Simulation Study for Multi-Echelon Multi-Depot Supply Chain System Using Live Data

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Abstract: The manufacturing industry is eager to implement the advancements of the fourth industrial revolution (Industry 4.0) due to the magnitude of the benefits it can provide. Hence, Industry 4.0 opens a wide avenue for researchers to explore possibilities in the field of the supply chain. This project focuses on building a decision framework for a supply chain system with disruptions. The impact of strategic decisions under the condition of unprecedented events for a vehicle routing problem (VRP) using simulation models is studied here. Those results help the supply chain managers in making sound decisions regarding different scenarios of disruption in VRP. To achieve this, multiple cases under different scenarios of facility disruption are considered. For all cases, the dependent parameter, namely, retailer service level and lost revenue, form the basis of the decision framework. The concept of live data is implemented by making retailer demand, current inventory at the depot, the position of the vehicle in the network and the current number of units in transit as the input data.

Keywords: Vehicle Routing Problem (VRP), Industry 4.0, Simulation

1. Introduction

The fourth industrial revolution (Industry 4.0) is setting a new way of doing business. Many industries have identified their scope and are fast moving forward with its implementation. Putting Industry 4.0 into practice is a herculean task; it requires everyone adding value to the business to participate in the process. Real-time information access (Kagermann et al., 2013), optimization of production process through real-time feedback (Heloand et.al, 2017), improved collaboration between various machines and production systems due to efficient information sharing (Shamsuzzoha et.al, 2016), optimal decision framework for operation managers (Lang et al., 2014) etc. are some of the benefits of the fourth industrial revolution. This requires an efficient information and product flow throughout the business, especially in the supply chain. Thus, the ability of the supply chain system to stand against any disruption that hampers the flow of information or product is crucial. Hence, proactive decisions are to be framed for such disruptive scenarios which can help improve the level of customer service. The paper focuses on developing a decision framework for a vehicle routing problem under conditions of disruptions using live/real-time data.

The benefits of the fourth industrial revolution will not be complete if the movement of goods from and into the factory is not set to pace with the rapid change caused by the technology components. This leads to the revolution in the logistics sectors called Logistic 4.0. According to (Bukova et.al, 2018) a logistic system which integrates the necessary level of automation and learning capability into a digital platform to make informed decisions based on readily available data is termed as Logistic 4.0. Today, many organizations such as GE, Bosch, Rockwell automation, XPO, and UPS etc., have already started focusing on implementing IoT where information/data from different nodes (i.e. retailer, distributor, vehicle, supplier, and manufacturing plant) collected and stored under one cloud-based network called the Digital Connected Network (DCN). In a digitally connected supply chain system, nodes outside the factory walls such as a retailer, distributor, vehicle, supplier, and all workstations inside the factory walls, always stay informed about the events happening in each part of the network, which further translates into good decisions. The benefits of connected systems cascade down to the end user in the form of better service in terms of reduced lead-time, better after sale service, reduced cost, better quality products, etc. Also, the increased data transparency and readily available information between the players in the network helps weed out the traditional operational delays in a supply chain network. Unlike a reactive approach where decisions are taken post-disruption, the potential downtime is eliminated by proactive preventive measures in a DCN due to the availability of the right information at the right time. And the data thus readily available is called live/real-time data.

When dealing with disruption, it is important to know the type of disruption that is being dealt with in a supply chain network. Disruption can be any event, which will disturb the normal operation of the network. This includes failures in logistic activities, sourcing activities, weather-related disruption, human resource related disruption, facility disruption, network disruption, etc. The paper focuses on developing a decision framework for a supply chain network whose system state changes dynamically. Live/real-time data (representing the dynamic system state change) is used to develop a decision framework for a multi-echelon supply chain network using qualitative parameter (Service level) under complete disruption facility/node using simulation. The various backup options to counter the effect of disruption in a multi-echelon multi-depot supply chain network are evaluated based on the qualitative parameter (service level). When designing a decision framework for a supply chain network, a planner's options for improving resilience depends on the type of network, risk preference, available financial resource, and other factors. The two decision parameters along with the knowledge on the available financial resources are used to frame quick and informed decisions. In addition, different cases were built to evaluate the multiple backup options using the decision parameter and available financial resources. The remainder of the paper is organized as follows: Section 2 explains about the previous research in vehicle routing problems in disruptive cases, parameters used to frame decisions under both deterministic and stochastic cases. Section 3 discusses the methodology of the model. Implementation of three case study model is developed in section 4. Finally, the report concludes by discussing the results and future work of this paper in section 5.

