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Supply Chain Optimization of a Local Small Business from the Food-Service Industry Using Simulation Models

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by

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ABSTRACT

Various supply chain disruptions can cause revenue losses, low productivity, and damaged reputations. Some examples of such disruptions include increased supply costs, labor shortages, pandemics, natural disasters, or transportation delays. For instance, during the COVID-19 pandemic, several small and medium enterprises (SMEs) suffered greatly from labor shortages, delayed and costly supplies, and decreased demand. In this research, we present a case study of a small local business from the fast-food industry that experienced the loss of employees and delays and analyzed the increased cost of supplies. We created visualization modules with the SMEs supply chain performance measures to see the effects of switching suppliers and adjusting shift schedules using simulation models. We used data gathered from the SME's point of sale system and developed a simulation model to replicate the SME's supply chain network. The model used information about various suppliers, their location, lead time, transportation costs, operational costs, inventory level, and customer location. The simulation model explored the impact of supplier disruption on the SME's key performance indicators (KPI). We developed scenarios and experiments to evaluate the outputs (i.e., KPIs) and provided recommendations to improve the SME's supply chain network.

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1. INTRODUCTION

The COVID-19 pandemic has affected the population's health and economic activities in all countries. Lockdowns, government guidelines, and the increase of cases have disrupted the supply and demand of many goods and have negatively impacted the supply chains (Moretto and Caniato, 2021). Small and Medium Enterprises (SME) had several unique challenges due to the disruptions in their supply chains. However, the Large Enterprises (LE) had the resources and technology budgets to implement strategies to continue working normally, whereas SMEs with limited resources could not do so. SMEs are the backbone of many economies accounting for 60% employment from 95% of companies worldwide. They are the most fundamental and significant economic units globally (Baral et al., 2021).

It was found that during the COVID-19 pandemic, most of the SME organizations and restaurants were not ready for such a disruptive event and lacked the planning to overcome such a situation. SMEs need to develop short-term and long-term strategies for being resilient during an uncertain business environment (Baral et al., 2021). Businesses always have the opportunity to strengthen their operations during adversity and prepare to respond positively to similar future events (de Freitas et al., 2020).

One of the most crucial service parameters for restaurant customers is the waiting time. Studies have shown that customers switch to other restaurants from a particular restaurant because of insufficient personnel and long waiting times (Jain and Ali, 2016). Other reasons include an inventory of the ingredients to prepare all menu items and other essential supplies. These businesses require a reliable supply chain to become competitive and successful. SMEs could take actions to minimize the risk of disruptions in the supply chain that are usually uncertain. A simulation model is an effective analysis tool that dynamically changes various internal supply chain variables to improve their services.

This research aims to help a small local business from the fast-food industry reduce production time and delivery time, meet deadlines, and find the best option for suppliers with a simulation model using the AnyLogic® software. Furthermore, the study's findings will contribute to setting up strategies that will improve service and develop a resilient supply chain. The rest of the paper is organized as follows: Section 2 discusses the literature review with factors that caused the disruptions in the supply chain; section 3 discusses the supply chain modeling approach; section 4 states the experiments and scenarios implemented to the model; Section 5 contains the results and recommendations, and finally Section 6 presents conclusions, limitations, and future work of this research.

2. LITERATURE REVIEW

This section discusses the unprecedented effects that the COVID-19 pandemic had on the food supply chain and SME industry. Moreover, the extraordinary challenges that were faced in all stages of the supply chain including preparation, processing, distribution, consumption, and disposal (Boyacı-Gündüz et al., 2021).

2.1 CHALLENGES DURING COVID-19 PANDEMIC

Predicting trends that influence consumer demand is fundamental for business owners in the SME industry, such as restaurants, to facilitate operations and keep a positive reputation. According to (Tokassynoya and Akbaba, 2017), many variables affect the business image, including price, service, and product quality. These variables have been difficult to sustain because trends have been affected during the COVID-19 pandemic. Stay-at-home orders and the increase or decrease of COVID-19 cases have fluctuated the consumer demand without warnings. For every 1% increase of confirmed cases in a county, the restaurant demand would decrease by 0.06%. With stay-at-home orders, the demand would decline by 3.25% (Yang et al., 2020). In early 2020, consumers forgo public venues, ate at homes, and stocked up on groceries and supplies.

Meanwhile, sales declined at dine-in restaurants, fast-food locations, coffee places, and other casual dining locations by 27% (Felix et al., 2020). Many companies 3reported 50%-90% revenue reduction between June 2019 and June 2020 (de Freitas et al., 2020). Restaurants were not prepared for such a situation, and a few restaurants had to declare bankruptcy; others reported that they soon will not be able to cover their rent and personnel costs (Becker et al., 2020). In addition, shutdowns of non-essential businesses and stay-at-home orders have decreased many consumers' incomes, forcing them to spend less and choosing more affordable options such as cooking at home.

