58
Scenario 5	5	$ 831,445.48	$ 1,053,661.62
Scenario 5	5	$ 704,492.58	$ 895,718.12

As the model is simulated with further considerations of attrition rate and rollover capability, using the fulltime and seasonal count as input from the output of the stochastic; here it is running for various combinations of fulltime and seasonal to determine the lowest cost for the usage of fulltime, seasonal and CSL resources meeting the demand. Figures 48 and 49 give the total cost comparison for the output from stochastic and simulation runs.

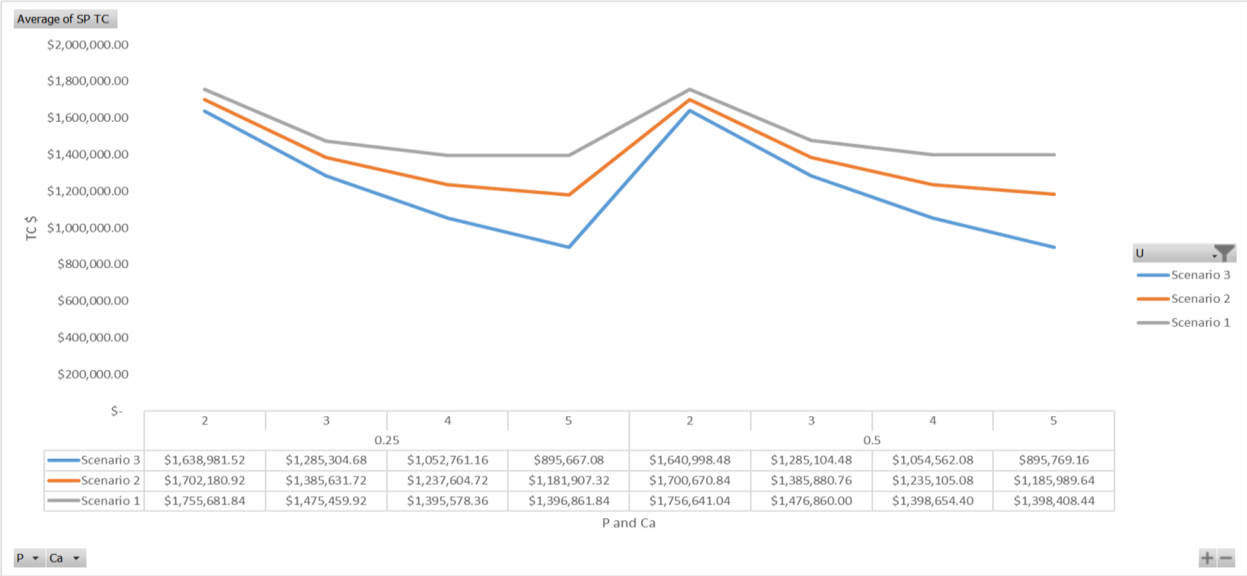


Figure 48. Cost trend from stochastic model for scenarios 1-3, Ca, and P.

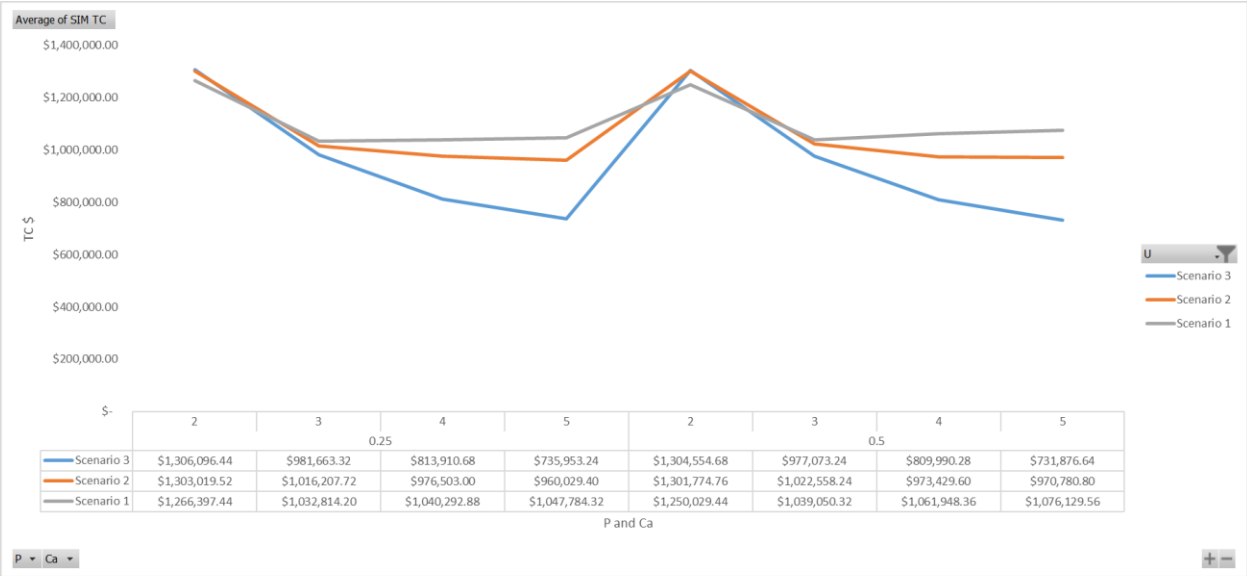
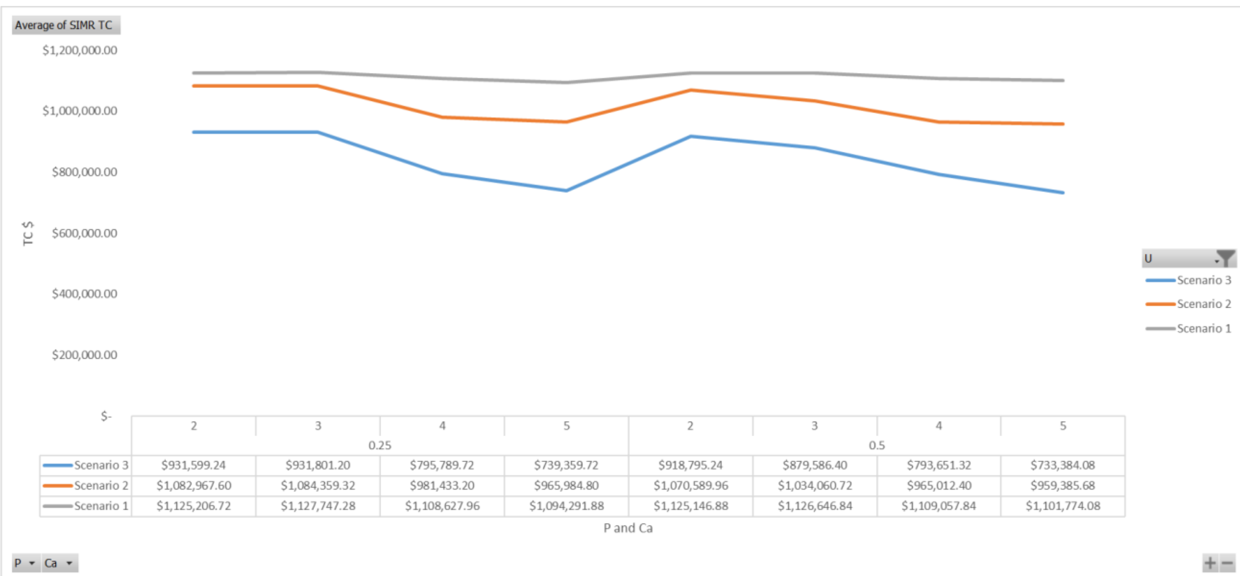


Figure 49. Cost trend from simulation for scenarios 1-3, Ca, and P.

Comparing the two Figures 48 and 49, simulation does lead to a lower operational cost for the optimal combination of fulltime and seasonal. Results lead us to the conclusion that a CSL resource is an option that could lead in operations savings and thus achieving an objective lowering LMD costs. When the capacity of CSL is high and cost is low, is when maximum utilization of CSL is experienced, followed by fulltime and lastly seasonal.

Furthermore, an exercise was also performed where newer automation concepts, like use of delivery robots for LMD services, were modeled in the simulation. It was shown that it further helps reduce costs of fulltime fixed resources and better addresses varying demand than seasonal and CSL capacity as shown in Figure 50 for certain combinations when compared with earlier simulation. This exercise showed us that automation will increase reliance on fulltime capacity while reducing the overall amount and cost of fulltime capacity. Appendix F and Appendix Tables I1 and L1, show the optimal combination of resources for stochastic, simulation and simulation with robot usage respectively.



	0.25				0.5			
	2	3	4	5	2	3	4	5
Scenario 3	$931,599.24	$931,801.20	$795,789.72	$739,359.72	$918,795.24	$879,586.40	$793,651.32	$733,384.08
Scenario 2	$1,082,967.60	$1,084,359.32	$981,433.20	$965,984.80	$1,070,589.96	$1,034,060.72	$965,012.40	$959,385.68
Scenario 1	$1,125,206.72	$1,127,747.28	$1,108,627.96	$1,094,291.88	$1,125,146.88	$1,126,646.84	$1,109,057.84	$1,101,774.08

Figure 50. Cost trend from simulation with robot for scenarios 1-3, Ca, and P.

One critical aspect to note between the three figures comparing stochastic Vs simulation Vs simulation with robot, is the shift between the scenarios that is observed when comparing the values at Ca = 2, P = 0.25 and Ca = 2 and P = 0.5, they all exhibit a downward trend as Ca increases. These shifts happen to capture the effects of the variables and provide an opportunity for decision making or utilize information for aggregate planning of capacity.

Given the forecasts and market characteristics, it would be an added advantage to use this approach for decision making at a managerial level. Cost optimization or savings will always be a medium where the benefits can be transferred to end customers by offering free or reduced cost shipping, as well as timely service, to garner higher customer satisfaction and appreciation.

6.2. Future Research

This study can be further extended by considering additional aspects of the daily operations such as considering the perishable nature of goods and or returns of goods from customers to retailers. Future research plans include considering perishable aspects of the products and how these costs can be added in the model to refine the total operational expenses and determine if they affect profits. With these perishable items having no return or salvage value it would be a direct hit to the operating expenses and thus this category of items will need to be delivered timely, especially in the case of groceries consisting of fresh produce. To complement this research, it will be intriguing to see how reverse logistics of these goods will impact labor costs. Addressing the role of CSL in reverse logistics could be an avenue to explore. Finally, regarding the use of automation or integration of new technologies in LMD services, to further lower the LMD costs more research can be done to understand the challenges and benefits new technologies will provide in the long run.

Thus, in conclusion, an aggregate capacity planning tool is provided here to identify optimal capacity levels to meet random seasonal demand. This tool considers the utilization of available CSL resources in each region or locality. Utilizing the tool would provide cost efficient delivery capacity planning with little impact on revenue generation or profits by providing quality and timely service to end customers.

7. DISCUSSION OF RESULTS FROM ANALYTICAL, STOCHASTIC PROGRAMMING AND SIMULATION MODELS

In the previous sections, the outputs from each model, analytical, stochastic programming, and simulation, gave key information with regards to the use of CSL for LMD services. From an aggregate planning level, it would give an organization a better opportunity to budget their labor resources needed for LMD services meeting random demand with seasonality. The models from the previous sections vary based on their inputs. The analytical model reflects a simplified high-level view of the problem, whereas the simulation captures more details of the problem with the stochastic program falling in between the two. A final analysis considered using advanced technologies, such as a robot, to deliver the goods for LMD services.

Given the random seasonal demand, each model included fulltime capacity which was employed over the entire year. As well as seasonal capacity which was employed during the busy season. Demand which exceeded the combined fulltime and seasonal capacities was satisfied by CSL capacity, the quantity of which was exogenous to the models. In the analytical model the cost of a crowdsourced delivery and the CSL capacity were deterministic, whereas in the stochastic program and simulation they were random variables. Any demand which exceeded the CSL capacity incurred a penalty cost in the analytical model and stochastic program or was rolled over to be handled the following day in the simulation.

7.1. Observations Regarding Delivery Capacity

From the three exercises with analyzing the objective of achieving the lowest operational cost, it was intriguing to see how the optimal capacity levels varied. As the cost of CSL decreases or the capacity of CSL increases, seasonal capacity first increases and then decreases as observed in the stochastic program section and decreases per simulation section. When CSL cost is low, the lowest cost is achieved, but at a lower service level as measured by deliveries being made within total available capacity, compared to scenarios with higher CSL costs. This is due to a CSL resource being more prone cause delivery errors and that the CSL resource reduced fulltime capacity rather than seasonal capacity so that overall capacity was lower during the busy season.

In the stochastic program and simulation, the cost and capacity of CSL are random. In the simulation, deliveries which could not be completed within capacity were rolled over to the next day. Also, the simulation incorporates attrition among fulltime and seasonal workers with a delay between replacing them. Looking at the output from stochastic from stochastic and simulation, similar results are found for both models. With the simulation model, the case of enabling the units to be rolled over is leading to an outcome where there is no penalty incurred, as there are enough resources to meet the new demand and thus no missed deliveries for both the seasons. In case if stochastic, there are some undelivered unit's observed but most of them in season 1.

Fulltime capacity follows a similar pattern for the stochastic program and simulation, i.e. decreasing or being steady when expected CSL capacity is at its maximum, expected CSL cost is at its lowest, and the variation in CSL cost increases. However, in other scenarios, fulltime capacity for the stochastic program tends to increase with the number of CSL price points, whereas in the simulation, it is either steady or decreasing in the number of price points. Seasonal resource in stochastic programming does follow s a similar between the percentage variation in the CSL costs, but in simulation influence of the percentage variation in the CSL costs seem to affect seasonal pattern especially when capacity is at 4 and at scenario 1. It is where the increased utilization of CSL can be observed in simulation model. In stochastic version the utilization of CSL tend to be similar, whereas in the simulation, increased utilization is observed scenario 2 onwards and higher than P at 25%. Contributing factors, might be the variation in demand and the rollover units that were missed yesterday would need additional impromptu resources to meet the targets and this is when CSL resource add to the zero missed deliveries as observed in simulation output.

7.2. Managerial Decision Making

LMD services being the most expensive portion of the supply chain, continuously go through innovative improvements to achieve significant operational improvements and thus the resource needs vary between improvement cycles. Along with this, the evolution in the availability of CSL, can add further cost optimization opportunities for managerial decision making during aggregate capacity planning. The set up here is more prone to situations like a retail establishment or third-party logistics provider delivering products to residences. Cost savings when shared with the end customer, for example being able to provide free delivery will always be a plus and can increase the customer base, optimal plan is very important. In addition, growing competition and innovations lead to a very competitive environment and for a business to be sustainable, planning and budgeting will be key. After all, low capacities will affect delivery service and high capacities will impact profit margins.

This model also helps in decision making when seasonal variations are accounted for with demand fluctuations. Having a steady resource is one thing, but being able to be flexible and adapt to spikes in demand is one of the strategies that gives managers better opportunities to reduce operational costs. As observed in the analytical, stochastic program and simulation sections, the total operational costs were optimized for the level of inputs considered. Between the stochastic program and simulation, the variation in price points and the varying capacities of CSL gives a completely new visibility when planning for resource capacity at an aggregate level.

Here the objective being the lowest total operational cost but at an expected service level to be ensured by the organization.

The three approaches vary in their need for information, each providing a more refined solution for the given set of inputs. For an organization, the need for aggregate planning of resources stems up from meeting demand for a fiscal year and benefit from a tool to assist with the planning and budgeting of resources. Given the current environment it is important that such a tool consider the use of CSL as it can assist with spikes in demand without requiring a potentially unused resource commitment. Variations in demand on a daily basis, seasonal spikes, employee attrition, and employee hiring and onboarding are some of the issues that leadership is constantly dealing with while trying to optimize performance. This issues are relevant to fulltime and seasonal capacity, but the flexibility of CSL may provide added value to the overall objective of the organization to keep the LMD related costs to a minimum. With CSL readily available in the market, an organization can use it to their advantage but at the same time needs to ensure not to risk their service rate and thus needs a balance mix of resources. Depending on availability of CSL, an organization can assess their optimal labor needs for LMD services.

Thus, from the above three exercises of running the analytical model, stochastic program and simulation, one can understand the impact of CSL on LMD services. This can help an organization at an aggregate planning level to determine the best combination of resources between fulltime, seasonal and CSL at the lowest operational cost with or without automation.

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APPENDIX A. DETAILED PROOF OF SCENARIO 1 EQUATIONS

Theorem 1: For Scenario 1, where $U > S + E_S \; and \; F + E_F$

$H_j(T)$ is solved using equations A.2 and A.3, with T_j being determined by solving equation A.1.

$$S + (E_S - U) * (1 - G_j(T_j) + (U - O) * \left(1 - G_j(T_j + C)\right) = 0 \tag{A.1}$$

$$H_j(T) = F + (E_F - U) * \left(1 - G_j(T)\right) + (U - O) * (1 - G_j(T + C) \; if \; T \geq T_j \tag{A.2}$$

$$H_j(T) = (F - S) - (E_F - E_S) * \left(1 - G_j(T)\right) \; if \; T < T_j \tag{A.3}$$

The *T** which is the optimal value of *T* which minimizes the expected cost is solved for using equation A.4.

$$\sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{n_j H_j(T^*)} = 0 \tag{A.4}$$

Following that, the optimal seasonal capacity T_j^* is determined using equation A.5.

$$T_j^* = \left(T_j - T^*\right)^+ \tag{A.5}$$

Proof for scenario 1.

The optimal seasonal capacity from equation A.5 is the difference between the seasonal capacity per period determined by equation A.1 and the optimal *T* determined by solving equations A.2, A.3 and A.4.

The expected cost for scenario 1 with random variable demand x is given in the below equation where E_j is expected the per period cost during season j.

$$E_j = F * T + S * T_j + E_F * \left(\int_0^T x * g_j(x)dx + \left(1 - G_j(T)\right) * T\right) + E_S * \left(\int_T^{T+T_j}(x - T) * g_j(x)dx + \left(1 - G_j(T + T_j)\right) * T_j\right) + U * \left(\int_{T+T_j}^{T+T_j+C}\left(x - (T + T_j)\right) * g_j(x)dx + \left(1 - G_j(T + T_j + C)\right) * C\right) + O * \int_{T+T_j+C}^{\infty}\left(x - (T + T_j + C)\right) * g_j(x)dx$$

Simplifying the equation.

$$E_j = F * T + S * T_j + E_F * \left(\int_0^T x\, g_j(x)dx + \left(1 - G_j(T)\right) * T\right) + E_S * \left(\int_T^{T+T_j}(x - T) * g_j(x)dx + \left(1 - G_j(T + T_j)\right) * T_j\right) + U * \left(\int_{T+T_j}^{T+T_j+C} x * g_j(x)dx - (T + T_j)\int_{T+T_j}^{T+T_j+C} g_j(x)dx + \left(1 - G_j(T + T_j + C)\right) * C\right) + O * (\int_{T+T_j+C}^{\infty} x * g_j(x)dx - (T + T_j + C)\int_{T+T_j+C}^{\infty} g_j(x)dx) \quad \text{(A.6)}$$

In the next few steps, the derivative of the equation A.6 w.r.t. T_j is taken and equated it to zero to solve for equation A.1 which is used to solve for T_j.

$$S + E_S * \left(T_j * g_j(T + T_j) - T_j * g_j(T + T_j) + (1 - G_j(T + T_j))\right) + U * \left((T + T_j + C) * g_j(T + T_j + C) - (T + T_j) * g_j(T + T_j) - G_j(T + T_j) + G_j(T + T_j + C) + (T + T_j) * \left(g_j(T + T_j) - g_j(T + T_j + C)\right) - C * g_j(T + T_j + C)\right) + O * (¥ * g_j(¥) - (T + T_j + C) * g_j(T + T_j + C) - G_j(¥) + G_j(T + T_j + C) + (T + T_j + C) * g_j(T + T_j + C) = 0$$

Simplifying and substituting $g_j(¥) = 0$ and $G_j(¥) = 1$, the equation becomes as below:

$$S + E_S * \left(1 - G_j(T + T_j)\right) + U * (1 - G_j(T + T_j + C) - U * \left(1 - G_j(T + T_j)\right) - O * \left(1 - G_j(T + T_j + C)\right) = 0$$

Further enhancements lead to equation as below.

$$S + (E_S - U) * \left(1 - G_j\left(T + T_j\right)\right) + (U - O) * \left(1 - G_j\left(T + T_j + C\right)\right) = \ 0\ .$$

To solve for the optimal value of T_j, it is assumed that the value of T is equal to zero. Substituting this assumption in the above equation leads to equation A.1 repeated here for the reader's convenience.

$$S + (E_S - U) * (1 - G_j\left(T_j\right) + (U - O) * \left(1 - G_j\left(T_j + C\right)\right) = 0 \qquad \text{(A.1)}$$

To prove for the correctness of $H_j(T)$, the derivative of equation A.6 w.r.t. T is taken considering if $T \geq T_j\ or\ T < T_j$.

Case I - $T \geq T_j$

In the next few steps, the derivative of equation A.6, w.r.t. T is taken, given that $T_j^* = 0$ since $T \geq T_j$.

$$F + E_F * \left(T * g_j(T) - T * g_j(T) + \left(1 - G_j(T)\right)\right) + U * (\ (T + C) * g_j(T + C) - T * g_j(T) + G_j(T + C) - G_j(T) - T * g_j(T + C) + T * g_j(T)\ - C *\ g_j(T + C)\ +\ O * (¥ * g_j(¥) -\ (T + C) * g_j(T + C) - G_j(¥) + G_j(T + C) + (T + C) * g_j(T + C)$$

Simplifying and substituting $g_j(¥) = 0$ and $G_j(¥) = 1$ we get:

$$F + E_F * \left(1 - G_j(T)\right) + U * (1 - G_j(T + C) - U * \left(1 - G_j(T)\right) - O * \left(1 -\ G_j(T + C)\right)$$

Further enhancements leads to equation A.2 ($H_j(T)\ when\ T \geq T_j$) repeated here for the reader's convenience.

$$F + (E_F - U) * \left(1 - G_j(T)\right) + (U - O) * (1 - G_j(T + C)\ if\ T \geq T_j \qquad \text{(A.2)}$$

Case II - $T < T_j$

In the next few steps, the derivative of equation A.6 w.r.t. T is taken, given that $T_j^* = T - T_j$ since $T \geq T_j$.

$$E_j = F * T + S * (-T) + E_F * \left(\int_0^T x\, g_j(x)dx + \left(1 - G_j(T)\right) * T\right) + E_S *$$
$$\left(\int_T^0 (x-T) * g_j(x)dx + \left(1 - G_j\left(T + T_j\right)\right) * T_j\right) + U * \left(\int_0^C x * g_j(x)dx - (0)\int_0^C g_j(x)dx +\right.$$
$$\left.\left(1 - G_j(C)\right) * C\right) + O * (\int_C^\infty x * g_j(x)dx - (C)\int_C^\infty g_j(x)dx)$$

Eliminating U and O terms from above equation as their derivative w.r.t. T is 0 leads to below equation -

$$E_j = F * T + S * (-T) + E_F * \left(\int_0^T x\, g_j(x)dx + \left(1 - G_j(T)\right) * T\right) + E_S *$$
$$\left(\int_T^0 x * g_j(x)dx + T * \int_T^0 g_j(x)dx + \left(1 - G_j(0)\right) * (-T)\right) \quad .$$

Solving the equation further.

$$F - S + E_F * \left(T * g_j(T) - T * g_j(T) + \left(1 - G_j(T)\right)\right) + E_s * \left(-T g_j(T) - G_j(0) +\right.$$
$$\left.G_j(T) + T g_j(T) - 1 + G_j(0)\right)$$

Simplifying the above.

$$F - S + E_F * \left(1 - G_j(T)\right) - E_S * \left(1 - G_j(T)\right)$$

Further enhancements leads to equation A.3 (for $H_j(T)\ when\ T < T_j$) repeated here for the reader's convenience.

$$H_j(T) = (F - S) - (E_F - E_S) * \left(1 - G_j(T)\right)\ if\ T < T_j \qquad \text{(A.3)}$$

The following observations can be made from this theorem:

The optimal seasonal capacity T_j^* is determined once the optimal fulltime capacity T^* is determined and compared with the maximum seasonal need T_j. From, this theorem it is understood how the minimum cost is expensed given the demand profile and the delivery costs by capacity type. The optimal fulltime T^* indicates the fulltime capacity needed for the entire year and at the lowest possible cost to meet the demand. Any demand beyond fulltime capacity is handled by seasonal or CSL capacity. Furthermore, it also considers the expected penalty cost for a given demand profile when demand exceeds capacity. A similar approach applies to the proofs for scenarios 2 and 3.