2. Literature review

2.1 State of art of Industry 4.0

Internet of things (IoT): In simple terms, IoT refers to an internet network where physical entities are connected to and exchange data or information seamlessly. This emerging and already existing networking technology opens a wide scope for industrial applications in various sectors of industries such as healthcare, firefighting, mining, production, transportation sector, etc. Kranenburg (2007) gave a definition for IoT as global and ever-changing network infrastructure which can automatically configure according to interoperable communication protocols and standards and where both virtual and physical things have identities and attributes and use intelligent interface to transfer information to the network. For effective implementation of this network technology, Kranenburg (2011) describes, the foundation of IoT lies in the efficient integration of communication technologies with data coming from sensors and RFID tags.

Cyber-Physical Systems (CPS): One of the most important information technology parts of IoT is a cyber-physical system (CPS). Ivanov et al. (2016) states the adaptability of the factory network achieved by CPS. Aydin et al. (2017) gave a simple definition of CPS for a manufacturing environment as a system, which integrates various physical systems say lathe, CNC, etc. with a digital computing device such as a computer. The computing device handles all the imputed data and takes decisions, and the physical system connected to the network acts accordingly. The adaptive capability of the CPS system that makes IoT applicable to most industrial application.

Cloud computing: The cloud computing technology provides a provision for storing data retrieved from the physical entities. This makes the storage capability very convenient for the industrial scale of operations where millions of data handled every second. Yu (2017) describes the massive operational scale, monetary benefits, easiness, and reliability of data access from cloud data.

Logistic 4.0: Bukova (2018) defines Logistic 4.0, as a logistic system which integrates the necessary level of automation and learning capability into a digital platform to make informed decisions based on readily available data. The author adds to the definition by mentioning the fine balance between the intelligent autonomous system and human inputs in taking fast proactive decisions. In such a scenario the biggest challenge for the logistics industry is to keep up with the rapid changes and stay proactive to counteract the unexpected scenarios that can disrupt their physical movement. The vision of industry 4.0 for optimizing the whole value chain cannot be envisioned unless the logistics sector is smart enough to deal with the fast pace flow of information and need for physical entities between the manufacturer and end customer. For that, the network technology must prove its authenticity for efficient data communication without any security issues. The next section provides appropriate decision frameworks for vehicle routing problems under disruptions.

2.2. Vehicle Routing Problem (VRP) under facility disruption

While framing decisions for supply chain network it is important to know the best sequence/route for transferring goods from point of origin to the destination. In addition, the parameters selected for framing decisions for a supply chain network under disruption is crucial. Hence, reviews prioritize on literature in VRP under disruptive scenarios. Various methods for framing decisions to solve VRP under disruption for both deterministic and stochastic cases looked into. The objective for this review was to identify parameters to frame decision for VRP under facility disruption.

Hadjiconstantinou and Baldacci (1998), discussed the Vehicle routing problem in the context of a multi-depot system for improving service level at a lower cost. Kleindorfer (2004) provided a framework for the design of a supply chain management system for the implication of a natural disaster. This paper discusses about using simulation software for making probabilistic, vulnerability assessment and decision analysis for finding out the risk assessment and mitigation strategies. Ratick (2008), used a set cover, anticover and complimentary anticover distance for locating facilities as supplementary in the case for long-term natural calamity, which affects the storage facility. The method ensures that demand be safely served in any case and the locations between storage facilities are chosen in such a way that no two facilities be affected by the same natural calamity. The importance of getting prepared for facing the unexpected had greatly benefitted companies to recoup at the shortest possible time and with a minimum cost of damage by taking proper decisions on how many backup storage facilities needed and where to locate these storage facilities. This points to the importance of data collection and analysis, which helps in predicting future events with a reasonable degree of accuracy. Hence, it is important to know the various methods and parameters, which help in framing good decision.