APPENDIX B. INPUTS USED FOR ANALYTICAL MODEL

Organization information			
Parameter	Definitions	Value	Note(s)
C_F	Average Capacity of delivery per full time employee per day (per 8 hour shift)	32	Selecting value from literature approximating to 8-hour window with a certain customer density.
FT_{RH}	Full time regular hours per day	8	Standard work day with no over time.
C_S	Average Capacity of delivery per seasonal employee per day (per 4 hour shift)	16	Assuming half of Full time capacity.
S_{RH}	Seasonal employee regular hours per day	4	Seasonal = Part time employees.
FT_W	Full time wages per hour	$ 22.00	Includes benefits.
E_{PF}	Error percentage for full time delivery	2%	Error percentage assumed.
E_{PS}	Error percentage for seasonal delivery	4%	Error percentage assumed to be higher than full time.
E_{PV}	Error percentage for crowdsourcing delivery	6%	Error percentage assumed to be higher than full time and part time.
n	Number of seasons	4	Fiscal year.
n_j	Number of periods in season j	66	Assuming period = 1 day 8 hour shift.
N	Number of periods (j=1…n Σn_j)	264	Standard working days in year (4 seasons) and weekdays only.
VC_F	Vehicle cost when using full time per 8 hour shift	$ 64	Referred from literature for delivery van annual depreciation cost and miles traveled per day.
VC_S	Vehicle cost when using seasonal per shift	$ 32	Referred from literature for delivery van annual depreciation cost and miles traveled per day for part time hours.

APPENDIX C. CALCULATED INPUTS USED FOR ANALYTICAL MODEL

Model information			
Parameter	Definitions	Value	Note(s)
F	Per period cost of full time capacity to satisfy 1 unit of demand	$ 7.49	
S	Per period cost of seasonal (part time) capacity to satisfy 1 unit of demand	$ 11.23	S = 1.5*F
E_F	Expected error cost of 1 unit of demand being satisfied by full time capacity	$ 0.15	
E_S	Expected error cost of 1 unit of demand being satisfied by seasonal (part time) capacity	$ 0.45	Error cost is assumed to be fixed by full time employee and in overtime
U	Per unit cost to satisfy with crowd sourcing includes Expected error cost of 1 unit of demand being satisfied by crowd sourcing	$ 13.67 $ 10.03 $ 6.29	For scenario 1, 2 and 3 and includes error cost E_U
O	Cost per unit of unsatisfied demand	$ 59.88	

APPENDIX D. SEASON 1 AND SEASON 2 VALUES FOR UD AND ND

The mean and standard deviation for Normal Distribution were calculated referencing the minimum and maximum values of Uniform Distribution using the formula below.

$$Mean\ for\ ND = \frac{minmum\ demand + maximum\ demand}{2}$$

$$Standard\ deviation\ for\ ND = \frac{minmum\ demand + maximum\ demand}{\sqrt{12}}$$

APPENDIX E. SAS PROGRAM FOR ONE COMBINATION AS AN EXAMPLE

```
data seasonfile;
infile
'C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\SP\seasons.csv'
firstobs =2 dlm=',';
input Day Season;
run;

data demandfile;
infile
'C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\SP\demand.csv'
firstobs =2 dlm=',';
input Season Para1 Para2;
run;
proc optmodel;
number Hi=0.17;
number Low=0.17;
number DemandMultiplier;
number F=7.49/1000;
number Ef=0.15/1000;
number S=11.23/1000;
number Es=0.45/1000;
number O=59.88/1000;
number U1=13.67/1000; /*scenario 1 = 13.67 for U > F and S */
number U2=10.03/1000; /*scenario 2 = 10.03 for F < U < S*/
number U3=6.29/1000;  /*scenario 3 =  6.29 for U < F and S */
number Ca1=0;
number Ca2=258;
number Ca3=516;
number Ca4=774;
number Ca5=1032;
number J=264;
number K=2;
number I=1;
number H=100;
set<num> Days=1..J;
set<num> Days2;
set<num> Scenarios=1..H;
set<num> Intervals=1..I;
set<num> Seasons=1..K;
set<num> Seasons2;
number Map{Days};
number Parameter1{Seasons};
number Parameter2{Seasons};
number Demand{Days,Scenarios};
number Cost{Intervals,Days,Scenarios};
number Capacity{Intervals,Days,Scenarios};
read data seasonfile into Days2=[Day] Map[Day]= col("Season");
read data demandfile into Seasons2=[Season] Parameter1[Season]= col("Para1");
read data demandfile into Seasons2=[Season] Parameter2[Season]= col("Para2");
number a;
number b;
number c;
number Lambda;
number xavgs1; /* average for season 1 */
```

```
number xavgs2; /* average for season 2 */
number Dfavgs1;
number Dfavgs2;
number Dsavgs1;
number Dsavgs2;
number Uavgs1;
number Uavgs2;
number Cam; /* Ca mean*/
Cam = Ca2/I;
set<num> DaysA;
DaysA = 1 to 132;
set<num> DaysB;
DaysB = 133 to 264;
do b = 1 to H;
      DemandMultiplier=1;
      if RAND('UNIFORM') < Hi then DemandMultiplier = 2;
      else if RAND('UNIFORM') < Low/(1-Hi) then DemandMultiplier = 0.5;
      do a = 1 to J;
Demand[a,b] =
RAND('POISSON',(Parameter1[Map[a]]+Parameter2[Map[a]])*DemandMultiplier/2);
      end;
end;
do c = 1 to I;
do a = 1 to J;
do b = 1 to H;
      Cost[c,a,b] = (10.25+(13.67/2)*RAND('UNIFORM'))/1000;
      Capacity[c,a,b] = RAND('POISSON',Cam);
end;
end;
end;
var TL >= 0;
var TkL{Seasons} >= 0;
var xL{Intervals,Days,Scenarios} >= 0;
var UL{Days,Scenarios} >= 0;
var DfL{Days,Scenarios} >= 0;
var DsL{Days,Scenarios} >= 0;
var ScenarioCostL{Scenarios} >= 0;
var XSquareL >= 0;
var SquareXL >= 0;
constraint FullTimeL{a2 in Days, b2 in Scenarios}: DfL[a2,b2] <= TL;
constraint SeasonalTimeL{a2 in Days, b2 in Scenarios}: DsL[a2,b2] <=
TkL[Map[a2]];
constraint CrowdTimeL{c2 in Intervals, a2 in Days, b2 in Scenarios}:
xL[c2,a2,b2] <= Capacity[c2,a2,b2];
constraint ShortageL{a2 in Days, b2 in Scenarios}:
DfL[a2,b2]+DsL[a2,b2]+UL[a2,b2]+sum{c2 in Intervals}xL[c2,a2,b2] >=
Demand[a2,b2];
constraint LogicalL: TkL[2]=0;
constraint SetObjectiveL{b2 in Scenarios}: ScenarioCostL[b2] = sum{a2 in
Days}(F*TL + S*TkL[Map[a2]] + sum{c2 in
Intervals}(Cost[c2,a2,b2]*xL[c2,a2,b2]) + Ef*DfL[a2,b2] + Es*DsL[a2,b2] +
O*UL[a2,b2]);
constraint SetSquareXL: SquareXL = sum{b2 in Scenarios}(ScenarioCostL[b2]/H);
Lambda = 0;
solve;
filename OUTTER
'C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\SP\U1Ca2I1P25.csv';
```

```
number Variance;
Variance = 0;
do b = 1 to H;
end;
number DummyXSquare;
DummyXSquare = Variance;
Variance = Variance - SquareXL*SquareXL;
number TM;
TM = TL;
number TkM{Seasons};
do a = 1 to K;
      TkM[a] = TkL[a];
end;
number xM{Intervals, Days, Scenarios};
do c = 1 to I;
do a = 1 to J;
do b = 1 to H;
      xM[c,a,b] = xL[c,a,b];
end;
end;
end;
number UM{Days,Scenarios};
number DfM{Days,Scenarios};
number DsM{Days,Scenarios};
do a = 1 to J;
do b = 1 to H;
      UM[a,b] = UL[a,b];
      DfM[a,b] = DfL[a,b];
      DsM[a,b] = DsL[a,b];
end;
end;
number ScenarioCostM{Scenarios};
do b = 1 to H;
      ScenarioCostM[b] = ScenarioCostL[b];
end;
number SquareXM;
SquareXM = SquareXL;
file OUTTER;
put
'Lambda,T,Tk[1],meanvar,Mean,Variance,xavgs1,xavgs2,Dfavgs1,Dfavgs2,Dsavgs1,D
savgs2,Uavgs1,Uavgs2';
/*put Lambda ',' TL ',' TkL[1] ',' meanvarL ',' SquareXL ',' Variance ','
xavgs1 ',' xavgs2 ',' Dfavgs1 ',' Dfavgs2 ',' Dsavgs1 ',' Dsavgs2 ',' Uavgs1
',' Uavgs2;*/
var T init TM >= 0;
var Tk{a2 in Seasons} init TKM[a2]>= 0;
var x{c2 in Intervals, a2 in Days, b2 in Scenarios} init xM[c2,a2,b2]>= 0;
var U{a2 in Days, b2 in Scenarios} init UM[a2,b2] >= 0;
var Df{a2 in Days, b2 in Scenarios} init DfM[a2,b2] >= 0;
var Ds{a2 in Days, b2 in Scenarios} init DsM[a2,b2] >= 0;
var ScenarioCost{b2 in Scenarios} init ScenarioCostM[b2] >= 0;
var XSquare init DummyXSquare >= 0;
var SquareX init SquareXM >= 0;
min meanvar = (1-Lambda)*SquareX+Lambda*(XSquare-SquareX*SquareX);
constraint FullTime{a2 in Days, b2 in Scenarios}: Df[a2,b2] <= T;
constraint SeasonalTime{a2 in Days, b2 in Scenarios}: Ds[a2,b2] <=
Tk[Map[a2]];
```

```
constraint CrowdTime{c2 in Intervals, a2 in Days, b2 in Scenarios}:
x[c2,a2,b2] <= Capacity[c2,a2,b2];
constraint Shortage{a2 in Days, b2 in Scenarios}:
Df[a2,b2]+DsL[a2,b2]+U[a2,b2]+sum{c2 in Intervals}x[c2,a2,b2] >=
Demand[a2,b2];
constraint Logical: Tk[2]=0;
constraint SetObjective{b2 in Scenarios}: ScenarioCost[b2] = sum{a2 in
Days}(F*T + S*Tk[Map[a2]] + sum{c2 in Intervals}(Cost[c2,a2,b2]*x[c2,a2,b2])
+ Ef*Df[a2,b2] + Es*Ds[a2,b2] + O*U[a2,b2]);
constraint SetSquareX: SquareX = sum{b2 in Scenarios}(ScenarioCost[b2]/H);
constraint SetXSquare: XSquare = sum{b2 in
Scenarios}(ScenarioCost[b2]*ScenarioCost[b2]/H);
problem Utility include T Tk x U Df Ds ScenarioCost XSquare SquareX meanvar
FullTime SeasonalTime CrowdTime Shortage Logical SetObjective SetSquareX
SetXSquare;
do Lambda = 0.1 to 1 by 0.1;
Use problem Utility;
solve;
Variance = Xsquare - SquareX*SquareX;
xavgs1 =  (sum{c2 in Intervals, a2 in DaysA, b2 in Scenarios}
x[c2,a2,b2])/(H*132);
xavgs2 =  (sum{c2 in Intervals, a2 in DaysB, b2 in Scenarios}
x[c2,a2,b2])/(H*132);
Dfavgs1 = (sum{a2 in DaysA, b2 in Scenarios} Df[a2,b2])/(H*132);
Dfavgs2 = (sum{a2 in DaysB, b2 in Scenarios} Df[a2,b2])/(H*132);
Dsavgs1 = (sum{a2 in DaysA, b2 in Scenarios} Ds[a2,b2])/(H*132);
Dsavgs2 = (sum{a2 in DaysB, b2 in Scenarios} Ds[a2,b2])/(H*132);
Uavgs1 =  (sum{a2 in DaysA, b2 in Scenarios} U[a2,b2])/(H*132);
Uavgs2 =  (sum{a2 in DaysB, b2 in Scenarios} U[a2,b2])/(H*132);
put Lambda ',' T ',' Tk[1] ',' meanvar ','  SquareX ','  Variance ',' xavgs1
',' xavgs2 ',' Dfavgs1 ',' Dfavgs2 ',' Dsavgs1 ',' Dsavgs2 ',' Uavgs1 ','
Uavgs2;
end;
closefile OUTTER;
```

APPENDIX F. SAS OPTIMAL COMBINATION OUTPUT FROM STOCHASTIC PROGRAM

P	U	Ca	I	T	Tk[1]	xavgs1	xavgs2	Uavgs1	Uavgs2
0.25	13.67	2	1	366	500	62	47	6	0
0.25	13.67	2	3	401	466	62	39	6	0
0.25	13.67	2	5	408	458	63	37	6	0
0.25	13.67	3	1	316	294	127	60	6	0
0.25	13.67	3	3	315	295	127	60	6	0
0.25	13.67	3	5	313	297	127	61	6	0
0.25	13.67	4	1	315	206	185	60	0	0
0.25	13.67	4	3	305	137	253	63	0	0
0.25	13.67	4	5	304	135	255	63	0	0
0.25	13.67	5	1	315	207	184	60	0	0
0.25	13.67	5	3	300	0	375	64	0	0
0.25	13.67	5	5	304	5	368	63	0	0
0.25	10.03	2	1	336	527	63	55	7	0
0.25	10.03	2	3	341	521	63	54	7	0
0.25	10.03	2	5	342	522	63	53	7	0
0.25	10.03	3	1	294	312	127	66	7	0
0.25	10.03	3	3	292	314	127	67	7	0
0.25	10.03	3	5	292	315	127	67	7	0
0.25	10.03	4	1	294	103	290	66	2	0
0.25	10.03	4	3	291	101	294	67	2	0
0.25	10.03	4	5	290	103	293	68	2	0
0.25	10.03	5	1	277	0	397	74	0	0
0.25	10.03	5	3	269	0	404	79	0	0
0.25	10.03	5	5	270	0	403	78	0	0
0.25	6.29	2	1	327	532	63	57	7	1
0.25	6.29	2	3	329	532	63	56	7	0
0.25	6.29	2	5	329	531	63	56	7	0
0.25	6.29	3	1	278	325	128	74	7	0
0.25	6.29	3	3	274	330	128	76	7	0
0.25	6.29	3	5	273	330	128	77	7	0
0.25	6.29	4	1	278	92	311	74	4	0
0.25	6.29	4	3	274	94	312	76	4	0
0.25	6.29	4	5	271	98	312	78	4	0
0.25	6.29	5	1	142	0	530	187	2	0
0.25	6.29	5	3	138	0	533	191	2	0
0.25	6.29	5	5	135	0	536	194	2	0

P	U	Ca	I	T	Tk[1]	xavgs1	xavgs2	Uavgs1	Uavgs2
0.5	13.67	2	1	364	501	63	48	6	0
0.5	13.67	2	3	411	456	63	36	6	0
0.5	13.67	2	5	418	450	62	34	6	0
0.5	13.67	3	1	318	291	127	60	6	0
0.5	13.67	3	3	314	297	127	61	6	0
0.5	13.67	3	5	310	301	127	62	6	0
0.5	13.67	4	1	316	208	183	60	0	0
0.5	13.67	4	3	300	123	269	64	1	0
0.5	13.67	4	5	298	127	267	65	0	0
0.5	13.67	5	1	316	202	188	60	0	0
0.5	13.67	5	3	290	0	384	68	0	0
0.5	13.67	5	5	297	0	378	65	0	0
0.5	10.03	2	1	338	524	63	54	7	0
0.5	10.03	2	3	347	517	63	52	7	0
0.5	10.03	2	5	349	515	63	52	6	0
0.5	10.03	3	1	294	311	128	66	7	0
0.5	10.03	3	3	291	316	127	67	7	0
0.5	10.03	3	5	289	318	127	68	7	0
0.5	10.03	4	1	294	105	289	66	1	0
0.5	10.03	4	3	288	98	299	69	2	0
0.5	10.03	4	5	285	107	294	70	2	0
0.5	10.03	5	1	278	0	396	74	0	0
0.5	10.03	5	3	254	0	419	91	0	0
0.5	10.03	5	5	252	0	421	92	0	0
0.5	6.29	2	1	327	534	63	57	7	1
0.5	6.29	2	3	330	531	63	56	7	0
0.5	6.29	2	5	331	530	63	56	7	0
0.5	6.29	3	1	278	325	128	74	7	0
0.5	6.29	3	3	270	333	128	78	7	0
0.5	6.29	3	5	267	337	127	81	7	0
0.5	6.29	4	1	278	92	311	74	4	0
0.5	6.29	4	3	269	96	315	79	5	0
0.5	6.29	4	5	261	107	312	85	4	0
0.5	6.29	5	1	141	0	530	188	2	0
0.5	6.29	5	3	134	0	537	194	2	0
0.5	6.29	5	5	128	0	542	200	3	0

APPENDIX G. CHARTS FOR VARIOUS COMBINATIONS OF SCENARIOS 1-3, P, Ca AND I FROM STOCHASTIC PROGRAM.

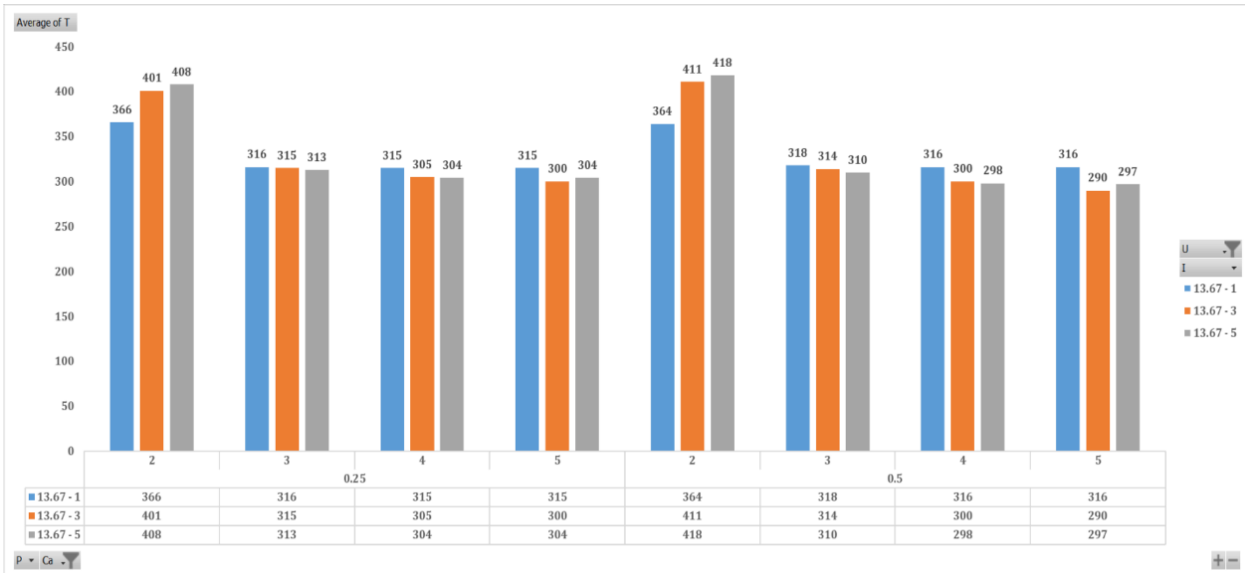


Figure G1. Optimal T values for given case of Scenario 1, P, Ca and I.

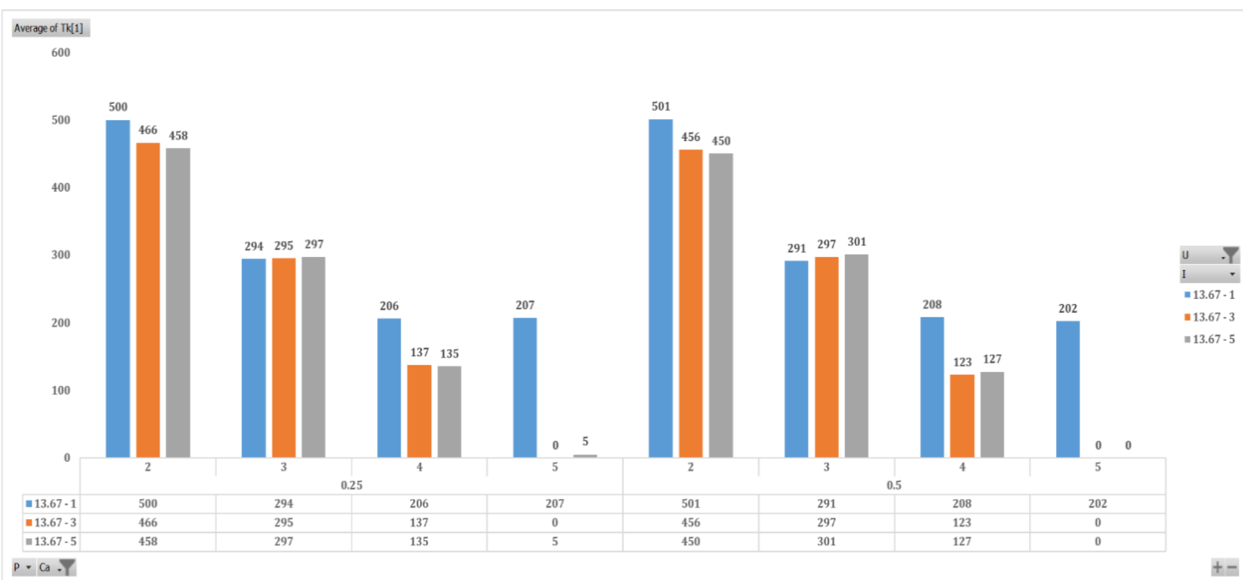


Figure G2. Optimal T_k values for given case of Scenario 1, P, Ca and I.

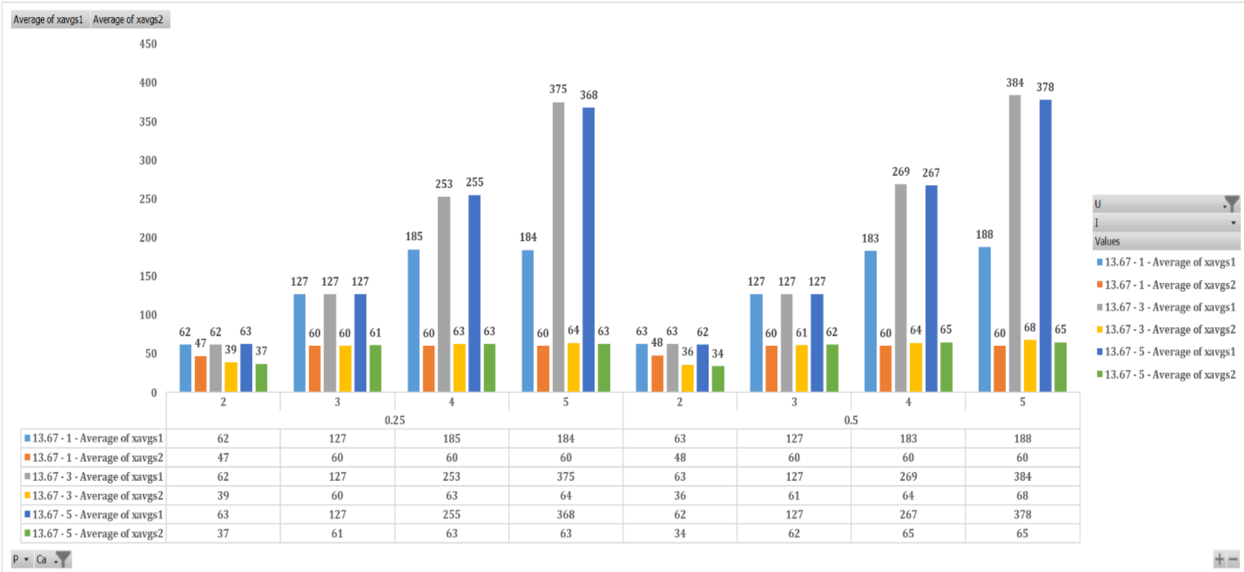


Figure G3. Optimal x values for given case of Scenario 1, P, Ca and I.

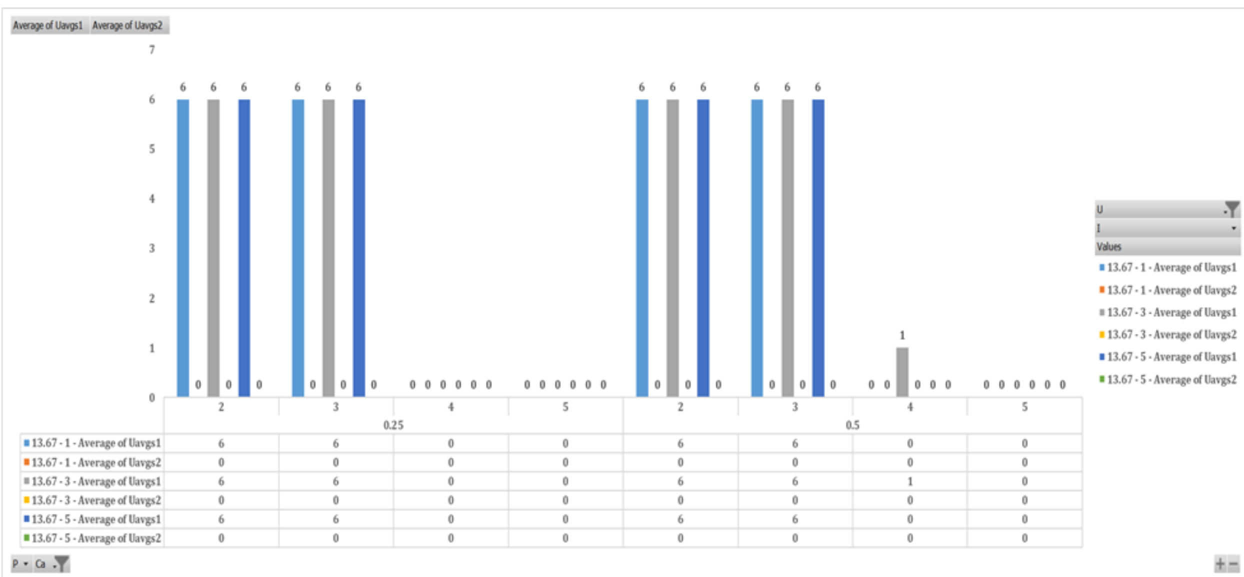


Figure G4. Optimal U values for given case of Scenario 1, P, Ca and I.

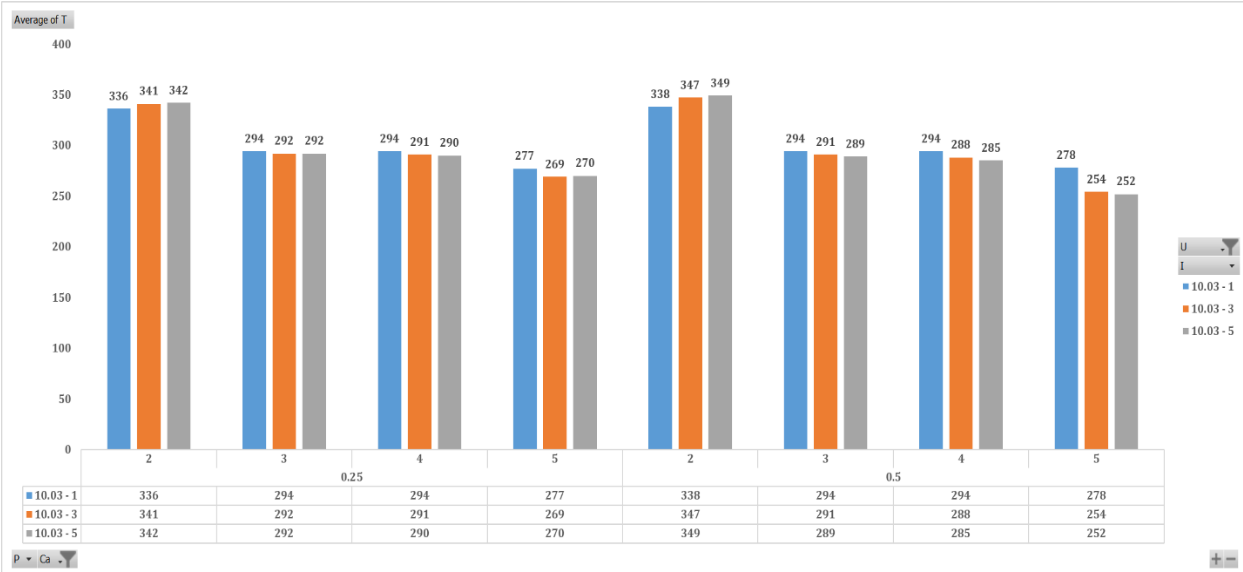


Figure G5. Optimal T values for given case of Scenario 2, P, Ca and I.

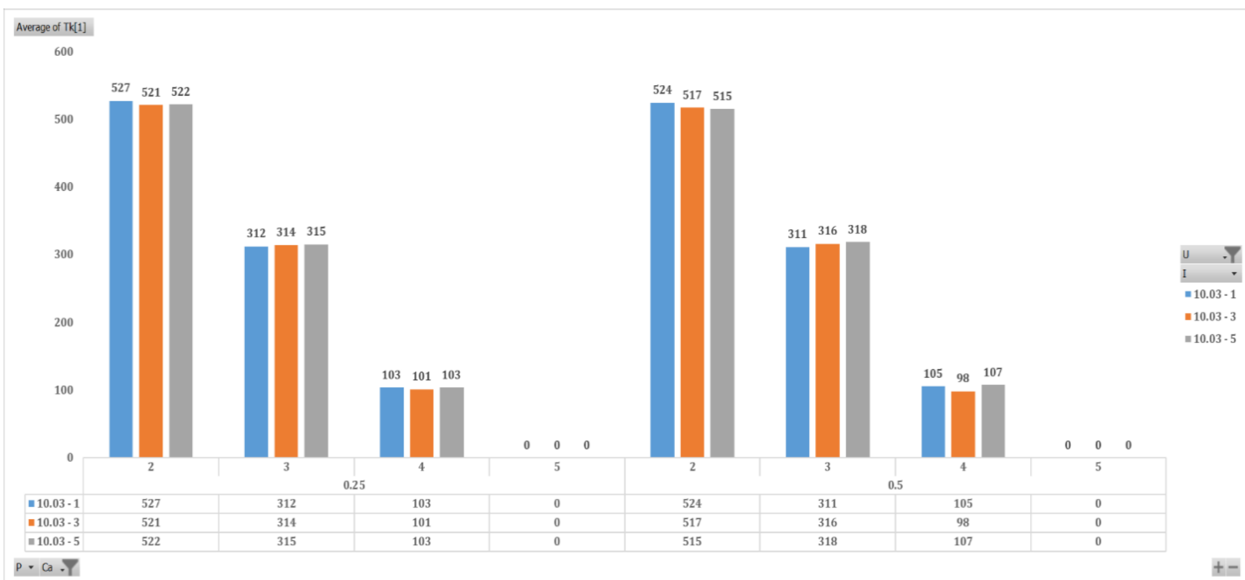
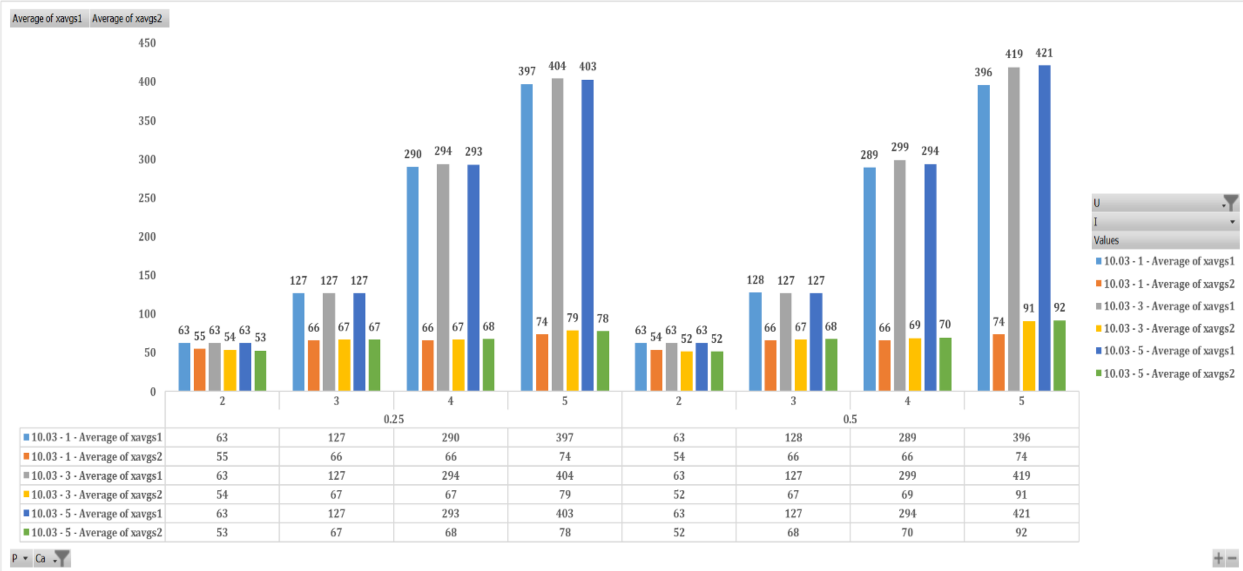
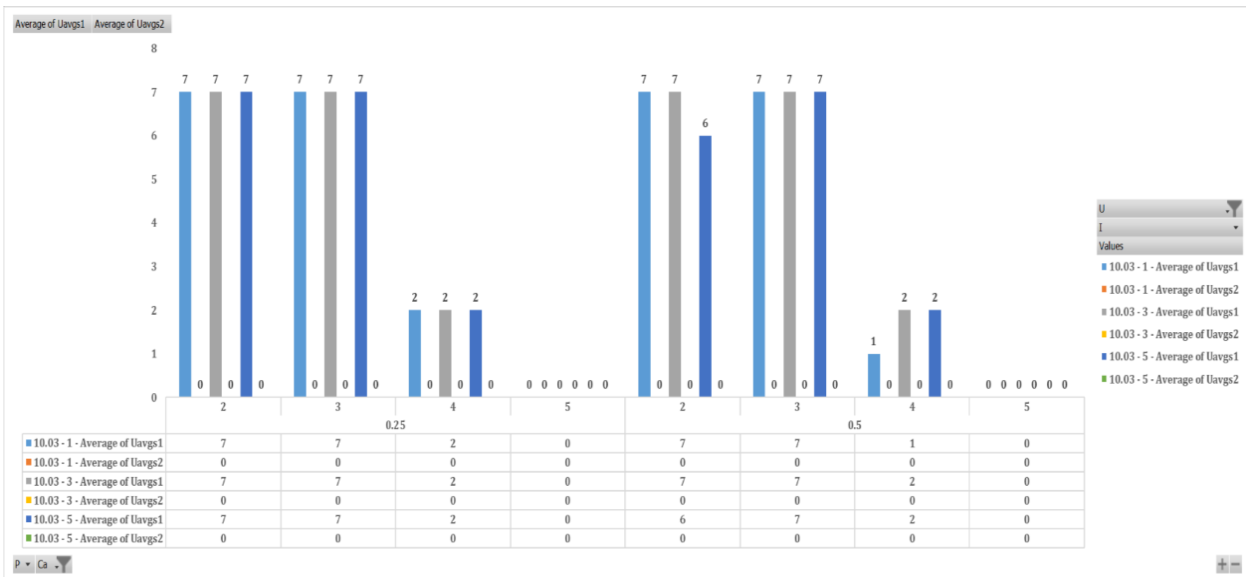


Figure G6. Optimal T_k values for given case of Scenario 2, P, Ca and I.



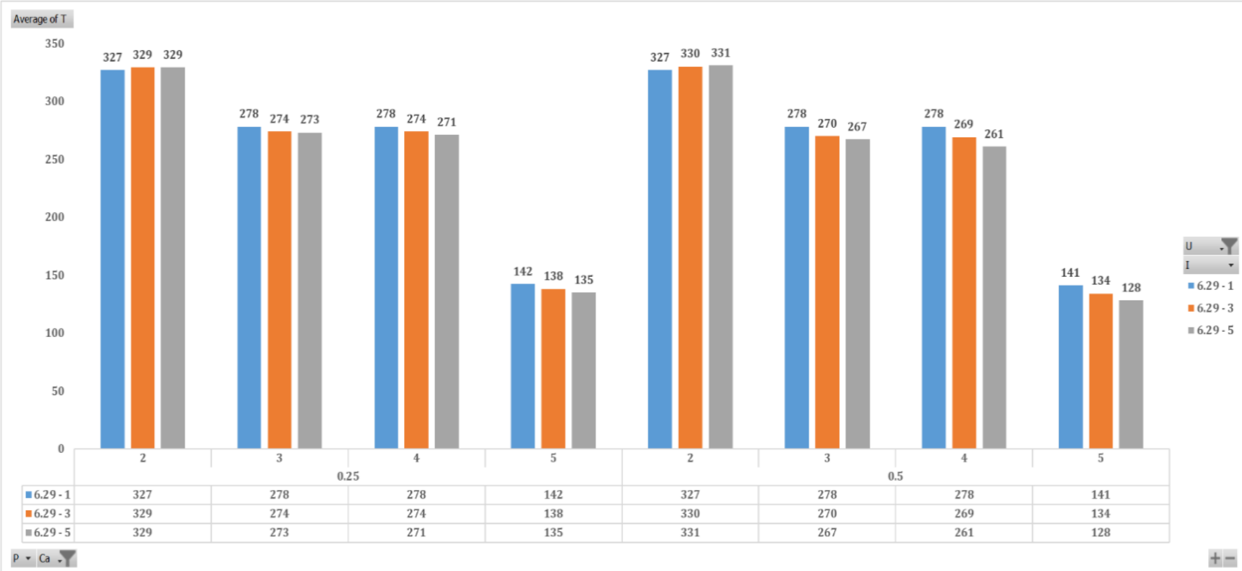
	0.25				0.5			
	2	3	4	5	2	3	4	5
10.03 - 1 - Average of xavgs1	63	127	290	397	63	128	289	396
10.03 - 1 - Average of xavgs2	55	66	66	74	54	66	66	74
10.03 - 3 - Average of xavgs1	63	127	294	404	63	127	299	419
10.03 - 3 - Average of xavgs2	54	67	67	79	52	67	69	91
10.03 - 5 - Average of xavgs1	63	127	293	403	63	127	294	421
10.03 - 5 - Average of xavgs2	53	67	68	78	52	68	70	92

Figure G7. Optimal x values for given case of Scenario 2, P, Ca and I.



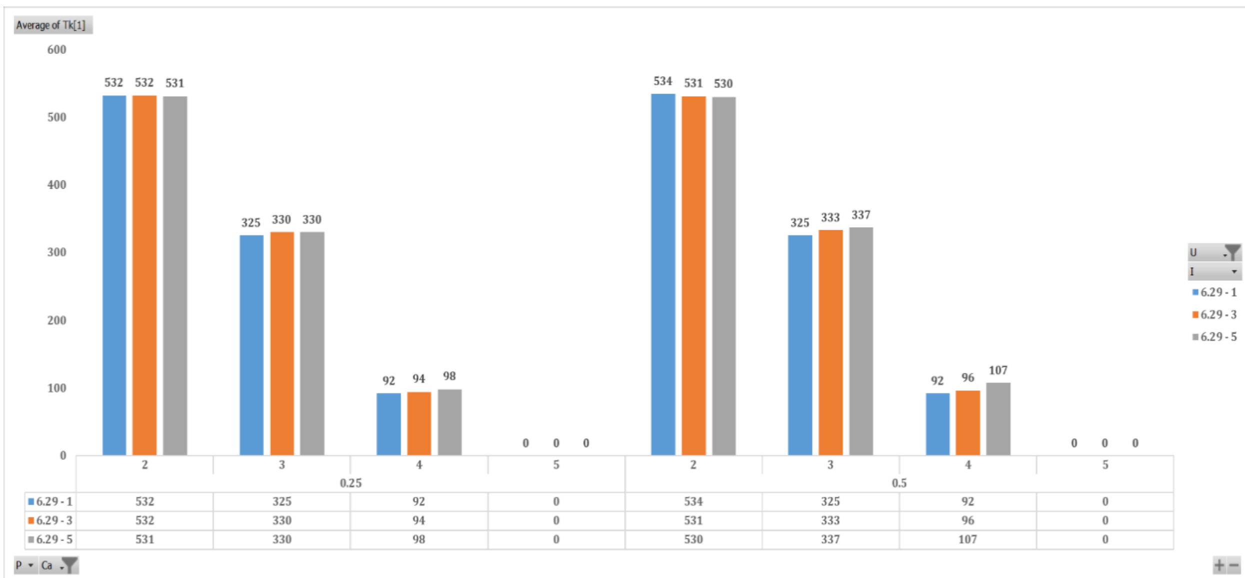
	0.25				0.5			
	2	3	4	5	2	3	4	5
10.03 - 1 - Average of Uavgs1	7	7	2	0	7	7	1	0
10.03 - 1 - Average of Uavgs2	0	0	0	0	0	0	0	0
10.03 - 3 - Average of Uavgs1	7	7	2	0	7	7	2	0
10.03 - 3 - Average of Uavgs2	0	0	0	0	0	0	0	0
10.03 - 5 - Average of Uavgs1	7	7	2	0	6	7	2	0
10.03 - 5 - Average of Uavgs2	0	0	0	0	0	0	0	0

Figure G8. Optimal U values for given case of Scenario 2, P, Ca and I.



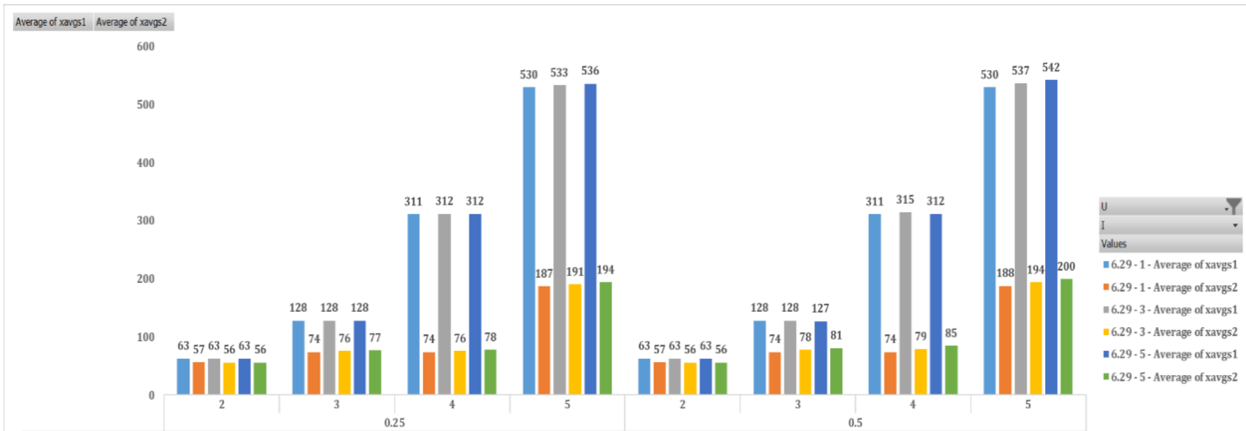
P	0.25				0.5			
Ca	2	3	4	5	2	3	4	5
6.29 - 1	327	278	278	142	327	278	278	141
6.29 - 3	329	274	274	138	330	270	269	134
6.29 - 5	329	273	271	135	331	267	261	128

Figure G9. Optimal T values for given case of Scenario 3, P, Ca and I.



P	0.25				0.5			
Ca	2	3	4	5	2	3	4	5
6.29 - 1	532	325	92	0	534	325	92	0
6.29 - 3	532	330	94	0	531	333	96	0
6.29 - 5	531	330	98	0	530	337	107	0

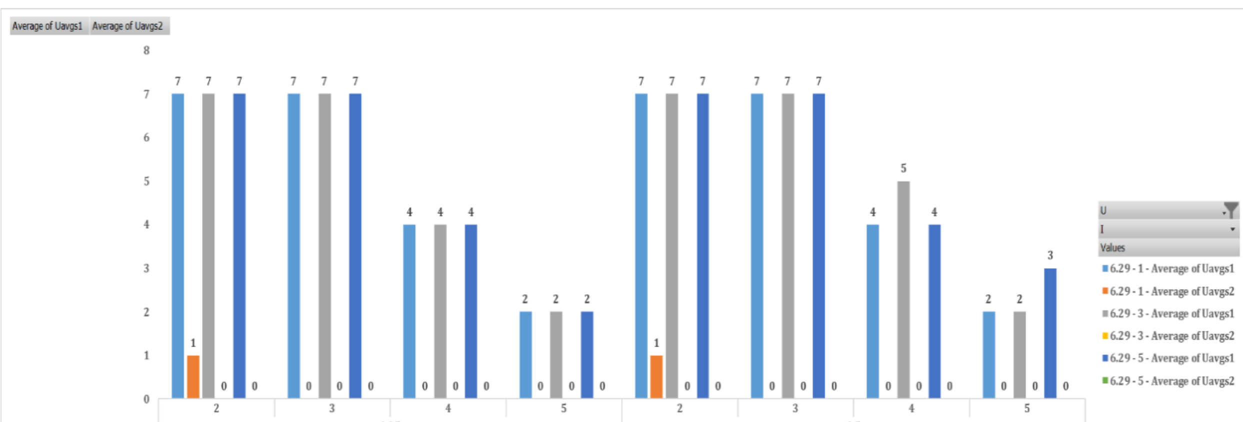
Figure G10. Optimal T_k values for given case of Scenario 3, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
6.29 - 1 - Average of xavgs1	63	128	311	530	63	128	311	530
6.29 - 1 - Average of xavgs2	57	74	74	187	57	74	74	188
6.29 - 3 - Average of xavgs1	63	128	312	533	63	128	315	537
6.29 - 3 - Average of xavgs2	56	76	76	191	56	78	79	194
6.29 - 5 - Average of xavgs1	63	128	312	536	63	127	312	542
6.29 - 5 - Average of xavgs2	56	77	78	194	56	81	85	200

P Ca

Figure G11. Optimal x values for given case of Scenario 3, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
6.29 - 1 - Average of Uavgs1	7	7	4	2	7	7	4	2
6.29 - 1 - Average of Uavgs2	1	0	0	0	1	0	0	0
6.29 - 3 - Average of Uavgs1	7	7	4	2	7	7	5	2
6.29 - 3 - Average of Uavgs2	0	0	0	0	0	0	0	0
6.29 - 5 - Average of Uavgs1	7	7	4	2	7	7	4	3
6.29 - 5 - Average of Uavgs2	0	0	0	0	0	0	0	0

P Ca

Figure G12. Optimal U values for given case of Scenario 3, P, Ca and I.