3. Methodology

To find how proactive decisions can help reduce the loss of revenue and better functioning of a supply chain network is studied in this paper. For this, a multi-echelon supply chain network model is developed using simulation. Readily available relevant data (live data), in the form of demand/storage/ vehicle position data, is used as the input to the simulation model for making informed decisions. Later, facility disruptions are introduced in the network. Different disruptions are introduced in the network as what if scenarios i.e. for any type of similar disruption happening in the network, decisions must be framed.

Once disruptions or any unprecedented events occur in a multi-depot network, multiple options are available such as increasing the storage or delivery capacity or addition of a new vehicle or different distribution strategies, etc. For both non-disruptive and disruptive cases, qualitative parameter lost revenue and available resources are used for framing informed decisions. The qualitative parameter in the form of service level (in terms of the proportion of demand satisfied) and lost revenue (calculated based on per unit cost and a number of units not delivered are used. In addition, an analysis based on the various disruption frequency is done on possible cases for both disruption and non-disruption scenarios to justify the decision. Figure 1 shows the schematic diagram of the multi-echelon supply chain network used for building the decision-making process. In each echelon, there are home and target nodes. A home node is the starting point and the target node is the destination point for a vehicle. During the simulation, when demand arrives each vehicle carries the required number of products from their respective home node and after fulfilling demand at the target node, the vehicle returns to the home node. At zero demand conditions, all vehicles remain at their respective home nodes. The following section provides model assumptions and formulations respectively.

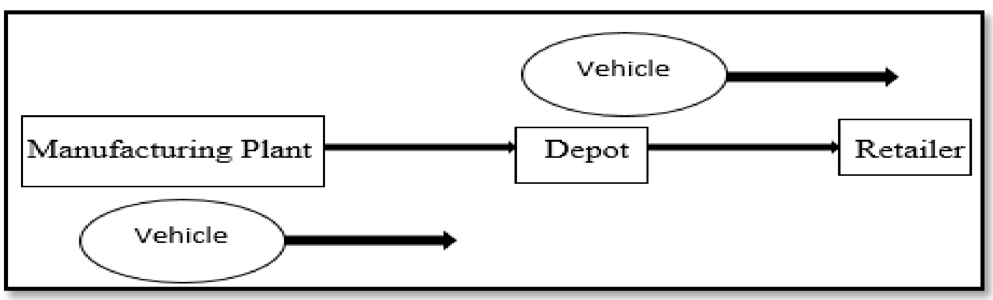

Figure 1. Schematic of the network diagram

3.1 Model Assumptions

1. The manufacturing plant has finite production capacity
2. Depot has infinite storage capacity
3. Retailer’s storage capacity is known
4. Vehicle capacity can be modified
5. Single product is considered
6. When disruption happens to the node or to the link, the service level drops to zero

3.2 Model Formulations

Indices

- T Trip index, T = 0, 1…n where 'n' is the total number of completed trips by the associated vehicle from depot
- t Demand arrival time index, t = 0, 1, 2…∞
- a Manufacturing plant index, a =1, 2
- j Depot index, j = 1, 2, 3, 4
- i Retailer index, i = 1, 2...9

Parameters

- B_{iT} backlog at retailer i for trip T
- O_i Overage at retailer i during trip T

Decision Variables

- Current Demand (C_{iTt}) – is the demand when vehicle is about to leave for retailer 'i' at a given time 't' for trip 'T'
- Actual Demand (A_{iTt}) – is the demand at retailer 'i' at time 't' when vehicle reaches the retailer i for trip 'T'
- Expected Demand (E_{iTt}) - Expected demand value when the vehicle reaches retailer 'i' consisting of the expected number of order arrivals at time 't'

$$E_{iTt} = B_{i(T-1)} + C_{iTt} + X_{iT} * y_{iT} \quad (1)$$

- X_{iT} =Expected # of order arrivals per unit time at retailer 'i' during the trip 'T'
- y_{iT} = Time taken by the vehicle to reach retailer 'i' if retailer 'i' is served first in trip 'T'

$$\text{Service level, } \mathbf{SL_{iT}} = \frac{\mathbf{E_{iTt}}}{\mathbf{A_{iTt}}} \quad (2)$$

Demand data from the retailer is monitored and the instantaneous demand from the retailer is defined as the current demand (C_{iTt}), where 'i' is the retailer index, 'T' represents trip index and 't' represents the instantaneous time at which retailer demand arrives. The expected demand value when the vehicle reaches retailer 'i' consisting of the expected number of order arrivals at time 't' is given in Equation 1. Service level is calculated by dividing the expected demand by the actual demand at retailer 'i' as shown in Equation 2. For demonstration purpose, we present the implementation and results by considering three case studies which are explained below.