APPENDIX H. SIMULATION PROGRAM FOR ONE COMBINATION AS AN EXAMPLE

```
data TTksp;
infile
'C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\Paper3\U1Ca2IxP25TT
k.csv'
firstobs =2 dlm=',';
input T Tk;
run;

data values;
 set TTksp;
      %LET mT = T;
      %LET mTk = Tk;
      CT = 32;
      CTk = 16;
      O = 59.88;
      F = 7.49;
      Ef = 0.15;
      S = 11.23;
      Es = 0.45;
      hiring = 239.68; /* F*CT */
      Ca2=258;
      Ca2I1 = Ca2/1;
      Ca2I3 = Ca2/3;
      Ca2I5 = Ca2/5;
      s1min=109;
      s1max=1032;
      s2min=97;
      s2max=459;
run;

data Actual;
 set values;
 do i = 1 to 50;

      do j = 1 to 132;
      U1P25_1 = (10.25+(13.67/2)*RAND('UNIFORM'));
      U1P25_2 = (10.25+(13.67/2)*RAND('UNIFORM'));
      U1P25_3 = (10.25+(13.67/2)*RAND('UNIFORM'));
      U1P25_4 = (10.25+(13.67/2)*RAND('UNIFORM'));
      U1P25_5 = (10.25+(13.67/2)*RAND('UNIFORM'));
      d=RAND('POISSON',(s1min + s1max)/2);
      Tatt = RAND('POISSON',(0.04/100)*T);
      Tact = &mT-Tatt;                                /* Tact = actual T */
      hc = (&mT - Tact)/CT;                           /* hc = headcount */
      hcT= hc * hiring;
      Tkatt = RAND('POISSON',(0.04/100)*Tk);
      Tkact = &mTk - Tkatt;                           /* Tkact = actual Tk */
      hck = (&mTk - Tkact)/CTk;
      hcTk= hck * hiring;
      Tk2 = Tk;
      Tkact2 = Tkact;
      hck2 = hck;
```

```
      hcTk2 = hcTk;
    B1 = U1P25_1;
    B31 = min(U1P25_1, U1P25_2, U1P25_3);
    B32 = smallest(2, of U1P25_1, U1P25_2, U1P25_3);
    B33 = smallest(3, of U1P25_1, U1P25_2, U1P25_3);
    B51 = min(U1P25_1, U1P25_2, U1P25_3, U1P25_4, U1P25_5);
    B52 = smallest(2, of U1P25_1, U1P25_2, U1P25_3, U1P25_4, U1P25_5);
    B53 = smallest(3, of U1P25_1, U1P25_2, U1P25_3, U1P25_4, U1P25_5);
    B54 = smallest(4, of U1P25_1, U1P25_2, U1P25_3, U1P25_4, U1P25_5);
    B55 = smallest(5, of U1P25_1, U1P25_2, U1P25_3, U1P25_4, U1P25_5);
    /* S1 when I =1 */
    if d > (Tact + Tkact2) then xd1S1 = d - (Tact + Tkact2);
    else xd1S1 = 0;
      xc1S1 = RAND('POISSON',Ca2I1); /* capacity of x */
      if xd1S1 > xc1S1 then U1S1 = xd1S1 - xc1S1;
    else U1S1 = 0;
      Ulag_lagU1S1 = lag(U1S1);
    dnew1S1 = d + Ulag_lagU1S1;
      if dnew1S1 > (Tact + Tkact2) then xdnew1S1 = dnew1S1 - (Tact + Tkact2);
    else xdnew1S1 = 0;
      if xdnew1S1 > xc1S1 then Unew1S1 = xdnew1S1 - xc1S1;
      else Unew1S1 = 0;
      if xdnew1S1 <= xc1S1 then xact11S1 = xdnew1S1;
      if xdnew1S1 > xc1S1 then xact11S1 = xc1S1;
      if j = 1 then Ulag_lagU1S1 = 0;
    if j = 1 then dnew1S1 = d;
    if j = 1 then xdnew1S1 = xd1S1;
      if j = 1 then Unew1S1 = U1S1;
      if j = 1 then xact11S1 = min(xc1S1,xdnew1S1);
      TC11S1 = xact11S1*B1;              /* TC = Total cost */
      TC1S1 = T * (F + Ef) + hcT + Tk2 * ( S + Es) + hcTk2 + TC11S1 +
(Unew1S1 * O);
    if d > (Tact + Tkact2) then xd3S1 = d - (Tact + Tkact2); else xd3S1 = 0;
      xc31S1 = RAND('POISSON',Ca2I3);
      xc32S1 = RAND('POISSON',Ca2I3);
      xc33S1 = RAND('POISSON',Ca2I3);
      if xd3S1 > (xc31S1+xc32S1+xc33S1) then U3S1 = xd3S1 -
(xc31S1+xc32S1+xc33S1); else U3S1 = 0;
      Ulag_lagU3S1 = lag(U3S1);
      dnew3S1 = d + Ulag_lagU3S1;
      if dnew3S1 > (Tact + Tkact2) then xdnew3S1 = dnew3S1 - (Tact + Tkact2);
else xdnew3S1 = 0;
      if xc31S1 => xdnew3S1 then xact31S1 = xdnew3S1;
      else if xc31S1 < xdnew3S1 =< (xc31S1+xc32S1) then xact31S1 = xc31S1;
      else if (xc31S1+xc32S1) < xdnew3S1 =< (xc31S1+xc32S1+xc33S1) then
xact31S1 = xc31S1;
      else if xdnew3S1 > (xc31S1+xc32S1+xc33S1) then xact31S1 = xc31S1; else
xact31S1 = 0;
      if xc31S1 < xdnew3S1 =< (xc31S1+xc32S1)  then  xact32S1 =
min((xdnew3S1-xact31S1),xc32S1);
      else if (xc31S1+xc32S1) < xdnew3S1 =< (xc31S1+xc32S1+xc33S1) then
xact32S1 = xc32S1;
      else if xdnew3S1 > (xc31S1+xc32S1+xc33S1) then xact32S1 = xc32S1; else
xact32S1 = 0;
    if (xc31S1+xc32S1) < xdnew3S1 =< (xc31S1+xc32S1+xc33S1) then xact33S1 =
min((xdnew3S1-xact31S1-xact32S1),xc33S1);
```

```
      else if xdnew3S1 > (xc31S1+xc32S1+xc33S1) then xact33S1 = xc33S1; else
xact33S1 = 0;
      if xdnew3S1 > (xc31S1+xc32S1+xc33S1) then Unew3S1=dnew3S1-Tact-Tkact2-
xact31S1-xact32S1-xact33S1; else Unew3S1 = 0;
      if j = 1 then Ulag_lagU3S1 = 0;
    if j = 1 then dnew3S1 = d;
    if j = 1 then xdnew3S1 = xd3S1;
      if j = 1 then Unew3S1 = U3S1;
      if j = 1 then xact31S1 = min(xc31S1,xdnew3S1);
      if j = 1 then xact32S1 = min((xdnew3S1-xact31S1),xc32S1);
      if j = 1 then xact33S1 = min((xdnew3S1-xact31S1-xact32S1),xc33S1);
      TC31S1 = xact31S1*B31;
      TC32S1 = xact32S1*B32;
      TC33S1 = xact33S1*B33;
      TC3S1 = T * (F + Ef) + hcT + Tk2 * ( S + Es) + hcTk2 + TC31S1 + TC32S1
+ TC33S1 + (Unew3S1 * O);
/* S1 when I =5 */
      if d > (Tact + Tkact2) then xd5S1 = d - (Tact + Tkact2);
    else xd5S1 = 0;
      xc51S1       = RAND('POISSON',Ca2I5);
      xc52S1       = RAND('POISSON',Ca2I5);
      xc53S1       = RAND('POISSON',Ca2I5);
      xc54S1       = RAND('POISSON',Ca2I5);
      xc55S1       = RAND('POISSON',Ca2I5);
      if xd5S1 > (xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then U5S1 = xd5S1 -
(xc51S1+xc52S1+xc53S1+xc54S1+xc55S1);
      else U5S1 = 0;
      Ulag_lagU5S1 = lag(U5S1);
    dnew5S1 = d + Ulag_lagU5S1;
      if dnew5S1 > (Tact + Tkact2) then xdnew5S1 = dnew5S1 - (Tact + Tkact2);
    else xdnew5S1 = 0;
      if xc51S1 >= xdnew5S1 then xact51S1 = xdnew5S1;
      else if xc51S1 < xdnew5S1 =< (xc51S1+xc52S1)  then xact51S1 = xc51S1;
      else if (xc51S1+xc52S1) < xdnew5S1 =< (xc51S1+xc52S1+xc53S1) then
xact51S1 = xc51S1;
      else if (xc51S1+xc52S1+xc53S1) < xdnew5S1 =<
(xc51S1+xc52S1+xc53S1+xc54S1) then xact51S1 = xc51S1;
      else if (xc51S1+xc52S1+xc53S1+xc54S1) < xdnew5S1 =<
(xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then xact51S1 = xc51S1;
      else if xdnew5S1 > (xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then xact51S1 =
xc51S1; else xact51S1 = 0;
      if xc51S1 < xdnew5S1 =< (xc51S1+xc52S1)  then  xact52S1 =
min((xdnew5S1-xact51S1),xc52S1);
      else if (xc51S1+xc52S1) < xdnew5S1 =< (xc51S1+xc52S1+xc53S1) then
xact52S1 = xc52S1;
      else if (xc51S1+xc52S1+xc53S1) < xdnew5S1 =<
(xc51S1+xc52S1+xc53S1+xc54S1) then xact52S1 = xc52S1;
      else if (xc51S1+xc52S1+xc53S1+xc54S1) < xdnew5S1 =<
(xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then xact52S1 = xc52S1;
      else if xdnew5S1 > (xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then xact52S1 =
xc52S1; else xact52S1 = 0;
    if (xc51S1+xc52S1) < xdnew5S1 =< (xc51S1+xc52S1+xc53S1) then xact53S1 =
min((xdnew5S1-xact51S1-xact52S1),xc53S1);
      else if (xc51S1+xc52S1+xc53S1) < xdnew5S1 =<
(xc51S1+xc52S1+xc53S1+xc54S1) then xact53S1 = xc53S1;
      else if (xc51S1+xc52S1+xc53S1+xc54S1) < xdnew5S1 =<
(xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then xact53S1 = xc53S1;
```

```
      else if xdnew5S1 > (xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then xact53S1 =
xc53S1; else xact53S1 = 0;
      if (xc51S1+xc52S1+xc53S1) < xdnew5S1 =< (xc51S1+xc52S1+xc53S1+xc54S1)
then xact54S1 = min((xdnew5S1-xact51S1-xact52S1-xact53S1),xc54S1);
    else if (xc51S1+xc52S1+xc53S1+xc54S1) < xdnew5S1 =<
(xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then xact54S1 = xc54S1;
      else if xdnew5S1 > (xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then xact54S1 =
xc54S1; else xact54S1 = 0;
      if (xc51S1+xc52S1+xc53S1+xc54S1) < xdnew5S1 =<
(xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then xact55S1 = min((xdnew5S1-xact51S1-
xact52S1-xact53S1-xact54S1),xc55S1);
      else if xdnew5S1 > (xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then xact55S1 =
xc55S1; else xact55S1 = 0;
            if xdnew5S1 > (xc51S1+xc52S1+xc53S1+xc54S1+xc55S1) then
Unew5S1=dnew5S1-Tact-Tkact2-xact51S1-xact52S1-xact53S1-xact54S1-xact55S1;
else Unew5S1 = 0;
      if j = 1 then Ulag_lagU5S1 = 0;
      if j = 1 then dnew5S1 = d;
      if j = 1 then xdnew5S1 = xd5S1;
      if j = 1 then Unew5S1 = U5S1;
      if j = 1 then xact51S1 = min(xc51S1,xdnew5S1);
      if j = 1 then xact52S1 = min((xdnew5S1-xact51S1),xc52S1);
      if j = 1 then xact53S1 = min((xdnew5S1-xact51S1-xact52S1),xc53S1);
      if j = 1 then xact54S1 = min((xdnew5S1-xact51S1-xact52S1-
xact53S1),xc54S1);
      if j = 1 then xact55S1 = min((xdnew5S1-xact51S1-xact52S1-xact53S1-
xact54S1),xc55S1);
      TC51S1 = xact51S1*B51;
      TC52S1 = xact52S1*B52;
      TC53S1 = xact53S1*B53;
      TC54S1 = xact54S1*B54;
      TC55S1 = xact55S1*B55;
      TC5S1 = T * (F + Ef) + hcT + Tk2 * ( S + Es) + hcTk2 + TC51S1 + TC52S1
+ TC53S1 + TC54S1 + TC55S1 + (Unew5S1 * O);
output;
end;
/* season 2 */
do j = 133 to 264;
      U1P25_1 = (10.25+(13.67/2)*RAND('UNIFORM'));
      U1P25_2 = (10.25+(13.67/2)*RAND('UNIFORM'));
      U1P25_3 = (10.25+(13.67/2)*RAND('UNIFORM'));
      U1P25_4 = (10.25+(13.67/2)*RAND('UNIFORM'));
      U1P25_5 = (10.25+(13.67/2)*RAND('UNIFORM'));
      d=RAND('POISSON',(s2min + s2max)/2);
      Tatt = RAND('POISSON',(0.04/100)*T);            /* Tatt = attrition
     Tact = &mT-Tatt;
     hc = (&mT - Tact)/CT;
     hcT= hc * hiring;
     Tkatt = RAND('POISSON',(0.04/100)*Tk);
     Tkact = &mTk - Tkatt;
     hck = (&mTk - Tkact)/CTk;
     hcTk= hck * hiring;
    Tk2 = 0;
    Tkact2 = 0;
      hck2 = 0;
      hcTk2 = 0;
    B1 = U1P25_1;
```

```
    B31 = min(U1P25_1, U1P25_2, U1P25_3);
    B32 = smallest(2, of U1P25_1, U1P25_2, U1P25_3);
    B33 = smallest(3, of U1P25_1, U1P25_2, U1P25_3);
    B51 = min(U1P25_1, U1P25_2, U1P25_3, U1P25_4, U1P25_5);
    B52 = smallest(2, of U1P25_1, U1P25_2, U1P25_3, U1P25_4, U1P25_5);
    B53 = smallest(3, of U1P25_1, U1P25_2, U1P25_3, U1P25_4, U1P25_5);
    B54 = smallest(4, of U1P25_1, U1P25_2, U1P25_3, U1P25_4, U1P25_5);
    B55 = smallest(5, of U1P25_1, U1P25_2, U1P25_3, U1P25_4, U1P25_5);
/* S2 when I =1 */
    if d > (Tact + Tkact2) then xd1S2 = d - (Tact + Tkact2);
    else xd1S2 = 0;
      xc1S2 = RAND('POISSON',Ca2I1); /* capacity of x */
      if xd1S2 > xc1S2 then U1S2 = xd1S2 - xc1S2;
    else U1S2 = 0;
      Ulag_lagU1S2 = lag(U1S2);
    dnew1S2 = d + Ulag_lagU1S2;
      if j = 133 then Ulag_lagU1S2 = Ulag_lagU1S1;
      if j = 133 then dnew1S2 = d+Ulag_lagU1S1;
      if dnew1S2 > (Tact + Tkact2) then xdnew1S2 = dnew1S2 - Tact - Tkact2;
    else xdnew1S2 = 0;
      if xdnew1S2 > xc1S2 then Unew1S2 = xdnew1S2 - xc1S2;
      else Unew1S2 = 0;
      if xdnew1S2 =< xc1S2 then xact11S2 = xdnew1S2;
      if xdnew1S2 > xc1S2 then xact11S2 = xc1S2;
      TC11S2 = xact11S2*B1;
      TC1S2 = T * (F + Ef) + hcT + Tk2 * ( S + Es) + hcTk2 + TC11S2 +
(Unew1S2 * O);
/* S2 when I =3 */
    if d > (Tact + Tkact2) then xd3S2 = d - (Tact + Tkact2);
    else xd3S2 = 0;
      xc31S2 = RAND('POISSON',Ca2I3);
      xc32S2 = RAND('POISSON',Ca2I3);
      xc33S2 = RAND('POISSON',Ca2I3);
      if xd3S2 > (xc31S2+xc32S2+xc33S2) then U3S2 = xd3S2 -
(xc31S2+xc32S2+xc33S2);
      else U3S2 = 0;
      Ulag_lagU3S2 = lag(U3S2);
    dnew3S2 = d + Ulag_lagU3S2;
      if j = 133 then Ulag_lagU3S2 = Ulag_lagU3S1;
      if j = 133 then dnew3S2 = d+Ulag_lagU3S1;
      if dnew3S2 > (Tact + Tkact2) then xdnew3S2 = dnew3S2-Tact-Tkact2;
    else xdnew3S2 = 0;
      if xdnew3S2 =< xc31S2 then xact31S2 = xdnew3S2;
      else if xc31S2 < xdnew3S2 =< (xc31S2+xc32S2) then xact31S2 = xc31S2;
      else if (xc31S2+xc32S2) < xdnew3S2 =< (xc31S2+xc32S2+xc33S2) then
xact31S2 = xc31S2;
      else if xdnew3S2 > (xc31S2+xc32S2+xc33S2) then xact31S2 = xc31S2; else
xact31S2=0;
      if xc31S2 < xdnew3S2 =< (xc31S2+xc32S2) then xact32S2 = min((xdnew3S2-
xact31S2),xc32S2);
      else if (xc31S2+xc32S2) < xdnew3S2 =< (xc31S2+xc32S2+xc33S2) then
xact32S2 = xc32S2
      else if xdnew3S2 > (xc31S2+xc32S2+xc33S2) then xact32S2 = xc32S2; else
xact32S2=0;
      if xdnew3S2 > (xc31S2+xc32S2+xc33S2) then Unew3S2=dnew3S2-Tact-Tkact2-
xact31S2-xact32S2-xact33S2; else Unew3S2 = 0;
      TC31S2 = xact31S2*B31;
```

```
      TC32S2 = xact32S2*B32;
      TC33S2 = xact33S2*B33;
      TC3S2 = T * (F + Ef) + hcT + Tk2 * ( S + Es) + hcTk2 + TC31S2 + TC32S2
+ TC33S2 + (Unew3S2 * O);
/* S2 when I=5 */
      if d > (Tact + Tkact2) then xd5S2 = d - (Tact + Tkact2);
    else xd5S2 = 0;
      xc51S2      = RAND('POISSON',Ca2I5);
      xc52S2      = RAND('POISSON',Ca2I5);
      xc53S2      = RAND('POISSON',Ca2I5);
      xc54S2      = RAND('POISSON',Ca2I5);
      xc55S2      = RAND('POISSON',Ca2I5);
      if xd5S2 > (xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then U5S2 = xd5S2 -
(xc51S2+xc52S2+xc53S2+xc54S2+xc55S2);
      else U5S2 = 0;
      Ulag_lagU5S2 = lag(U5S2);
    dnew5S2 = d + Ulag_lagU5S2;
      if j = 133 then Ulag_lagU5S2 = Ulag_lagU5S1;
      if j = 133 then dnew5S2=d+Ulag_lagU5S1;
      if dnew5S2 > (Tact + Tkact2) then xdnew5S2 = dnew5S2 - Tact - Tkact2;
    else xdnew5S2 = 0;
      if xc51S2 >= xdnew5S2 then xact51S2 = xdnew5S2;
      else if xc51S2 < xdnew5S2 =< (xc51S2+xc52S2)  then xact51S2 = xc51S2;
      else if (xc51S2+xc52S2) < xdnew5S2 =< (xc51S2+xc52S2+xc53S2) then
xact51S2 = xc51S2;
      else if (xc51S2+xc52S2+xc53S2) < xdnew5S2 =<
(xc51S2+xc52S2+xc53S2+xc54S2) then xact51S2 = xc51S2;
      else if (xc51S2+xc52S2+xc53S2+xc54S2) < xdnew5S2 =<
(xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then xact51S2 = xc51S2;
      else if xdnew5S2 > (xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then xact51S2 =
xc51S2; else xact51S2 = 0;
      if xc51S2 < xdnew5S2 =< (xc51S2+xc52S2)  then xact52S2 = min((xdnew5S2-
xact51S2),xc52S2);
      else if (xc51S2+xc52S2) < xdnew5S2 =< (xc51S2+xc52S2+xc53S2) then
xact52S2 = xc52S2
      else if (xc51S2+xc52S2+xc53S2) < xdnew5S2 =<
(xc51S2+xc52S2+xc53S2+xc54S2) then xact52S2 = xc52S2;
      else if (xc51S2+xc52S2+xc53S2+xc54S2) < xdnew5S2 =<
(xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then xact52S2 = xc52S2;
      else if xdnew5S2 > (xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then xact52S2 =
xc52S2; else xact52S2=0;
    if (xc51S2+xc52S2) < xdnew5S2 =< (xc51S2+xc52S2+xc53S2) then xact53S2 =
min((xdnew5S2-xact51S2-xact52S2),xc53S2);
      else if (xc51S2+xc52S2+xc53S2) < xdnew5S2 =<
(xc51S2+xc52S2+xc53S2+xc54S2) then xact53S2 = xc53S2;
      else if (xc51S2+xc52S2+xc53S2+xc54S2) < xdnew5S2 =<
(xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then xact53S2 = xc53S2;
      else if xdnew5S2 > (xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then xact53S2 =
xc53S2; else xact53S2 = 0;
      if (xc51S2+xc52S2+xc53S2) < xdnew5S2 =< (xc51S2+xc52S2+xc53S2+xc54S2)
then xact54S2 = min((xdnew5S2-xact51S2-xact52S2-xact53S2),xc54S2);
    else if (xc51S2+xc52S2+xc53S2+xc54S2) < xdnew5S2 =<
(xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then xact54S2 = xc54S2;
      else if xdnew5S2 > (xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then xact54S2 =
xc54S2; else xact54S2 = 0;
```

```
      if (xc51S2+xc52S2+xc53S2+xc54S2) < xdnew5S2 =<
(xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then xact55S2 = min((xdnew5S2-xact51S2-
xact52S2-xact53S2-xact54S2),xc55S2);
      else if xdnew5S2 > (xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then xact55S2 =
xc55S2; else xact55S2 = 0;
      if xdnew5S2 > (xc51S2+xc52S2+xc53S2+xc54S2+xc55S2) then
Unew5S2=dnew5S2-Tact-Tkact2-xact51S2-xact52S2-xact53S2-xact54S2-xact55S2;
else Unew5S2 = 0;
      TC51S2 = xact51S2*B51;
      TC52S2 = xact52S2*B52;
      TC53S2 = xact53S2*B53;
      TC54S2 = xact54S2*B54;
      TC55S2 = xact55S2*B55;
      TC5S2 = T * (F + Ef) + hcT + Tk2 * ( S + Es) + hcTk2 + TC51S2 + TC52S2
+ TC53S2 + TC54S2 + TC55S2 + (Unew5S2 * O);
      output;
      end;
end;
run;

ods csv
file='C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\Paper3\U1Ca2Ix
P25 I1S1.csv';
Proc means data = Actual mean;
Class T Tk;
where j < 133;
var T Tk d xdnew1S1 xact11S1 Unew1S1;
run;
ods csv close;

ods csv
file='C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\Paper3\U1Ca2Ix
P25 I1S2.csv';
Proc means data = Actual mean;
Class T Tk;
where j > 132;
var T Tk d xdnew1S2 xact11S2 Unew1S2;
run;
ods csv close;

ods csv
file='C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\Paper3\U1Ca2Ix
P25 I3S1.csv';
Proc means data = Actual mean;
Class T Tk;
where j < 133;
var T Tk d xdnew3S1 xact31S1 xact32S1 xact33S1 xc33S1 xc32S1 xc33S1 Unew3S1;
run;
ods csv close;

ods csv
file='C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\Paper3\U1Ca2Ix
P25 I3S2.csv';
Proc means data = Actual mean;
Class T Tk;
where j > 132;
var T Tk d xdnew3S2 xact31S2 xact32S2 xact33S2 xc31S2 xc32S2 xc33S2 Unew3S2;
```

```
run;
ods csv close;

ods csv
file='C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\Paper3\U1Ca2Ix
P25 I5S1.csv';
Proc means data = Actual mean;
Class T Tk;
where j < 133;
var T Tk d xdnew5S1 xact51S1 xact52S1 xact53S1 xact54S1 xact55S1 xc51S1
xc52S1 xc53S1 xc54S1 xc55S1 Unew5S1;
run;
ods csv close;

ods csv
file='C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\Paper3\U1Ca2Ix
P25 I5S2.csv';
Proc means data = Actual mean;
Class T Tk;
where j > 132;
var T Tk d xdnew5S2 xact51S2 xact52S2 xact53S2 xact54S2 xact55S2 xc51S2
xc52S2 xc53S2 xc54S2 xc55S2 Unew5S2;
run;
ods csv close;

ods csv
file='C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\Paper3\U1Ca2Ix
P25 TCS1.csv';
Proc means data = Actual mean;
Class T Tk;
where j < 133;
var T Tk d TC1S1 TC3S1 TC5S1;
run;
ods csv close;

ods csv
file='C:\Users\Joseph.Szmerekovsky\Documents\Research\Raghavan\Paper3\U1Ca2Ix
P25 TCS2.csv';
Proc means data = Actual mean;
Class T Tk;
where j > 132;
var T Tk d TC1S2 TC3S2 TC5S2;
run;
ods csv close;
```

APPENDIX I. SIMULATION OPTIMAL COMBINATION OUTPUT

Table I1. SAS Simulation program output.

P	U	Ca	I	T	Tk[1]	xavgs1	xavgs2	Uavgs1	Uavgs2
0.25	13.67	2	1	316	408	0	0	0	0
0.25	13.67	2	3	316	408	0	0	0	0
0.25	13.67	2	5	316	408	0	0	0	0
0.25	13.67	3	1	287	259	26	3	0	0
0.25	13.67	3	3	283	244	44	4	0	0
0.25	13.67	3	5	281	247	42	5	0	0
0.25	13.67	4	1	294	252	26	2	0	0
0.25	13.67	4	3	287	232	51	3	0	0
0.25	13.67	4	5	285	146	139	4	0	0
0.25	13.67	5	1	287	254	30	3	0	0
0.25	13.67	5	3	286	236	48	3	0	0
0.25	13.67	5	5	286	97	187	3	0	0
0.25	10.03	2	1	286	471	0	3	0	0
0.25	10.03	2	3	286	471	0	3	0	0
0.25	10.03	2	5	286	471	0	3	0	0
0.25	10.03	3	1	280	262	29	6	0	0
0.25	10.03	3	3	271	262	38	11	0	0
0.25	10.03	3	5	271	262	38	11	0	0
0.25	10.03	4	1	291	153	126	2	0	0
0.25	10.03	4	3	281	54	235	5	0	0
0.25	10.03	4	5	281	53	236	5	0	0
0.25	10.03	5	1	293	42	235	2	0	0
0.25	10.03	5	3	274	1	295	9	0	0
0.25	10.03	5	5	280	2	289	6	0	0
0.25	6.29	2	1	277	481	0	7	0	0
0.25	6.29	2	3	277	481	0	7	0	0
0.25	6.29	2	5	277	481	0	7	0	0
0.25	6.29	3	1	223	275	73	55	0	0
0.25	6.29	3	3	223	275	73	55	0	0
0.25	6.29	3	5	223	275	73	55	0	0
0.25	6.29	4	1	221	42	307	57	0	0
0.25	6.29	4	3	221	42	307	57	0	0
0.25	6.29	4	5	221	42	307	57	0	0
0.25	6.29	5	1	85	1	484	193	0	0
0.25	6.29	5	3	85	1	484	193	0	0
0.25	6.29	5	5	85	1	484	193	0	0
0.5	13.67	2	1	314	400	0	0	0	0
0.5	13.67	2	3	314	400	0	0	0	0
0.5	13.67	2	5	314	400	0	0	0	0
0.5	13.67	3	1	288	257	27	3	0	0
0.5	13.67	3	3	275	242	53	8	0	0
0.5	13.67	3	5	270	241	59	11	0	0
0.5	13.67	4	1	288	250	33	3	0	0
0.5	13.67	4	3	277	73	221	7	0	0
0.5	13.67	4	5	282	76	212	5	0	0
0.5	13.67	5	1	293	248	31	2	0	0
0.5	13.67	5	3	281	1	289	5	0	0

Table I1. SAS Simulation program output (continued).

P	U	Ca	I	T	Tk[1]	xavgs1	xavgs2	Uavgs1	Uavgs2
0.5	13.67	5	5	278	7	285	7	0	0
0.5	10.03	2	1	288	465	0	3	0	0
0.5	10.03	2	3	288	465	0	3	0	0
0.5	10.03	2	5	288	465	0	3	0	0
0.5	10.03	3	1	276	262	33	8	0	0
0.5	10.03	3	3	240	261	69	38	0	0
0.5	10.03	3	5	240	261	69	38	0	0
0.5	10.03	4	1	276	49	245	7	0	0
0.5	10.03	4	3	259	49	263	20	0	0
0.5	10.03	4	5	245	48	277	33	0	0
0.5	10.03	5	1	269	1	300	12	0	0
0.5	10.03	5	3	242	1	328	36	0	0
0.5	10.03	5	5	207	0	363	71	0	0
0.5	6.29	2	1	277	480	0	7	0	0
0.5	6.29	2	3	277	480	0	7	0	0
0.5	6.29	2	5	277	480	0	7	0	0
0.5	6.29	3	1	218	275	77	60	0	0
0.5	6.29	3	3	217	275	79	61	0	0
0.5	6.29	3	5	217	275	79	61	0	0
0.5	6.29	4	1	211	42	317	67	0	0
0.5	6.29	4	3	211	42	317	67	0	0
0.5	6.29	4	5	211	42	317	67	0	0
0.5	6.29	5	1	78	0	493	200	0	0
0.5	6.29	5	3	78	0	493	200	0	0
0.5	6.29	5	5	78	3	490	199	0	0

Table I2. Confidence interval (95%) for SAS Simulation program output.

Scenarios				TC S1				TC S2			
P	U	Ca	I	Mean cost	Standard error	Lower limit	Upper limit	Mean cost	Standard error	Lower limit	Upper limit
0.25	13.67	2	1	7183.13	0.08	7182.97	7183.29	2415.95	0.13	2415.70	2416.20
0.25	13.67	2	3	7183.13	0.08	7182.97	7183.29	2415.87	0.12	2415.64	2416.10
0.25	13.67	2	5	7183.13	0.08	7182.97	7183.29	2415.84	0.11	2415.62	2416.06
0.25	13.67	3	1	5576.90	3.63	5569.79	5584.01	2234.64	1.12	2232.45	2236.83
0.25	13.67	3	3	5535.63	3.54	5528.69	5542.57	2215.18	1.18	2212.86	2217.50
0.25	13.67	3	5	5515.30	3.32	5508.80	5521.80	2207.51	1.23	2205.10	2209.92
0.25	13.67	4	1	5543.61	3.56	5536.64	5550.58	2268.05	0.76	2266.56	2269.54
0.25	13.67	4	3	5516.13	3.59	5509.10	5523.16	2230.73	0.99	2228.79	2232.67
0.25	13.67	4	5	5470.47	3.84	5462.93	5478.01	2219.94	1.02	2217.94	2221.94
0.25	13.67	5	1	5577.04	3.67	5569.86	5584.22	2235.35	1.15	2233.10	2237.60
0.25	13.67	5	3	5519.75	3.57	5512.76	5526.74	2224.88	1.02	2222.89	2226.87
0.25	13.67	5	5	5451.31	4.09	5443.30	5459.32	2224.45	0.98	2222.54	2226.36
0.25	10.03	2	1	7690.06	0.08	7689.89	7690.23	2220.78	0.88	2219.05	2222.51
0.25	10.03	2	3	7690.06	0.08	7689.89	7690.23	2216.24	0.76	2214.75	2217.73
0.25	10.03	2	5	7690.06	0.08	7689.89	7690.23	2214.81	0.72	2213.39	2216.23
0.25	10.03	3	1	5570.12	3.59	5563.08	5577.16	2211.89	1.46	2209.03	2214.75
0.25	10.03	3	3	5513.42	2.99	5507.56	5519.28	2176.85	1.49	2173.93	2179.77
0.25	10.03	3	5	5481.95	2.67	5476.71	5487.19	2168.44	1.36	2165.77	2171.11
0.25	10.03	4	1	5589.33	5.89	5577.78	5600.88	2251.26	0.89	2249.52	2253.00
0.25	10.03	4	3	5137.39	6.36	5124.93	5149.85	2199.59	1.09	2197.45	2201.73
0.25	10.03	4	5	5067.69	5.2	5057.50	5077.88	2196.74	1.01	2194.77	2198.71
0.25	10.03	5	1	5657.33	9.1	5639.49	5675.17	2261.28	0.77	2259.77	2262.79
0.25	10.03	5	3	5050.80	7.55	5036.00	5065.60	2184.78	1.43	2181.97	2187.59
0.25	10.03	5	5	4945.75	5.85	4934.28	4957.22	2190.96	1.02	2188.97	2192.95
0.25	6.29	2	1	7738.13	0.09	7737.96	7738.30	2162.22	0.79	2160.67	2163.77
0.25	6.29	2	3	7738.13	0.09	7737.96	7738.30	2156.56	0.69	2155.22	2157.90
0.25	6.29	2	5	7738.13	0.09	7737.96	7738.30	2154.58	0.65	2153.31	2155.85
0.25	6.29	3	1	5375.20	2.03	5371.22	5379.18	2051.75	1.44	2048.94	2054.56
0.25	6.29	3	3	5317.99	1.71	5314.64	5321.34	2008.65	1.21	2006.28	2011.02
0.25	6.29	3	5	5300.21	1.61	5297.06	5303.36	1994.57	1.13	1992.36	1996.78
0.25	6.29	4	1	4114.08	3.93	4106.38	4121.78	2048.53	1.47	2045.64	2051.42
0.25	6.29	4	3	3909.58	2.89	3903.92	3915.24	2004.01	1.23	2001.60	2006.42
0.25	6.29	4	5	3878.53	2.49	3873.66	3883.40	1988.85	1.13	1986.63	1991.07
0.25	6.29	5	1	3707.25	5.7	3696.07	3718.43	1859.50	2.51	1854.58	1864.42
0.25	6.29	5	3	3437.72	3.91	3430.05	3445.39	1711.49	1.85	1707.86	1715.12
0.25	6.29	5	5	3379.38	3.26	3373.00	3385.76	1662.22	1.51	1659.26	1665.18

Table I2. Confidence interval (95%) for SAS Simulation program output (continued).

Scenarios				TC S1				TC S2			
P	U	Ca	I	Mean cost	Standard error	Lower limit	Upper limit	Mean cost	Standard error	Lower limit	Upper limit
0.5	13.67	2	1	7074.41	0.08	7074.25	7074.57	2401.22	0.19	2400.86	2401.58
0.5	13.67	2	3	7074.41	0.08	7074.25	7074.57	2400.88	0.14	2400.61	2401.15
0.5	13.67	2	5	7074.41	0.08	7074.25	7074.57	2400.78	0.13	2400.53	2401.03
0.5	13.67	3	1	5572.11	3.84	5564.58	5579.64	2240.74	1.14	2238.51	2242.97
0.5	13.67	3	3	5472.32	3.44	5465.58	5479.06	2184.76	1.4	2182.01	2187.51
0.5	13.67	3	5	5420.03	3.09	5413.97	5426.09	2167.66	1.43	2164.86	2170.46
0.5	13.67	4	1	5568.35	4.1	5560.32	5576.38	2240.66	1.15	2238.40	2242.92
0.5	13.67	4	3	5223.47	7.78	5208.21	5238.73	2191.60	1.34	2188.97	2194.23
0.5	13.67	4	5	5098.77	5.89	5087.23	5110.31	2199.76	0.96	2197.87	2201.65
0.5	13.67	5	1	5552.82	4.09	5544.81	5560.83	2261.01	0.8	2259.44	2262.58
0.5	13.67	5	3	5103.00	9.81	5083.78	5122.22	2201.34	1.14	2199.11	2203.57
0.5	13.67	5	5	4969.78	7.39	4955.29	4984.27	2185.45	1.13	2183.24	2187.66
0.5	10.03	2	1	7635.25	0.09	7635.08	7635.42	2229.80	0.82	2228.19	2231.41
0.5	10.03	2	3	7635.25	0.09	7635.08	7635.42	2222.77	0.61	2221.57	2223.97
0.5	10.03	2	5	7635.25	0.09	7635.08	7635.42	2220.40	0.54	2219.33	2221.47
0.5	10.03	3	1	5503.24	3.07	5497.23	5509.25	2185.47	1.34	2182.84	2188.10
0.5	10.03	3	3	5407.60	2.9	5401.92	5413.28	2119.88	1.81	2116.33	2123.43
0.5	10.03	3	5	5351.57	2.45	5346.77	5356.37	2088.23	1.55	2085.20	2091.26
0.5	10.03	4	1	5124.06	9.26	5105.90	5142.22	2183.83	1.36	2181.17	2186.49
0.5	10.03	4	3	4551.83	6.68	4538.74	4564.92	2128.72	1.48	2125.82	2131.62
0.5	10.03	4	5	4486.57	5.5	4475.80	4497.34	2095.01	1.5	2092.07	2097.95
0.5	10.03	5	1	5043.22	11.1	5021.50	5064.94	2177.30	1.69	2174.00	2180.60
0.5	10.03	5	3	4320.50	8.02	4304.78	4336.22	2119.25	1.75	2115.82	2122.68
0.5	10.03	5	5	4263.61	6.77	4250.34	4276.88	2057.51	1.86	2053.86	2061.16
0.5	6.29	2	1	7726.35	0.09	7726.18	7726.52	2161.44	0.84	2159.80	2163.08
0.5	6.29	2	3	7726.35	0.09	7726.18	7726.52	2150.02	0.61	2148.83	2151.21
0.5	6.29	2	5	7726.35	0.09	7726.18	7726.52	2146.31	0.53	2145.27	2147.35
0.5	6.29	3	1	5364.62	2.58	5359.57	5369.67	2045.04	1.87	2041.38	2048.70
0.5	6.29	3	3	5244.97	1.87	5241.31	5248.63	1947.37	1.38	1944.66	1950.08
0.5	6.29	3	5	5205.74	1.58	5202.65	5208.83	1915.17	1.13	1912.96	1917.38
0.5	6.29	4	1	4098.64	7.33	4084.27	4113.01	2034.08	2.01	2030.14	2038.02
0.5	6.29	4	3	3698.67	4.94	3689.00	3708.34	1927.58	1.39	1924.85	1930.31
0.5	6.29	4	5	3620.31	3.9	3612.67	3627.95	1893.19	1.12	1890.99	1895.39
0.5	6.29	5	1	3679.24	11.2	3657.33	3701.15	1859.66	4.66	1850.53	1868.79
0.5	6.29	5	3	3156.27	7.24	3142.09	3170.45	1539.21	3.12	1533.09	1545.33
0.5	6.29	5	5	3054.36	5.73	3043.13	3065.59	1434.07	2.35	1429.45	1438.69

APPENDIX J. CHARTS FOR VARIOUS COMBINATIONS OF SCENARIOS 1-3, P, Ca AND I FROM SIMULATION.

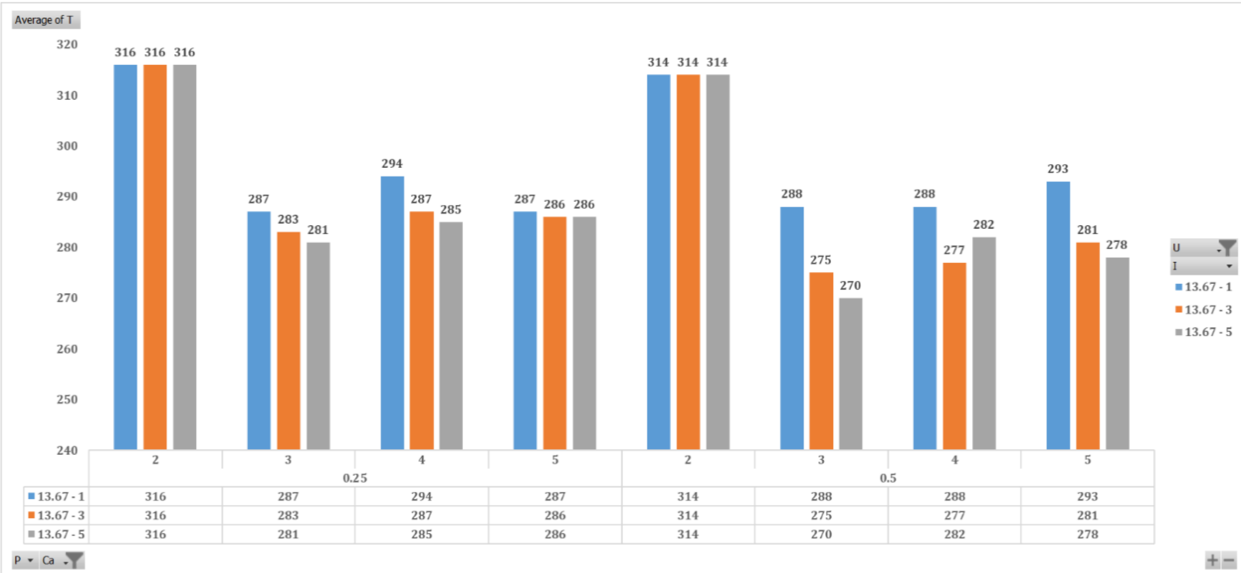


Figure J1. Optimal T values for given case of scenario 1, P, Ca and I.

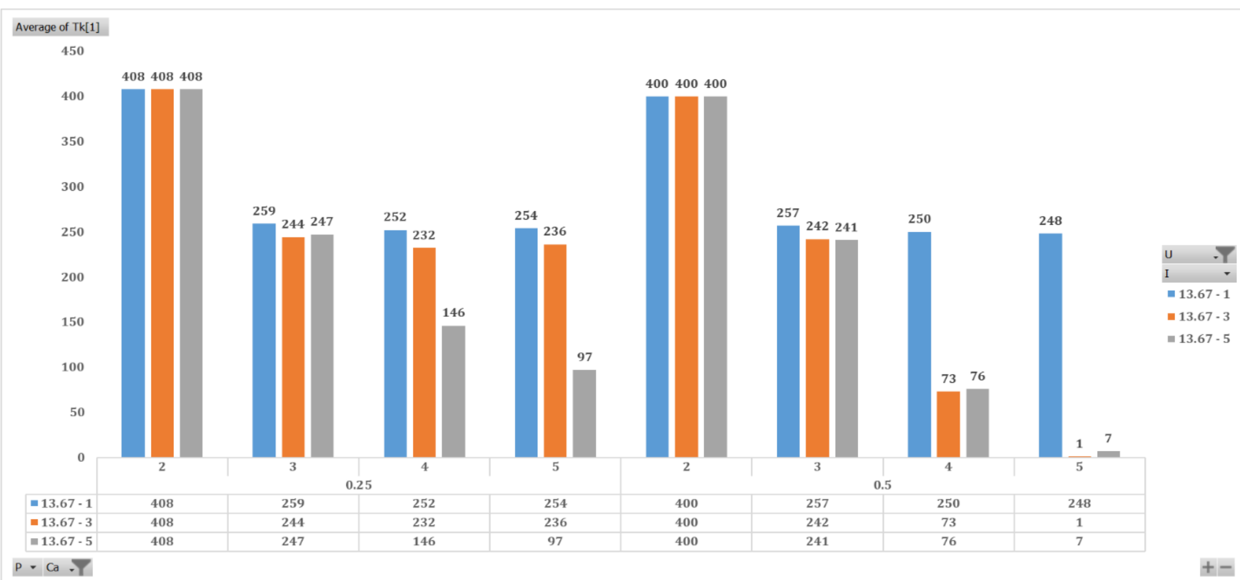
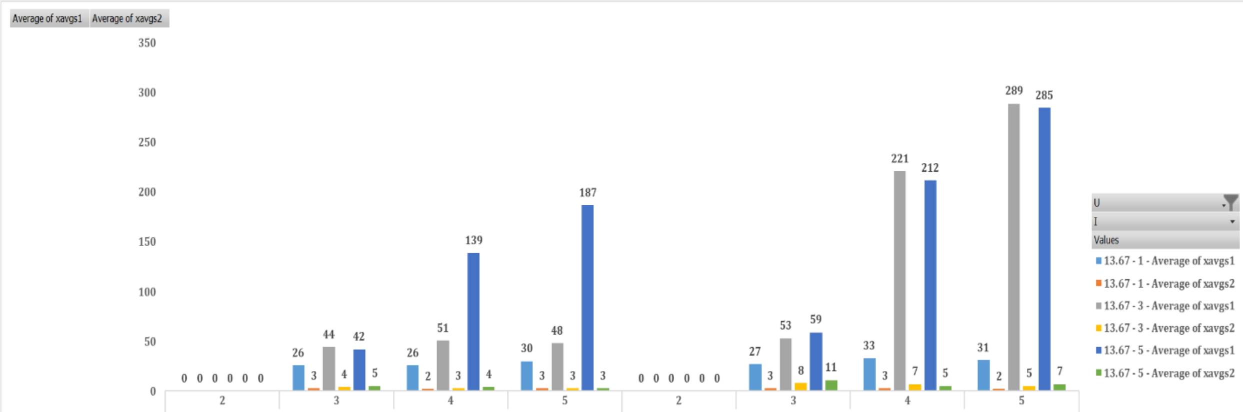


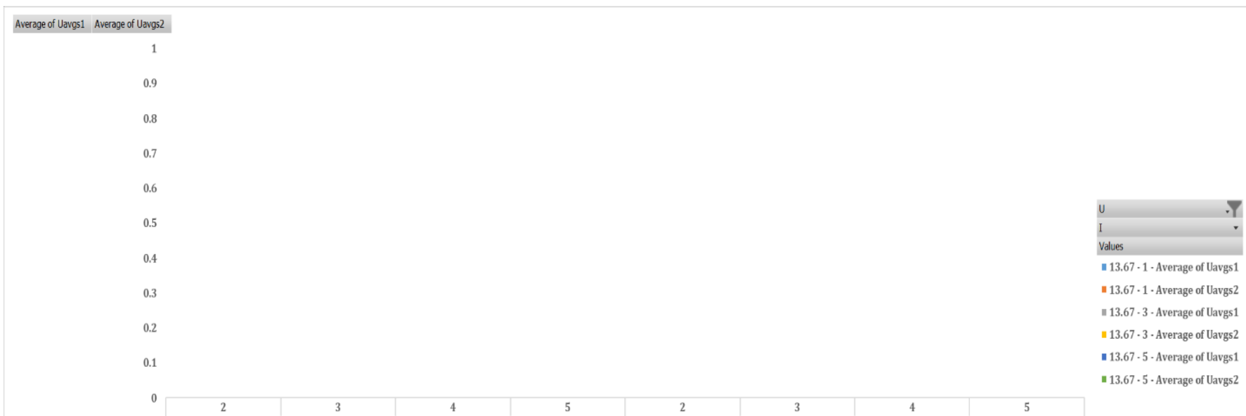
Figure J2. Optimal T_k values for given case of scenario 1, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
13.67 - 1 - Average of xavgs1	0	26	26	30	0	27	33	31
13.67 - 1 - Average of xavgs2	0	3	2	3	0	3	3	2
13.67 - 3 - Average of xavgs1	0	44	51	48	0	53	221	289
13.67 - 3 - Average of xavgs2	0	4	3	3	0	8	7	5
13.67 - 5 - Average of xavgs1	0	42	139	187	0	59	212	285
13.67 - 5 - Average of xavgs2	0	5	4	3	0	11	5	7

P Ca

Figure J3. Optimal x values for given case of scenario 1, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
13.67 - 1 - Average of Uavgs1	0	0	0	0	0	0	0	0
13.67 - 1 - Average of Uavgs2	0	0	0	0	0	0	0	0
13.67 - 3 - Average of Uavgs1	0	0	0	0	0	0	0	0
13.67 - 3 - Average of Uavgs2	0	0	0	0	0	0	0	0
13.67 - 5 - Average of Uavgs1	0	0	0	0	0	0	0	0
13.67 - 5 - Average of Uavgs2	0	0	0	0	0	0	0	0

P Ca

Figure J4. Optimal U values for given case of scenario 1, P, Ca and I.