4. Implementation

The case study explained in this section is based on the above mentioned VRP formulation and is formulated to replicate the actual supply chain network. By leveraging live data, proactive decision framework is build using parameters service level and lost revenue. Further subcases are built by introducing facility/path/both disruption in the network. Multiple options available to mitigate the effects of disruption in the network will be analyzed. The decision framework can act as a useful guide for managers to take an informed decision in case of an unprecedented event like facility or path disruption. Figure 2 shows the schematic of the network design of an operational supply chain system. It is a three-echelon supply chain network with multiple manufacturing plant (M), depot (D) and retailer (R). Each M and D are associated with a Vehicle (V) to transfer product between the echelons. The study uses a simulation software tool Simio10 to develop the network. Real-time/ live data in the form of retailer demand data, retail stores remaining storage capacity and inventory level at the depot are used as input for the simulation model. Table 1 shows the case studies developed. In all cases, simulation run time (SRT) is 100 days.

Figure 2. Schematic of the 3-echelon supply chain network under study

Table 1. Case study models

# of Case studies	Disruptions
Case 1	No Disruptions
Case 2	With Disruptions (Retailers not served)
Case 3	With disruptions (Retailers served)

For the operational supply chain network discussed, the manufacturing plant has a maximum production capacity of 1000 units/day. For every 10-hour production cycle, the production at M (home node) begins with the information on the remaining storage capacity value and product demand at the D (target node). Quantity produced during the 10-hour cycle is based on the aggregated values of the remaining storage capacity and product demand from the respective target nodes. In addition, every 10 hours finished products will be shipped from the manufacturing plant to the depots. After products are delivered to the retailer from the concerned depot, the service level of the network is measured. The service level is the average value of service level measured at the end of the simulation. Based on the above assumptions the following case study models are developed.

4.1 Case study model 1: No disruption

Figure 3 shows a completed operational network involving two manufacturing plants (M = 2), four depots (D = 4), and eight retailers (R=9). N, number of vehicles are associated with each M and D where N= 1. Each M serves two D's and each D serve two R's represented by the solid lines. The network is designed such that each manufacturing plant serves the demand of four or five retailers through two depots each. The manufacturing plant, M1 serves demand from the four retailers R1, R2, R3, and R4, through depots D1 and D2 whereas M2 serves retailers R5, R6, R7, R8 & R9 through D3 and D4. Table 2 shows the associated vehicles with the home and target nodes and their respective delivery capacity.

In simulation terms, manufacturing plant is the source object, which produces the product (P) associated with each manufacturing plants M1 and M2. All depots (D1, D2, D3, and D4) and retailers (R1, R2, R3, R4, R5, R6, R7, R8, and R9) defined using server object, which provides the service function for product storing and demand execution. Sink object (not shown in the figure) is defined to support simulation functionality of preventing product accumulation.

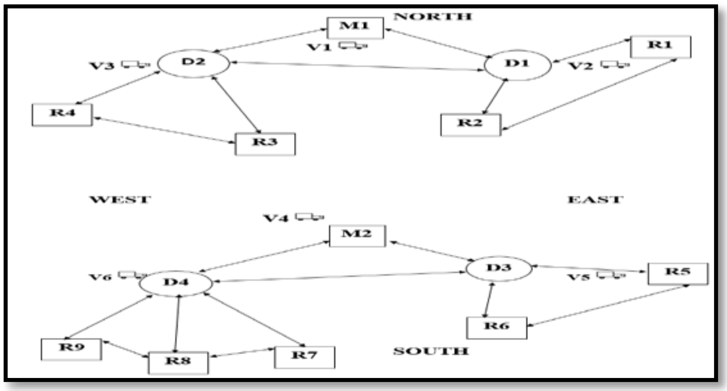

Figure 3. Network design with no disruption

Table 2. Respective home and target node with vehicle capacity

Home node	Target node	Associated vehicle	Vehicle capacity
M1	D1, D2	V1	400
M2	D3, D4	V4	550
D1	R1, R2	V2	100
D2	R3, R4	V3	120
D3	R5, R6	V5	150
D4	R7, R8, R9	V6	200

4.2 Case study model 2: With disruption (Retailers not served)

Figure 4 shows the disrupted case of an operational network involving two manufacturing plants (M = 2), three depots (D = 3), nine retailers (R=9), and N= 1. Case2 represents the condition of the operational network immediately after the disruption and where no backup options are considered. In this case, two retailers (R3 & R4) are not served when D2 and V3 are disrupted. Disruption defined here is a complete node disruption. Table 3 shows the respective home and target node with vehicle capacity for case 2.

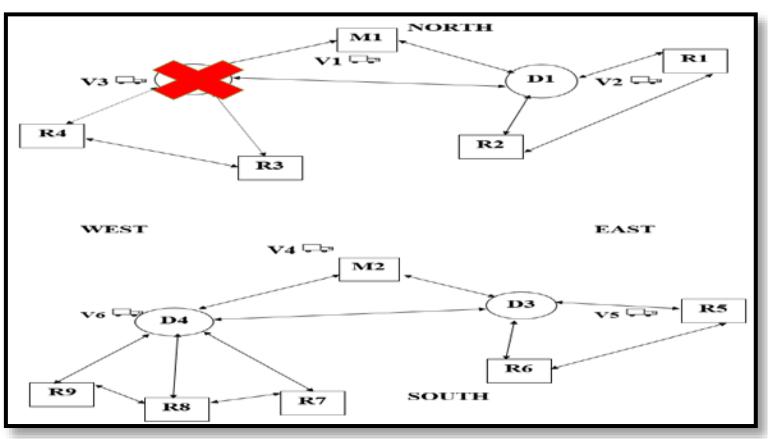

Figure 4. Network design with disruption

Table 3. Respective home and target node with vehicle capacity

Home node	Target node	Associated vehicle	Vehicle capacity
M1	D1, D2	V1	400
M2	D3, D4	V4	550
D1	R1, R2	V3	100
D3	R5, R6	V5	150
D4	R7, R8, R9	V6	200

4.3 Case study model 3: With disruption (Retailers served)

Figure 5 shows the case of a disrupted operational network involving two manufacturing plants (M = 2), three depots (D = 3), and nine retailers (R=9) and, N= 1. Here both facility (D2) and vehicle (V3) are disrupted. Table 4 shows the respective home and target node with vehicle capacity for case 3. The case considers vehicle V2 to serve all the four retailers R1, R2 & R3 using the existing delivery capacity of 100 units from D1 & R4 from depot D4 using vehicle V6. In this case, the quantity carried by the vehicle (V3) is split equally among the retailers (R1, R2 & R3) while quantity carried by vehicle V6 is split equally between retailers (R7, R8, R9 & R4). The decision to choose D1 to serve R4 and D to serve R based on the information of the current inventory level of the depots and the keeping in mind the shortest distance policy.

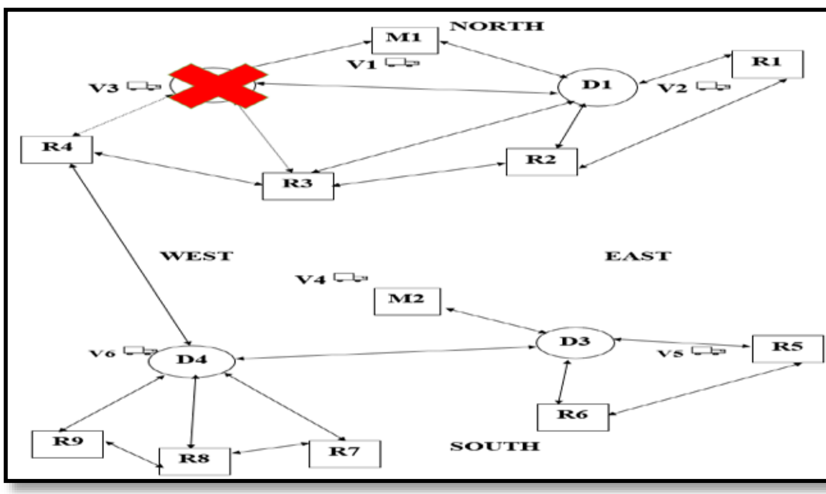

Figure 5. Network design with disruption, R3 &R4 served

Table 4. Respective home and target node with vehicle capacity

Home node	Target node	Associated vehicle	Vehicle capacity
M1	D1, D2	V1	400
M2	D3, D4	V4	550
D1	R1, R2, R3	V3	100
D3	R5, R6	V5	150
D4	R7, R8, R9 & R4	V6	200