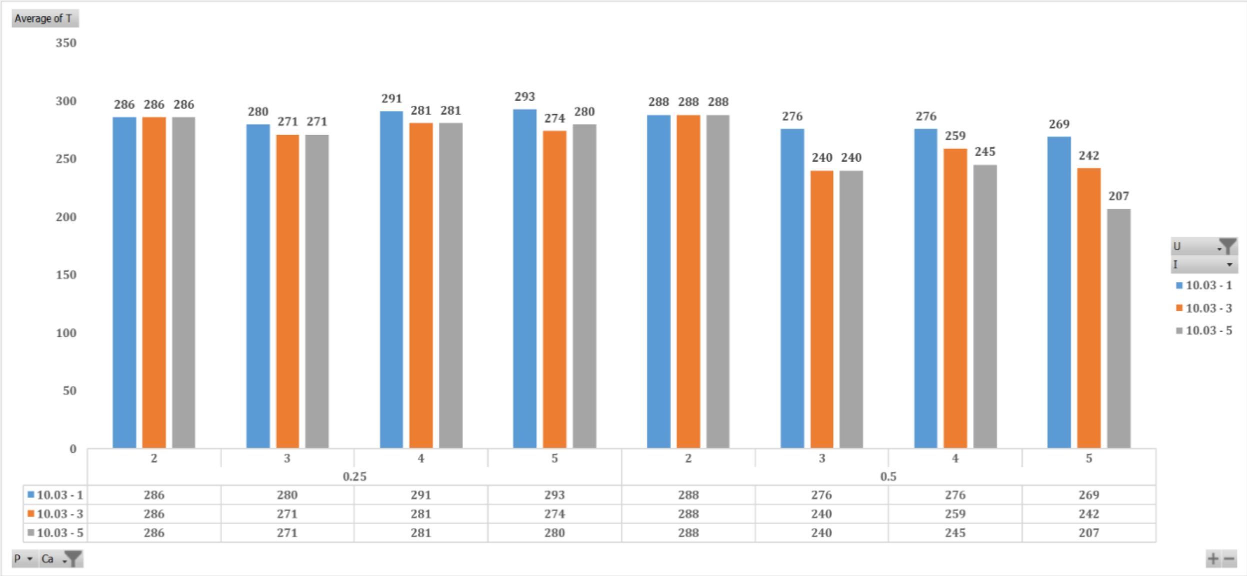


Figure J5. Optimal T values for given case of scenario 2, P, Ca and I.

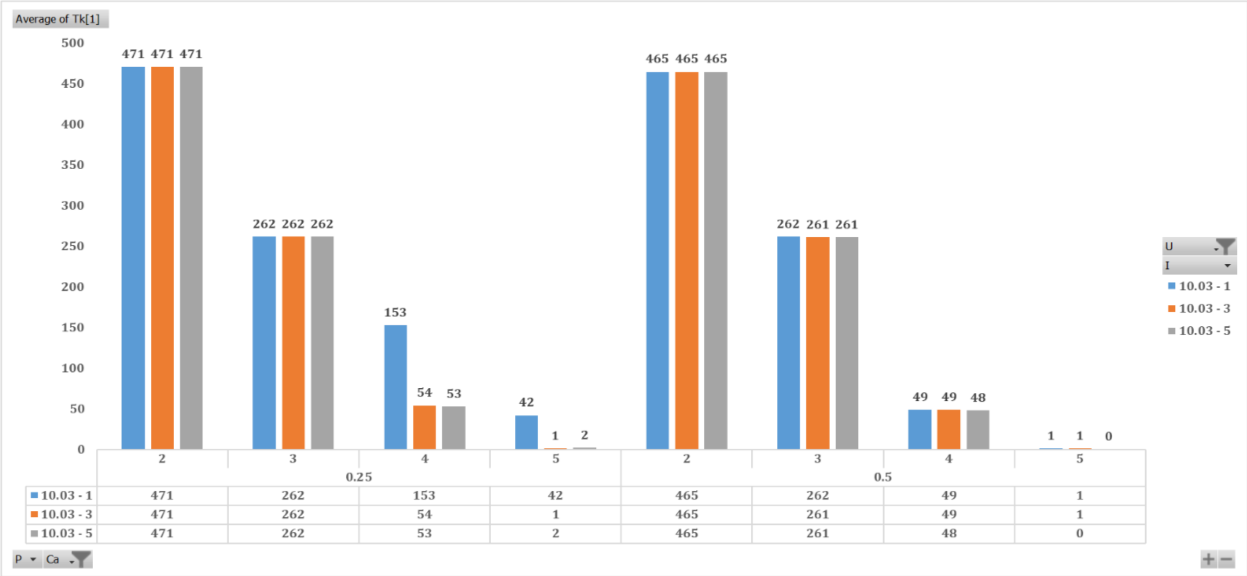
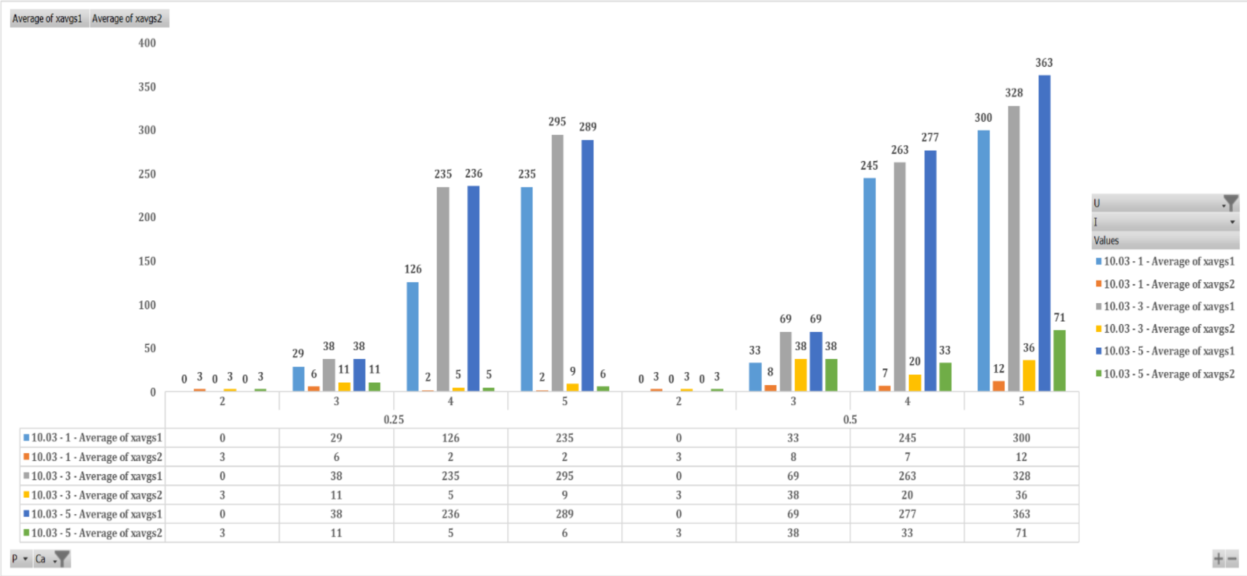
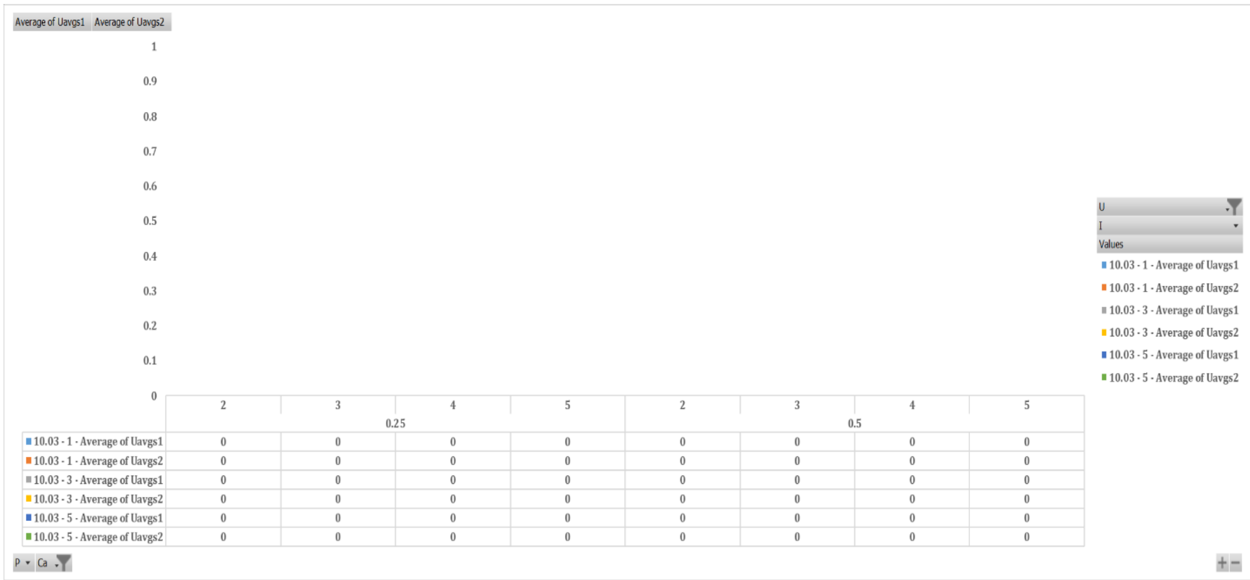


Figure J6. Optimal T_k values for given case of scenario 2, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
10.03 - 1 - Average of xavgs1	0	29	126	235	0	33	245	300
10.03 - 1 - Average of xavgs2	3	6	2	2	3	8	7	12
10.03 - 3 - Average of xavgs1	0	38	235	295	0	69	263	328
10.03 - 3 - Average of xavgs2	3	11	5	9	3	38	20	36
10.03 - 5 - Average of xavgs1	0	38	236	289	0	69	277	363
10.03 - 5 - Average of xavgs2	3	11	5	6	3	38	33	71

Figure J7. Optimal x values for given case of scenario 2, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
10.03 - 1 - Average of Uavgs1	0	0	0	0	0	0	0	0
10.03 - 1 - Average of Uavgs2	0	0	0	0	0	0	0	0
10.03 - 3 - Average of Uavgs1	0	0	0	0	0	0	0	0
10.03 - 3 - Average of Uavgs2	0	0	0	0	0	0	0	0
10.03 - 5 - Average of Uavgs1	0	0	0	0	0	0	0	0
10.03 - 5 - Average of Uavgs2	0	0	0	0	0	0	0	0

Figure J8. Optimal U values for given case of scenario 2, P, Ca and I.

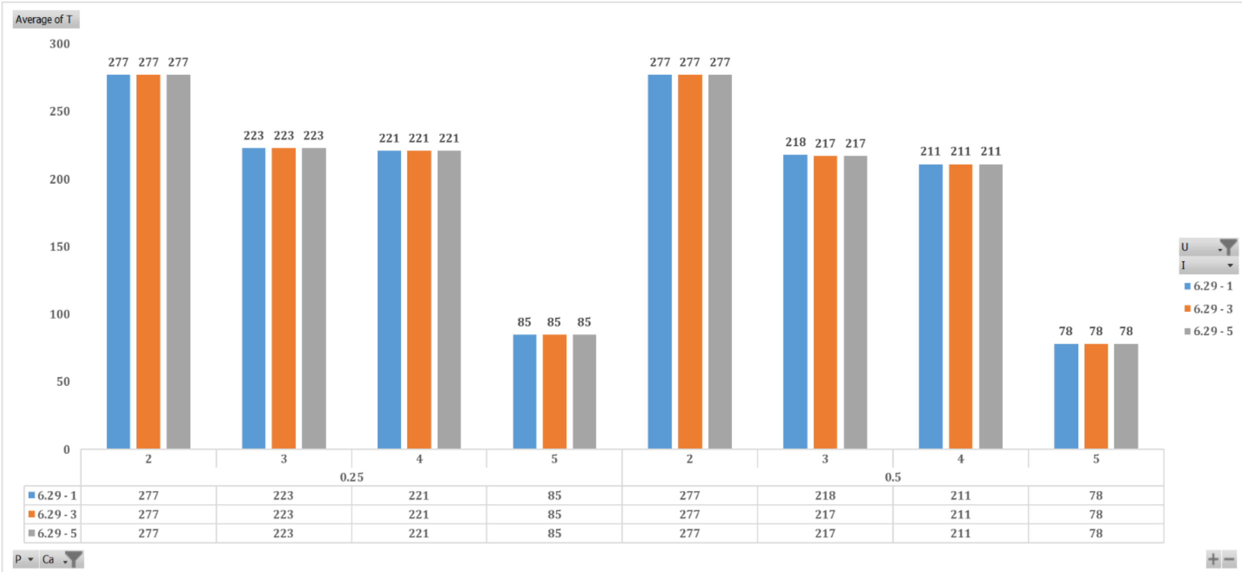


Figure J9. Optimal T values for given case of scenario 3, P, Ca and I.

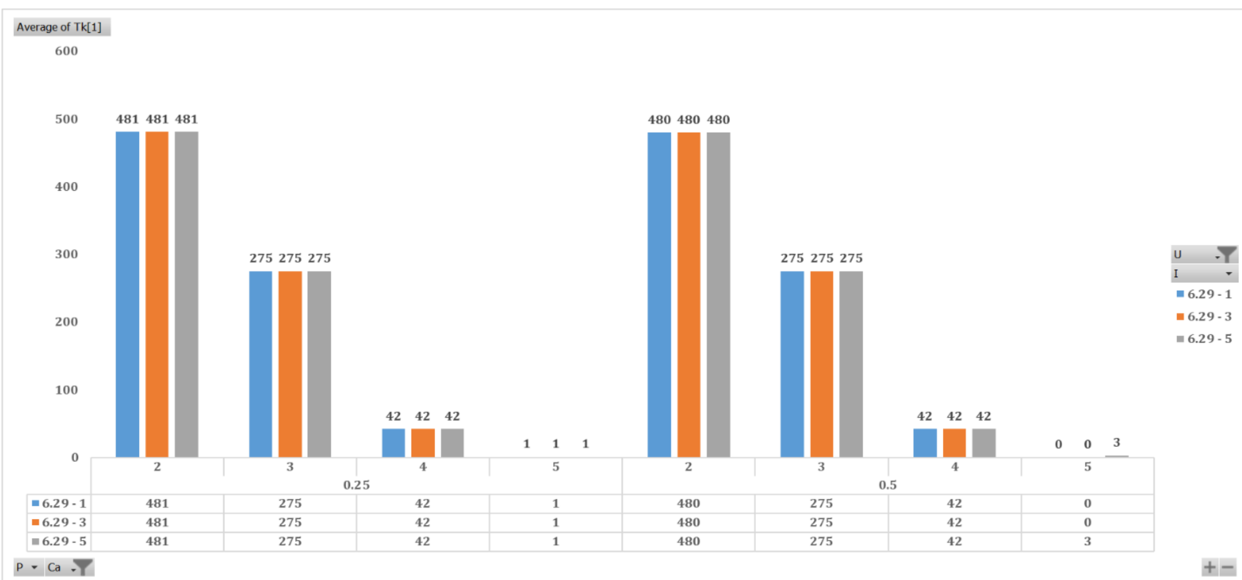
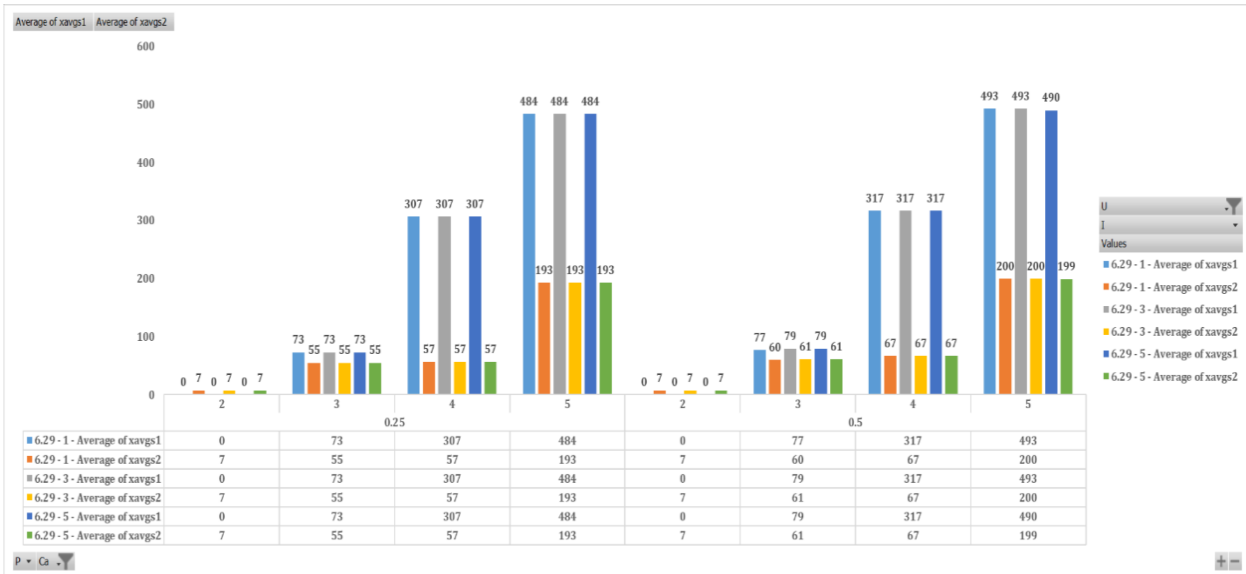
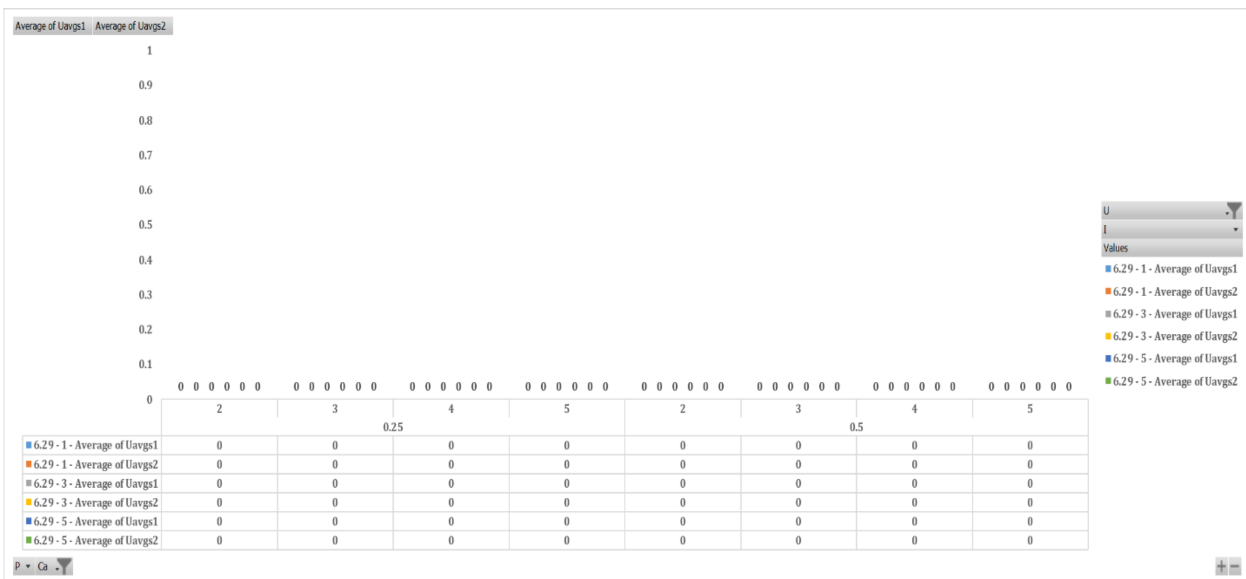


Figure J10. Optimal T_k values for given case of scenario 3, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
6.29 - 1 - Average of xavgs1	0	73	307	484	0	77	317	493
6.29 - 1 - Average of xavgs2	7	55	57	193	7	60	67	200
6.29 - 3 - Average of xavgs1	0	73	307	484	0	79	317	493
6.29 - 3 - Average of xavgs2	7	55	57	193	7	61	67	200
6.29 - 5 - Average of xavgs1	0	73	307	484	0	79	317	490
6.29 - 5 - Average of xavgs2	7	55	57	193	7	61	67	199

Figure J11. Optimal x values for given case of scenario 3, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
6.29 - 1 - Average of Uavgs1	0	0	0	0	0	0	0	0
6.29 - 1 - Average of Uavgs2	0	0	0	0	0	0	0	0
6.29 - 3 - Average of Uavgs1	0	0	0	0	0	0	0	0
6.29 - 3 - Average of Uavgs2	0	0	0	0	0	0	0	0
6.29 - 5 - Average of Uavgs1	0	0	0	0	0	0	0	0
6.29 - 5 - Average of Uavgs2	0	0	0	0	0	0	0	0

Figure J12. Optimal U values for given case of scenario 3, P, Ca and I.