4.4 Simulation results and discussion

The simulation run time (SRT) considered for the study is 100 days. To account for the variability, the model accuracy is improved by iterating the model 50 times. Table 5 shows the average service level of the affected retailers after a disruption. Table 6 shows the total value of lost revenue for Case 1, Case 2, and Case 3 based on the number of units not delivered. Per unit cost of $10 is considered for the calculation of lost revenue.

The study excludes costs such as transportation cost, production cost in manufacturing plant, holding cost at the depot, operating cost in manufacturing plant and in the depot, penalty cost for unsatisfied demand at the retailer, etc. Based on the values of service level, lost revenue and cost of available resources feasible decision are taken. The decision considers the duration of the disruption and the revenue lost based on the frequency of disruption or number of times similar disruption happens in the network. Whereas average service level value gives insight into the proportion of demand satisfied, which substantiates the decision taken.

Table 5. Average service level for case 1, case 2, and case 3

Retailer	**Average Service Level**		
	Case 1	**Case 2**	**Case 3**
R1	.91	.91	0.63
R2	.90	.90	0.57
R3	.90	0	0.55
R4	.89	0	0.41
R7	.99	.99	0.42
R8	.93	.93	0.61
R9	.97	.97	0.60

Table 6. Lost revenue in $ based on unsatisfied demand for case 1, case 2 and case 3

Case	**Total Demand (Quantity)**	**Satisfied demand (Quantity)**	**Total Revenue ($)**	**Lost Revenue ($)**
1	22366	21756	217560	6100
2	22360	13790	137900	85700
3	22363	17886	178860	44770

4.5 Decision framework

Based on the type of disruption (node, link or node, and link disruption), information on lost revenue, service level, and available resources (financial resources) a decision framework can be developed. The best investment decision can be taken based on available financial resources. Each of the decisions enumerated in the table will be evaluated using the service level value and lost revenue along with the cost of implementing the available resource. Table 7 shows the decision framework for complete node disruption. Table 8 shows the respective values of lost revenue against various disruption frequencies for disruption durations for 10 days.

Table 7. Decision framework

Type of Disruption	**Available Resources**	**Decision**
Node disruption	Cost of adding a trailer	Trailer added
	Cost of new vehicle	New vehicle or alternate depot
	Cost of building a new depot	New depot
	Cost of expansion of depot	Depot capacity increased

Table 8. Disruption duration of 10 days

Disruption frequency	**Lost Revenue ($)**	**Disruption frequency**	**Lost Revenue ($)**
1	8570	6	51420
2	17140	7	59990
3	25710	8	68560
4	34280	9	77130
5	42850	10	85700

5. Conclusion and Future work

The paper aimed at identifying the extent to which technology that can be leveraged to help make a proactive decision in supply chain network under conditions of uncertainty. Here live retailer demand data, the position of a truck in the network, the instantaneous capacity of the depot, etc, are used as input to calculate and make informed decisions. Based on the retailer's current demand, the number of units carried by the vehicle from the depot is calculated using the available depot capacity as input by the manufacturer at the beginning of each 10-hour production shift. Service level for each retailer and total revenue lost for the non-disruptive, disruptive and disruptive case after implementing mitigation strategy is analyzed against the available resource and disruption frequencies. This can be used as an informative framework for taking a proactive decision for a supply chain manager. Also, some of the benefits of having data readily available reduce conditions of stock outs in a non-disruptive situation. It improves investment decisions with the availability of right data at the right time. Prototyping the network using simulation helps visualize real problems better. Threats are easily identified, and changes can be made relatively easier compared to the analytical model. Finally, since the simulation model is compatible with another platform it is easier to run the model by using other analytical tools as well. In future work, it would be interesting to investigate machine learning algorithms for vehicle routing problem by which the model can intelligently make informed decisions under uncertain situations. Another interesting direction is to investigate other possible decisions to be made regarding the vehicle to serve more customer locations. A cost comparison can be done using the proposed model to see whether to increase the number of vehicles or to increase the individual vehicle capacity to serve all the customers with the minimum cost.

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