APPENDIX K. SIMULATION WITH ROBOT FULLTIME COST BENEFIT

Component	Value	Unit	Reference
Robots purchase price	$ 2,600.00	USD	Assumption from range of values observed
Amortization time	5	Years	
Operation weeks per year	52		
Days per week	5		
Hours per day	8		
Utilization rate - assuming continously utilized for shift hours in our case	100%		Pg 15, section 5.1
Robot cost per hour	$ 0.25		Ostermeier, M, Heimfarth, A, Hübner, A. Cost-optimal truck-and-robot routing for
Markup maintenance electricity	50%		last-mile delivery. Networks.. 2022; 79: 364– 389.
Robot cost per hour w mark up	$ 0.38		https://doi.org/10.1002/net.22030
Max speed	6	Km/h	https://starshipdeliveries.com/industry/
Operating time	12	Hours	https://www.uh.edu/news-events/stories/2019/november-2019/11102019-
Max load	10	Kg	starship-robots.php
Travel capacity of single robot in an 8 hr shift	28	Miles	Subtracting 30 mins from shift time to accommodate travel from WH to location and back, and converting to miles
One round trip distance from van to residence	4	Miles	Assumption and one delivery per round trip
Total deliveries in an 8 hour window per robot	5	Orders	Assuming 75% operating efficiency
Total robots in the van	8		Per Ostermeier et al.
Total deliveries in an 8 hour window	42		
Daily robots in the van cost w mark up	$ 24.00		
Daily rate per FT including vehicle expenses	$ 239.68		
Per order rate for LMD	$ 6.30		
Ef	$ 0.13		
Assumptions -			
Assuming Van robot combination used for distribution for residences within radius of cell B17 miles			
Assuming one robot able to work for entire 8 hour shift and package weight within the robot capacity			
Increasing productivity of delivery resources, primarily FT			
Assuming all deliveries happen to customer locations on ground level without any need for escalating steps			
Assuming customer comfortable interacting with robot to unlock cargo area and pick up packages			

APPENDIX L. SIMULATION WITH ROBOT OPTIMAL COMBINATION

Table L1. SAS Simulation with robot program output.

P	U	Ca	I	T	Tk[1]	xavgs1	xavgs2	Uavgs1	Uavgs2
0.25	13.67	2	1	494	49	29	0	0	0
0.25	13.67	2	3	493	25	52	0	0	0
0.25	13.67	2	5	495	27	48	0	0	0
0.25	13.67	3	1	496	50	26	0	0	0
0.25	13.67	3	3	493	26	51	0	0	0
0.25	13.67	3	5	494	0	76	0	0	0
0.25	13.67	4	1	477	50	43	0	0	0
0.25	13.67	4	3	396	41	133	0	0	0
0.25	13.67	4	5	396	40	134	0	0	0
0.25	13.67	5	1	479	50	42	0	0	0
0.25	13.67	5	3	312	37	221	0	0	0
0.25	13.67	5	5	312	37	221	0	0	0
0.25	10.03	2	1	473	1	96	0	0	0
0.25	10.03	2	3	473	1	96	0	0	0
0.25	10.03	2	5	473	1	96	0	0	0
0.25	10.03	3	1	468	59	43	0	0	0
0.25	10.03	3	3	468	3	99	0	0	0
0.25	10.03	3	5	468	3	99	0	0	0
0.25	10.03	4	1	328	50	192	0	0	0
0.25	10.03	4	3	321	0	249	0	0	0
0.25	10.03	4	5	321	0	249	0	0	0
0.25	10.03	5	1	306	49	215	0	0	0
0.25	10.03	5	3	284	3	284	4	0	0
0.25	10.03	5	5	284	3	284	4	0	0
0.25	6.29	2	1	301	141	128	0	0	0
0.25	6.29	2	3	301	141	128	0	0	0
0.25	6.29	2	5	301	141	128	0	0	0
0.25	6.29	3	1	254	190	127	25	0	0
0.25	6.29	3	3	254	190	127	25	0	0
0.25	6.29	3	5	254	190	127	25	0	0
0.25	6.29	4	1	254	0	316	25	0	0
0.25	6.29	4	3	253	0	318	26	0	0
0.25	6.29	4	5	254	0	316	25	0	0
0.25	6.29	5	1	112	0	458	166	0	0
0.25	6.29	5	3	96	0	474	182	0	0
0.25	6.29	5	5	97	0	474	181	0	0
0.5	13.67	2	1	482	61	29	0	0	0
0.5	13.67	2	3	483	6	81	0	0	0
0.5	13.67	2	5	483	9	78	0	0	0
0.5	13.67	3	1	484	65	23	0	0	0
0.5	13.67	3	3	480	0	91	0	0	0
0.5	13.67	3	5	480	1	89	0	0	0
0.5	13.67	4	1	484	46	40	0	0	0
0.5	13.67	4	3	356	7	207	0	0	0
0.5	13.67	4	5	355	4	211	0	0	0
0.5	13.67	5	1	482	49	40	0	0	0
0.5	13.67	5	3	288	1	282	3	0	0

Table L1. SAS Simulation with robot program output (continued).

P	U	Ca	I	T	Tk[1]	xavgs1	xavgs2	Uavgs1	Uavgs2
0.5	13.67	5	5	294	13	263	1	0	0
0.5	10.03	2	1	453	2	115	0	0	0
0.5	10.03	2	3	453	2	115	0	0	0
0.5	10.03	2	5	453	1	116	0	0	0
0.5	10.03	3	1	403	6	162	0	0	0
0.5	10.03	3	3	402	1	168	0	0	0
0.5	10.03	3	5	402	1	168	0	0	0
0.5	10.03	4	1	302	1	267	0	0	0
0.5	10.03	4	3	304	2	264	0	0	0
0.5	10.03	4	5	302	1	267	0	0	0
0.5	10.03	5	1	281	4	285	5	0	0
0.5	10.03	5	3	274	1	295	9	0	0
0.5	10.03	5	5	270	1	299	12	0	0
0.5	6.29	2	1	305	118	147	0	0	0
0.5	6.29	2	3	304	118	149	0	0	0
0.5	6.29	2	5	304	118	149	0	0	0
0.5	6.29	3	1	253	117	201	26	0	0
0.5	6.29	3	3	253	117	201	26	0	0
0.5	6.29	3	5	253	117	201	26	0	0
0.5	6.29	4	1	250	0	321	28	0	0
0.5	6.29	4	3	248	0	322	30	0	0
0.5	6.29	4	5	248	0	322	30	0	0
0.5	6.29	5	1	87	1	483	191	0	0
0.5	6.29	5	3	81	0	489	197	0	0
0.5	6.29	5	5	81	0	489	197	0	0

Table L2. Confidence interval (95%) for SAS Simulation with robot program output.

Scenarios				TC S1				TC S2			
P	U	Ca	I	Mean cost	Standard error	Lower limit	Upper limit	Mean cost	Standard error	Lower limit	Upper limit
0.25	13.67	2	1	4144.08	3.66	4136.91	4151.25	3177.51	0.03	3177.45	3177.57
0.25	13.67	2	3	4090.49	3.69	4083.26	4097.72	3171.12	0.03	3171.06	3171.18
0.25	13.67	2	5	4058.15	3.47	4051.35	4064.95	3183.95	0.03	3183.89	3184.01
0.25	13.67	3	1	4127.36	3.58	4120.35	4134.37	3190.36	0.03	3190.30	3190.42
0.25	13.67	3	3	4088.02	3.56	4081.05	4094.99	3171.16	0.03	3171.10	3171.22
0.25	13.67	3	5	4044.95	3.48	4038.12	4051.78	3177.55	0.03	3177.49	3177.61
0.25	13.67	4	1	4241.87	4.06	4233.91	4249.83	3068.18	0.03	3068.12	3068.24
0.25	13.67	4	3	4612.63	4.06	4604.66	4620.60	2547.18	0.03	2547.13	2547.23
0.25	13.67	4	5	4542.96	3.75	4535.61	4550.31	2547.13	0.03	2547.08	2547.18
0.25	13.67	5	1	4234.22	4.07	4226.24	4242.20	3081.04	0.03	3080.98	3081.10
0.25	13.67	5	3	5077.31	5.02	5067.47	5087.15	2008.39	0.18	2008.05	2008.73
0.25	13.67	5	5	4975.18	4.43	4966.49	4983.87	2008.31	0.17	2007.98	2008.64
0.25	10.03	2	1	4021.2	3.44	4014.45	4027.95	3042.43	0.03	3042.37	3042.49
0.25	10.03	2	3	3919.24	3.03	3913.30	3925.18	3042.43	0.03	3042.37	3042.49
0.25	10.03	2	5	3903.14	2.91	3897.44	3908.84	3042.43	0.03	3042.37	3042.49
0.25	10.03	3	1	4243.63	3.99	4235.82	4251.44	3010.35	0.03	3010.29	3010.41
0.25	10.03	3	3	4037.1	3.77	4029.71	4044.49	3010.34	0.03	3010.28	3010.40
0.25	10.03	3	5	3968.12	3.35	3961.54	3974.70	3010.34	0.03	3010.28	3010.40
0.25	10.03	4	1	5082.4	7.83	5067.06	5097.74	2109.89	0.04	2109.81	2109.97
0.25	10.03	4	3	4565.03	6.61	4552.07	4577.99	2065.01	0.06	2064.89	2065.13
0.25	10.03	4	5	4505.01	5.34	4494.55	4515.47	2065	0.06	2064.88	2065.12
0.25	10.03	5	1	5210.85	8.45	5194.28	5227.42	1972.2	0.31	1971.59	1972.81
0.25	10.03	5	3	4685.6	7.34	4671.22	4699.98	1866.84	0.95	1864.98	1868.70
0.25	10.03	5	5	4582.42	5.70	4571.24	4593.60	1863.47	0.86	1861.78	1865.16
0.25	6.29	2	1	4389.23	2.36	4384.61	4393.85	1940.14	0.21	1939.72	1940.56
0.25	6.29	2	3	4323.79	2.09	4319.70	4327.88	1939.69	0.19	1939.32	1940.06
0.25	6.29	2	5	4311.98	2.01	4308.04	4315.92	1939.55	0.18	1939.19	1939.91
0.25	6.29	3	1	4650.11	2.36	4645.48	4654.74	1788.79	1.27	1786.31	1791.27
0.25	6.29	3	3	4552.45	1.92	4548.69	4556.21	1769.49	1.09	1767.35	1771.63
0.25	6.29	3	5	4531.81	1.83	4528.23	4535.39	1762.81	1.03	1760.79	1764.83
0.25	6.29	4	1	3614	4.00	3606.17	3621.83	1790.7	1.26	1788.23	1793.17
0.25	6.29	4	3	3421.79	2.92	3416.06	3427.52	1768.56	1.10	1766.40	1770.72
0.25	6.29	4	5	3382.51	2.50	3377.61	3387.41	1764.52	1.02	1762.52	1766.52
0.25	6.29	5	1	3592.5	5.43	3581.85	3603.15	1764.55	2.27	1760.11	1768.99
0.25	6.29	5	3	3328.43	3.84	3320.91	3335.95	1621.44	1.79	1617.94	1624.94
0.25	6.29	5	5	3275.72	3.24	3269.38	3282.06	1572.95	1.47	1570.07	1575.83

Table L2. Confidence interval (95%) for SAS Simulation with robot program output (continued).

Scenarios				TC S1				TC S2			
P	U	Ca	I	Mean cost	Standard error	Lower limit	Upper limit	Mean cost	Standard error	Lower limit	Upper limit
0.5	13.67	2	1	4206.26	3.96	4198.50	4214.02	3100.34	0.03	3100.28	3100.40
0.5	13.67	2	3	4033.26	4.35	4024.73	4041.79	3106.77	0.03	3106.71	3106.83
0.5	13.67	2	5	3993.18	3.83	3985.67	4000.69	3106.83	0.03	3106.77	3106.89
0.5	13.67	3	1	4189.71	3.67	4182.52	4196.90	3113.26	0.03	3113.20	3113.32
0.5	13.67	3	3	4013.61	4.23	4005.31	4021.91	3087.49	0.03	3087.43	3087.55
0.5	13.67	3	5	3924.56	3.66	3917.39	3931.73	3087.56	0.03	3087.50	3087.62
0.5	13.67	4	1	4199.74	4.41	4191.09	4208.39	3113.19	0.03	3113.13	3113.25
0.5	13.67	4	3	4470.98	7.28	4456.72	4485.24	2289.89	0.03	2289.84	2289.94
0.5	13.67	4	5	4371.76	5.85	4360.29	4383.23	2289.89	0.03	2289.84	2289.94
0.5	13.67	5	1	4210.56	4.35	4202.03	4219.09	3100.38	0.03	3100.32	3100.44
0.5	13.67	5	3	4737.48	9.61	4718.65	4756.31	1881.13	0.81	1879.54	1882.72
0.5	13.67	5	5	4560.13	6.85	4546.70	4573.56	1904.19	0.51	1903.19	1905.19
0.5	10.03	2	1	4087.79	5.06	4077.87	4097.71	2913.84	0.03	2913.78	2913.90
0.5	10.03	2	3	3880.79	3.93	3873.08	3888.50	2913.84	0.03	2913.78	2913.90
0.5	10.03	2	5	3843.07	3.54	3836.14	3850.00	2913.88	0.03	2913.82	2913.94
0.5	10.03	3	1	4268.04	6.53	4255.24	4280.84	2592.19	0.03	2592.14	2592.24
0.5	10.03	3	3	3878.93	4.71	3869.71	3888.15	2585.78	0.03	2585.72	2585.84
0.5	10.03	3	5	3827.25	3.88	3819.64	3834.86	2585.78	0.03	2585.72	2585.84
0.5	10.03	4	1	4630.12	9.91	4610.69	4649.55	1948.47	0.35	1947.78	1949.16
0.5	10.03	4	3	3994.13	6.74	3980.91	4007.35	1958.55	0.22	1958.12	1958.98
0.5	10.03	4	5	3934.37	5.29	3924.00	3944.74	1946.5	0.23	1946.05	1946.95
0.5	10.03	5	1	4689.41	10.65	4668.53	4710.29	1862.52	1.15	1860.26	1864.78
0.5	10.03	5	3	3985.53	7.30	3971.22	3999.84	1829.15	1.05	1827.08	1831.22
0.5	10.03	5	5	3899.46	5.70	3888.28	3910.64	1813.88	1.06	1811.81	1815.95
0.5	6.29	2	1	4267.72	3.85	4260.18	4275.26	1964.14	0.17	1963.80	1964.48
0.5	6.29	2	3	4142.28	2.95	4136.49	4148.07	1957.56	0.15	1957.26	1957.86
0.5	6.29	2	5	4117.26	2.63	4112.11	4122.41	1957.29	0.13	1957.04	1957.54
0.5	6.29	3	1	4253.64	4.90	4244.03	4263.25	1788.77	1.40	1786.03	1791.51
0.5	6.29	3	3	3990.4	3.47	3983.60	3997.20	1748.85	1.04	1746.82	1750.88
0.5	6.29	3	5	3946.87	2.83	3941.32	3952.42	1734.57	0.88	1732.85	1736.29
0.5	6.29	4	1	3611.61	7.44	3597.02	3626.20	1785.39	1.42	1782.60	1788.18
0.5	6.29	4	3	3213.36	4.94	3203.67	3223.05	1738.04	1.07	1735.93	1740.15
0.5	6.29	4	5	3140.7	3.97	3132.92	3148.48	1721.96	0.91	1720.17	1723.75
0.5	6.29	5	1	3574.64	11.01	3553.06	3596.22	1758.6	4.49	1749.79	1767.41
0.5	6.29	5	3	3050.51	7.17	3036.47	3064.55	1450.48	3.05	1444.50	1456.46
0.5	6.29	5	5	2944.29	5.75	2933.02	2955.56	1354.99	2.33	1350.42	1359.56

APPENDIX M. CHARTS FOR VARIOUS COMBINATIONS OF SCENARIOS 1-3, P, Ca AND I FROM SIMULATION WITH ROBOT.

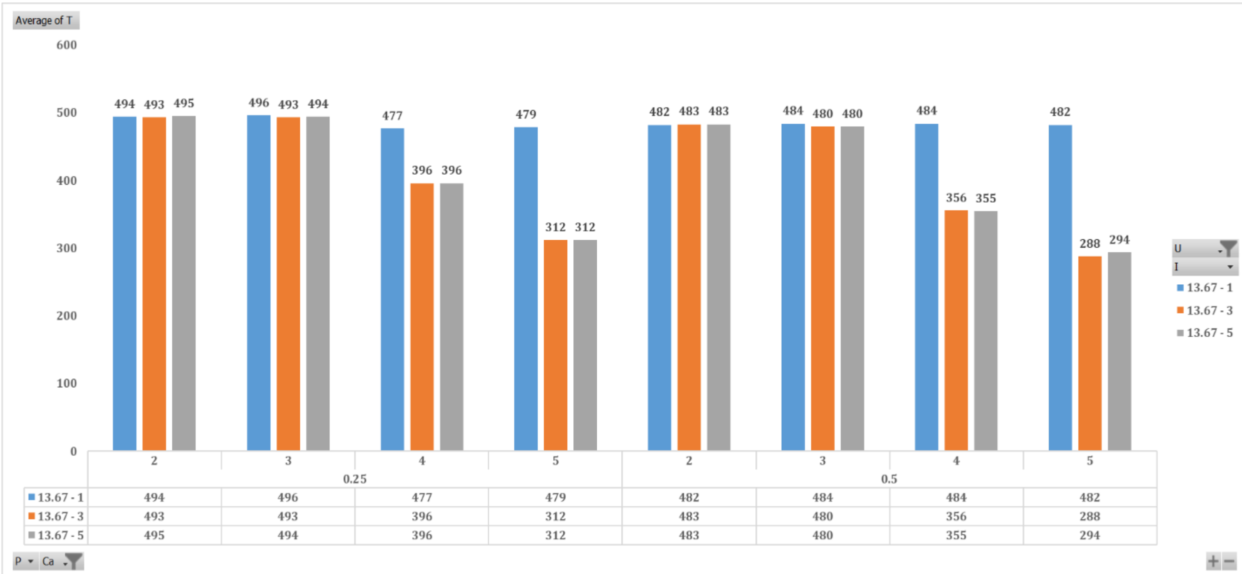


Figure M1. Optimal T values for given case of scenario 1, P, Ca and I.

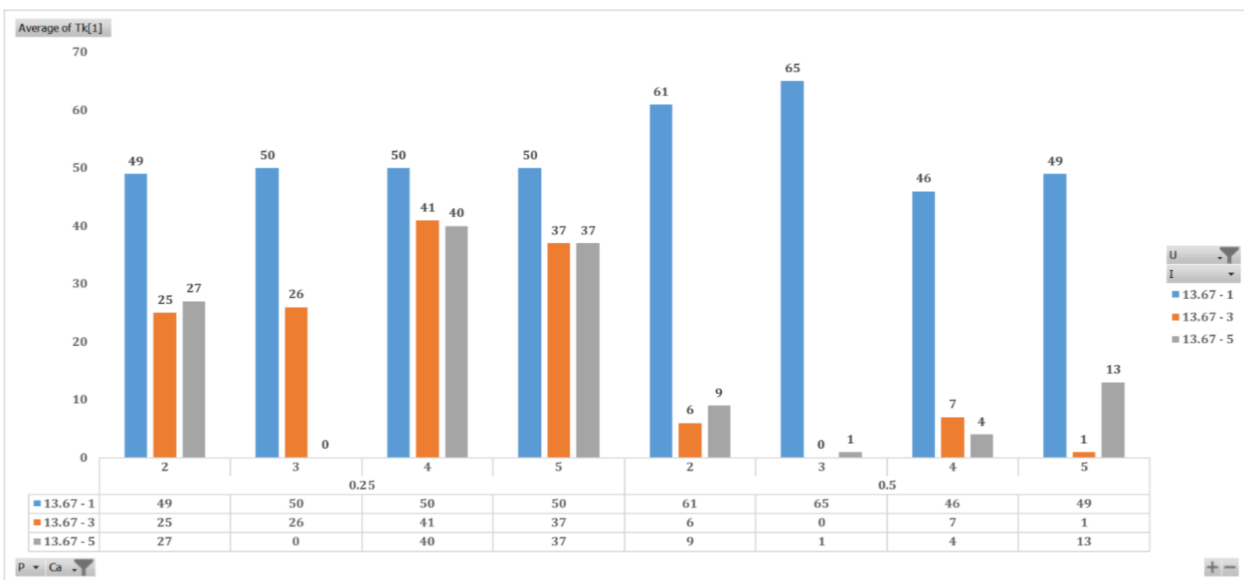
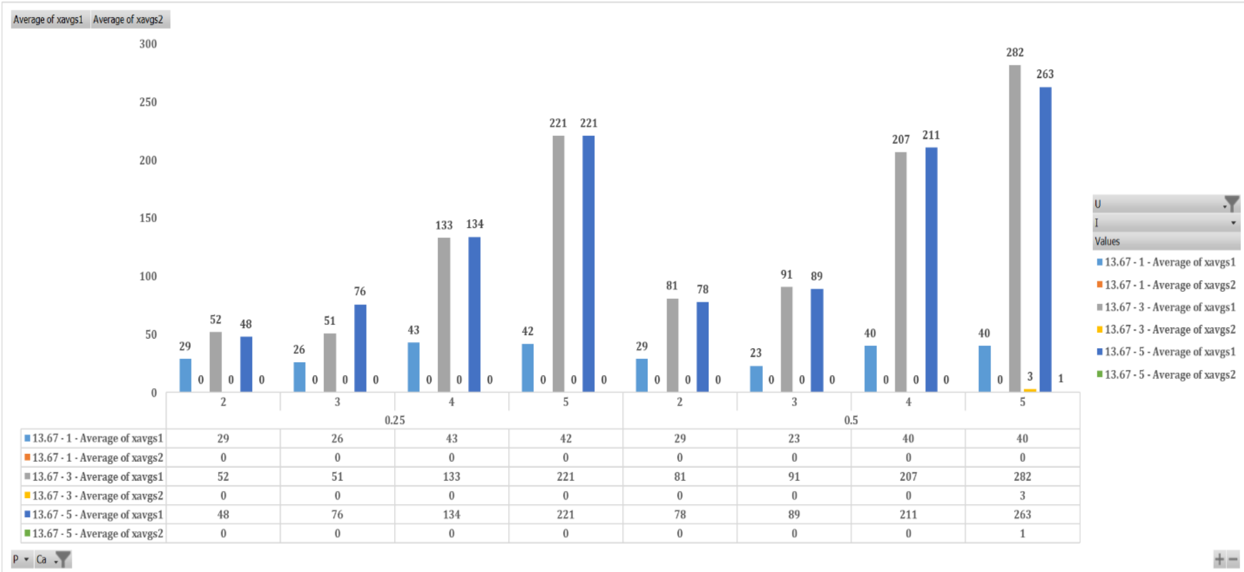
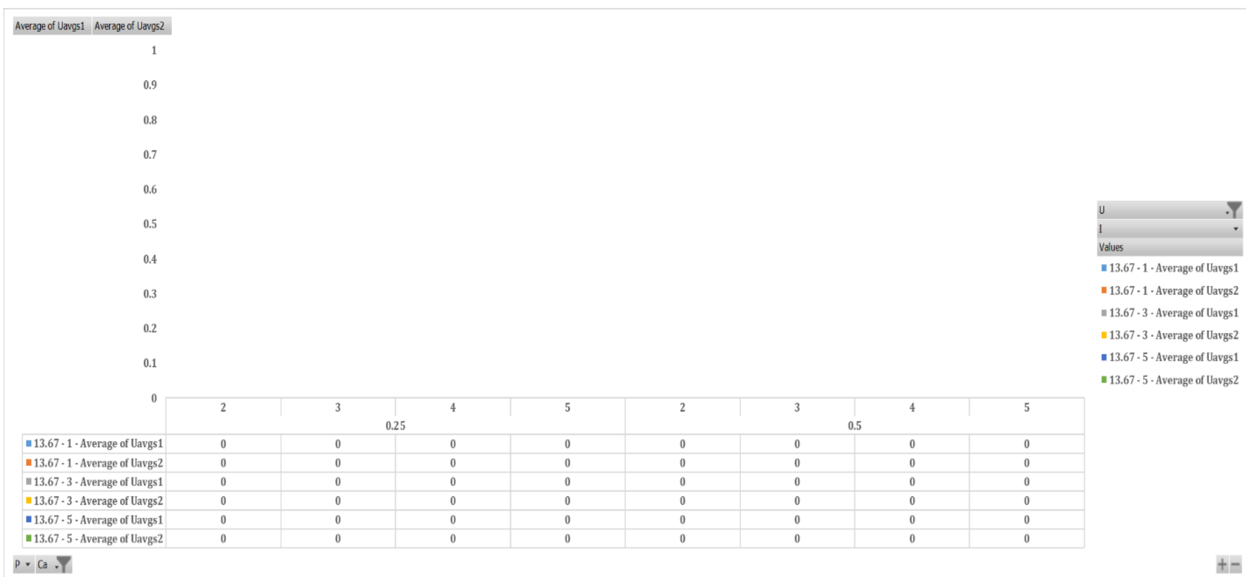


Figure M2. Optimal T_k values for given case of scenario 1, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
13.67 - 1 - Average of xavgs1	29	26	43	42	29	23	40	40
13.67 - 1 - Average of xavgs2	0	0	0	0	0	0	0	0
13.67 - 3 - Average of xavgs1	52	51	133	221	81	91	207	282
13.67 - 3 - Average of xavgs2	0	0	0	0	0	0	0	3
13.67 - 5 - Average of xavgs1	48	76	134	221	78	89	211	263
13.67 - 5 - Average of xavgs2	0	0	0	0	0	0	0	1

Figure M3. Optimal x values for given case of scenario 1, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
13.67 - 1 - Average of Uavgs1	0	0	0	0	0	0	0	0
13.67 - 1 - Average of Uavgs2	0	0	0	0	0	0	0	0
13.67 - 3 - Average of Uavgs1	0	0	0	0	0	0	0	0
13.67 - 3 - Average of Uavgs2	0	0	0	0	0	0	0	0
13.67 - 5 - Average of Uavgs1	0	0	0	0	0	0	0	0
13.67 - 5 - Average of Uavgs2	0	0	0	0	0	0	0	0

Figure M4. Optimal U values for given case of scenario 1, P, Ca and I.

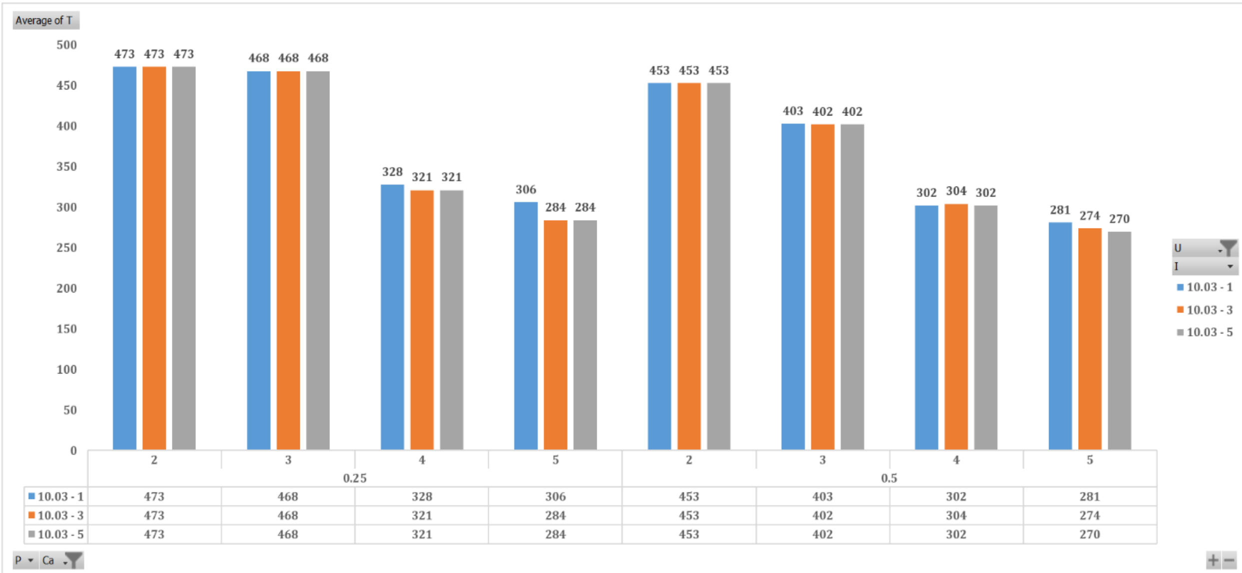


Figure M5. Optimal *T* values for given case of scenario 2, P, Ca and I.

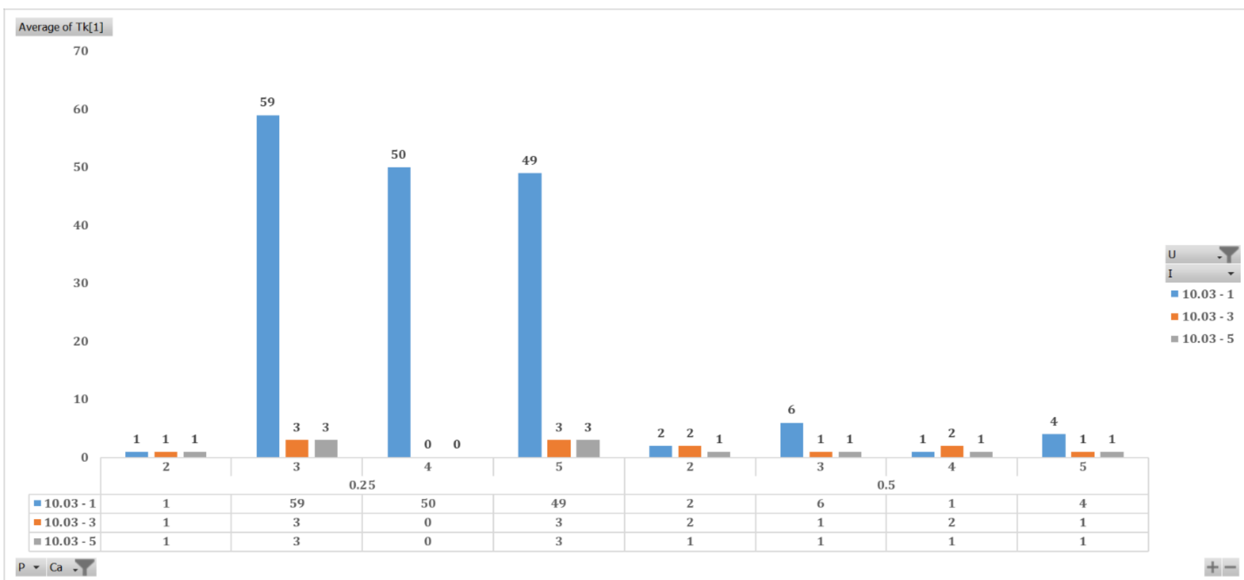
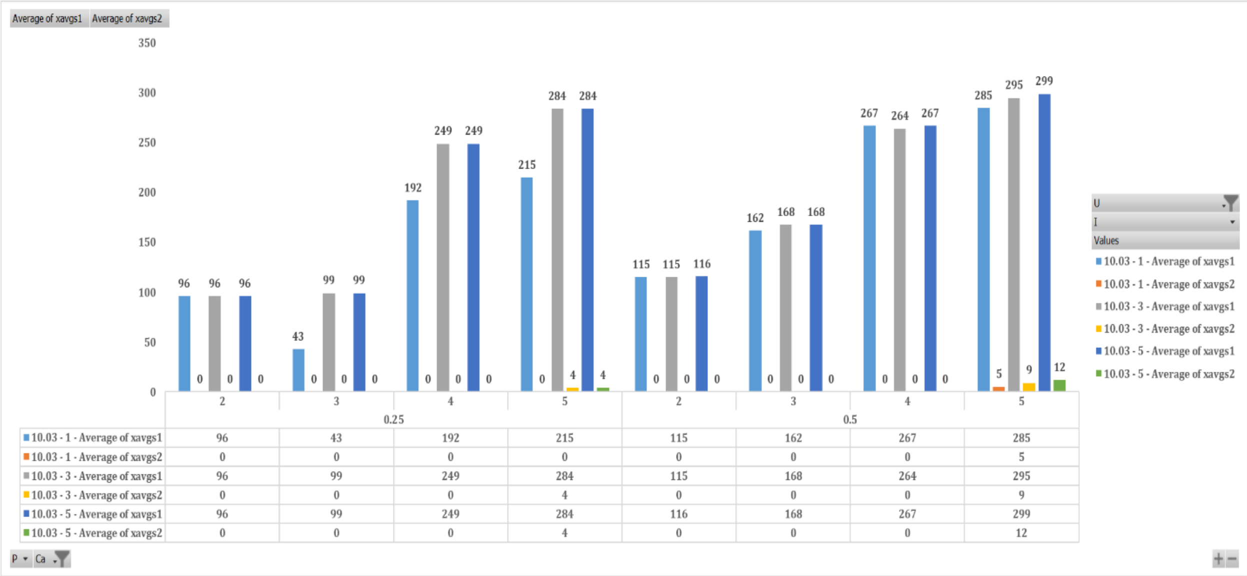
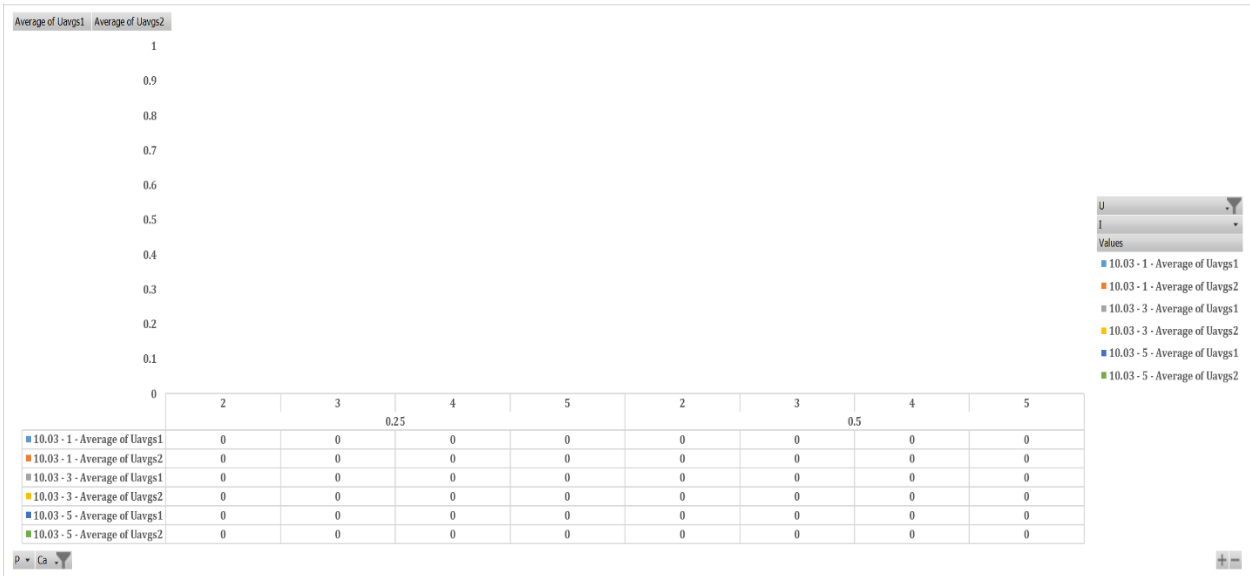


Figure M6. Optimal T_k values for given case of scenario 2, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
10.03 - 1 - Average of xavgs1	96	43	192	215	115	162	267	285
10.03 - 1 - Average of xavgs2	0	0	0	0	0	0	0	5
10.03 - 3 - Average of xavgs1	96	99	249	284	115	168	264	295
10.03 - 3 - Average of xavgs2	0	0	0	4	0	0	0	9
10.03 - 5 - Average of xavgs1	96	99	249	284	116	168	267	299
10.03 - 5 - Average of xavgs2	0	0	0	4	0	0	0	12

Figure M7. Optimal x values for given case of scenario 2, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
10.03 - 1 - Average of Uavgs1	0	0	0	0	0	0	0	0
10.03 - 1 - Average of Uavgs2	0	0	0	0	0	0	0	0
10.03 - 3 - Average of Uavgs1	0	0	0	0	0	0	0	0
10.03 - 3 - Average of Uavgs2	0	0	0	0	0	0	0	0
10.03 - 5 - Average of Uavgs1	0	0	0	0	0	0	0	0
10.03 - 5 - Average of Uavgs2	0	0	0	0	0	0	0	0

Figure M8. Optimal U values for given case of scenario 2, P, Ca and I.

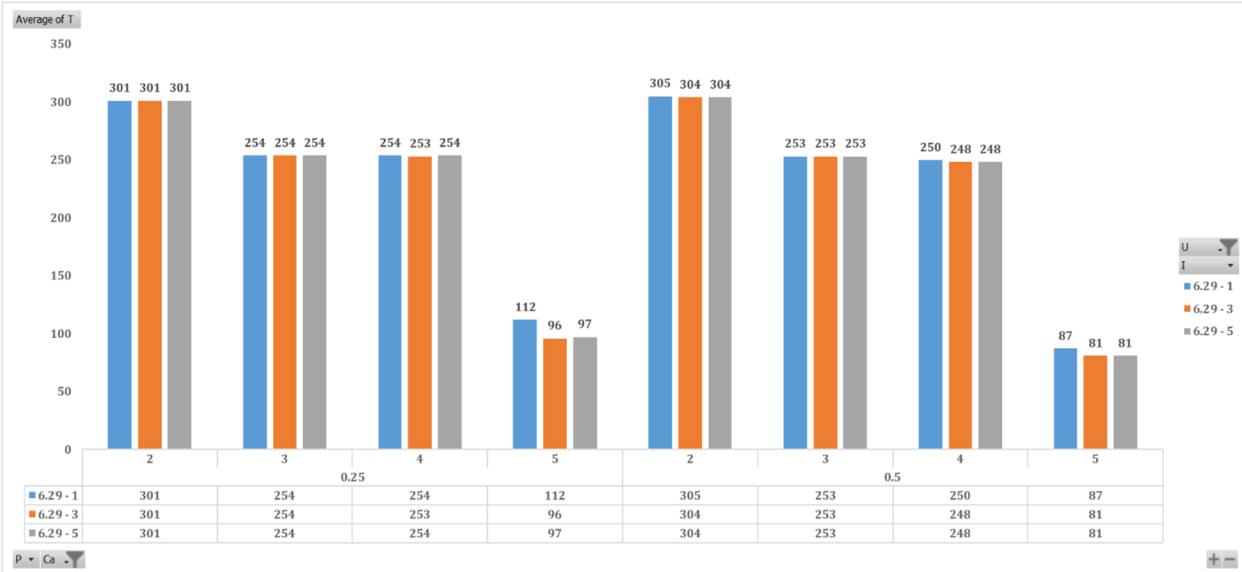


Figure M9. Optimal T values for given case of scenario 3, P, Ca and I.

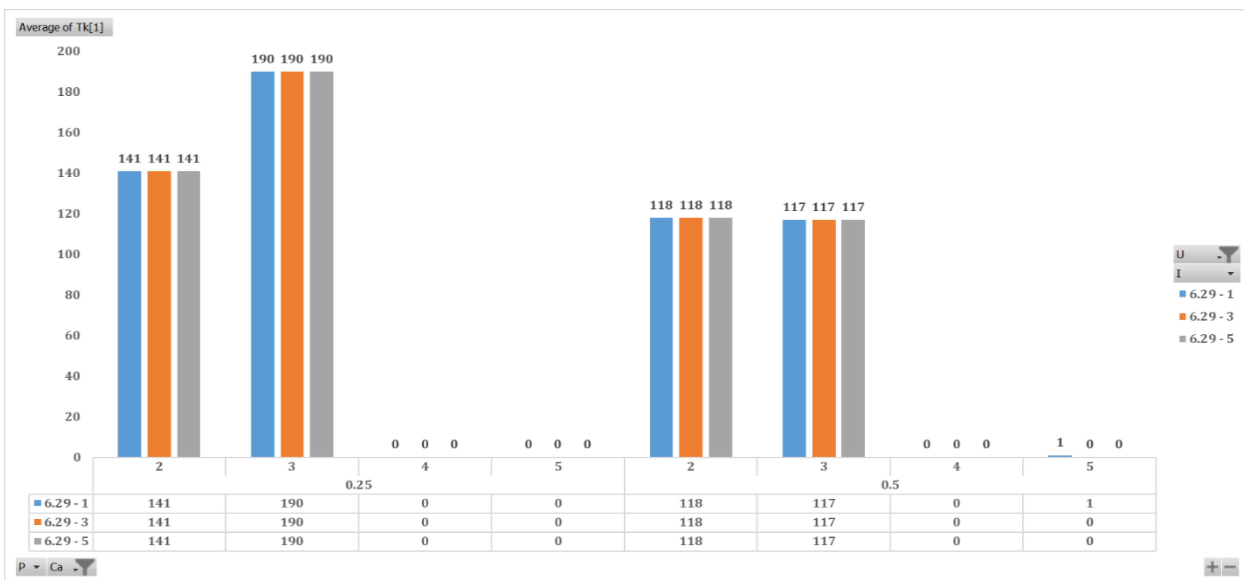
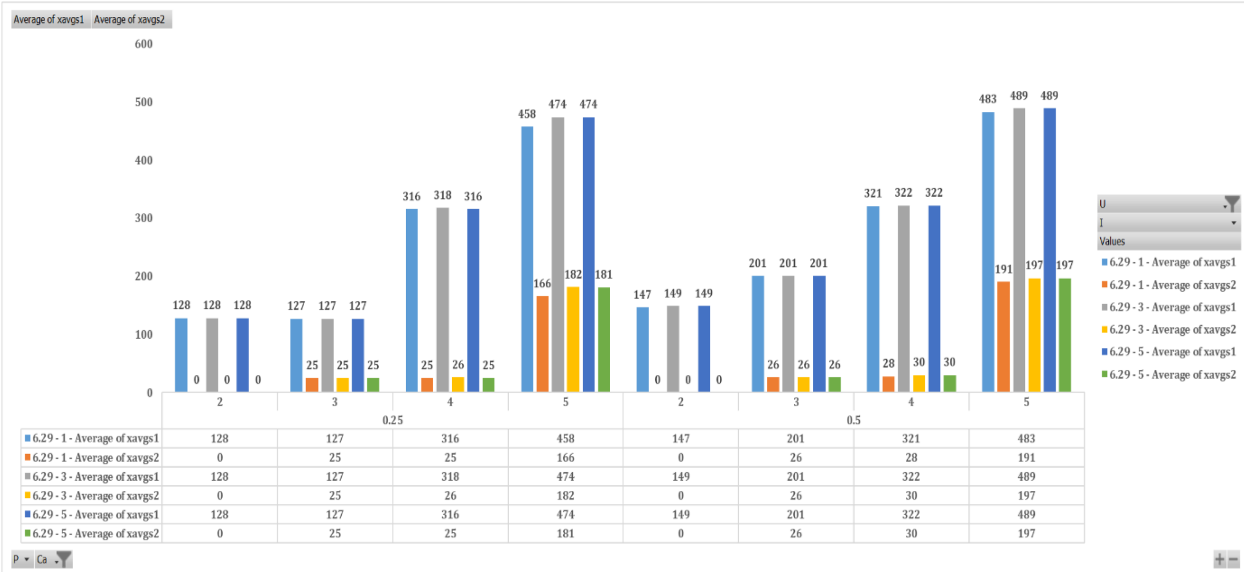
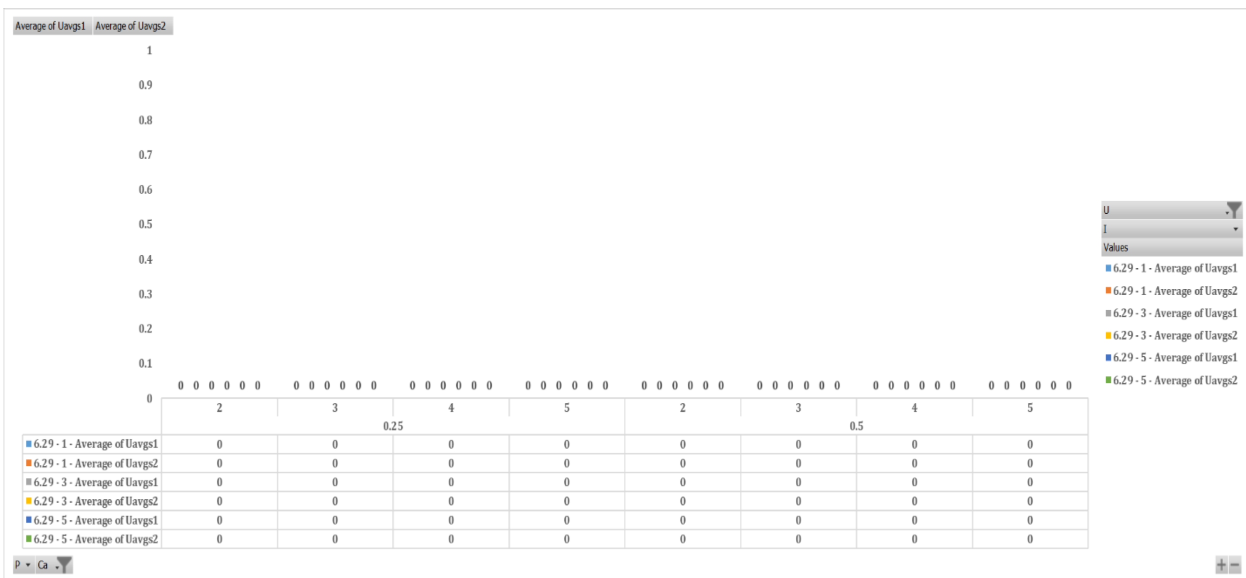


Figure M10. Optimal T_k values for given case of scenario 3, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
6.29 - 1 - Average of xavgs1	128	127	316	458	147	201	321	483
6.29 - 1 - Average of xavgs2	0	25	25	166	0	26	28	191
6.29 - 3 - Average of xavgs1	128	127	318	474	149	201	322	489
6.29 - 3 - Average of xavgs2	0	25	26	182	0	26	30	197
6.29 - 5 - Average of xavgs1	128	127	316	474	149	201	322	489
6.29 - 5 - Average of xavgs2	0	25	25	181	0	26	30	197

Figure M11. Optimal x values for given case of scenario 3, P, Ca and I.



	0.25				0.5			
	2	3	4	5	2	3	4	5
6.29 - 1 - Average of Uavgs1	0	0	0	0	0	0	0	0
6.29 - 1 - Average of Uavgs2	0	0	0	0	0	0	0	0
6.29 - 3 - Average of Uavgs1	0	0	0	0	0	0	0	0
6.29 - 3 - Average of Uavgs2	0	0	0	0	0	0	0	0
6.29 - 5 - Average of Uavgs1	0	0	0	0	0	0	0	0
6.29 - 5 - Average of Uavgs2	0	0	0	0	0	0	0	0

Figure M12. Optimal U values for given case of scenario 3, P, Ca and I.