With declines in restaurant consumer demands, a phenomenon called ripple effect or disruption propagation started to influence the entire supply chain network. Disruption propagation/ripple effect refers to an operational failure at one entity of the Supply Chain Network (SCN) that causes operating losses of other business entities (Li et al., 2021). Companies that produce, convert, and deliver food to consumers and businesses face a web of interrelated risks and uncertainties across all steps in the value chain – from farmers to end customer channels (Felix et al., 2020). Many food-service suppliers experienced order cancellations and loss of customers due to restaurants closures, either temporarily or permanently shut down, to prevent the spread of the virus. These restaurants' closures left suppliers with extensive inventory in their storage facilities that needed refrigeration, which increased their costs (Felix et al., 2020). Although there were some sudden increases in demand due to the distribution of stimulus checks, it only made a slight change in revenue. On the other hand, these stimulus checks encouraged economic activity, with increased spending, especially among low and medium-income households (Yang et al., 2021).

Food production and processing value chains also encountered multiple challenges in their production, transportation, and distribution (Nagurney, 2021). Many workers were being infected, especially in the meat-packing plants. At the beginning of 2020, over 57,000 workers tested positive for COVID-19 (Larue, 2021). Moreover, in the agriculture workforce, only three in ten workers are citizens of the United States. The rest of the workforce in the US are from other countries working with guest agricultural visas. Due to border closings, only a few workers were available for harvesting, production, and logistics. The COVID-19 also impacted freight service workers who delivered directly to retailers or customers. In addition, some seasonal workers could not travel for seasonal employment because of travel restrictions resulting longer lead times (Nagurney, 2021).

The food product prices increased with multiple supply chain disruptions (Boyacι-Gündüz et al., 2021). Canadian beef and pork experienced a significant temporary increase in price shortly after several meat plants were forced to operate at reduced speed and for fewer hours or shut down. By July 2020, 18 meat processing plants in the United States had already been closed (Felix et al., 2020). The lower volume of meat manufactured by meat-packing plants increased retail prices, widening the gap between farm and retail prices (Larue, 2021). This price rise left restaurants from the SME industry no choice but to increase the costs of their products to recover from the supply-chain-driven inflation. The Consumer Price Index (CPI) increased by 5.3 percent between October 2020 and October 2021 and is expected to increase between 3.0% and 4.0% by October 2022 (Chelius, C., MacLachlan, 2021)

Businesses were searching for many ways to survive the pandemic. Some business owners had to cut their staff by half by keeping key personnel. Meanwhile, others were forced to cut salaries (Al-Fadly, 2020). To keep their businesses open, many dine-in restaurants had to take advantage of the increase in demand for delivery. Restaurants had to invest in implementing new delivery systems. This new system forced restaurant owners, kitchen workers, and employees to reinvent their roles to adopt this new approach, which many were not adept at before the pandemic (de Freitas et al., 2020). Many restaurants also had to invest in developing mobile applications and internet and communication technologies that can be implemented with food ordering or delivery requests (Boyacι-Gündüz et al., 2021). Owners were also looking for other options for suppliers with a significant focus on cost reduction and lead time deduction (Baral et al., 2021). Process modeling and simulation can be crucial tools for businesses to continue adapting and improving operations (Grikštaitė, 2008).

2.2 Definition of Simulation Modeling

A simulation is a computerized visual and animated model or module that imitates an actual operation or system over time. Simulation is an indispensable problem-solving methodology for the solution of many real-world problems. Simulation is used to describe and analyze the behavior of a system, ask "what if" questions about the existing system, and aid in the design of existing systems (Banks, 2000). It plays a significant role in studying, analyzing, optimizing, comparing different scenarios, and measuring the effects in advance. It also helps organizations find ways to dimmish business risks and helps understand the operational links and impact of interactions (Grikštaitė, 2008).

In the case of a restaurant, simulation modeling can be used to explore labor productivity requirements to maximize sales volume while maintaining a quality experience, fast service for customers (Brann and Kulick, 2002). The model can track numerous performance measures, including wait time, average utilization, count of executions, and average delivery time (Brann and Kulick, 2002). *Table 2.1* summarizes the most important performance measurements.

Table 2.1. Key Performance Measures of a Restaurant's Supply Chain Simulation Model

Order Statistics	Orders Completed
	Avg. Time Orders are Completed
	Avg. Time Orders are Delivered
Process Statistics	Avg. Orders Processed at a time
	Count of Executions per Station

	Total Late Orders
	Avg. Time Orders are Late
Worker Statistics	Avg. Utilization
Food Statistics	Units in Inventory
	Avg. Time for Units to Restock

The simulation model allows the user to further understand the behavior of the system/restaurant by performing alterations in many factors such as physical layout, equipment availability, worker staffing levels, and positioning. The simulation provides an analysis platform for investigating the impacts of these factors on the performance measurements described in Table 2.1. It can process many hours of simulated transactions with gathered information within a short duration. It also allows for concepts to be screened and assists in making decisions before implementing the changes in the real-world system (Brann and Kulick, 2002). Some alterations/scenarios that can be performed and analyzed are changing the number of staff, introducing a new product, and exploring service impacts.

The number of businesses using simulation is rapidly increasing because of the many benefits that it offers (Banks, 2000). Warehouses, banks, restaurants, and many other industries use simulation to determine bottlenecks and improve their processes. In this case, simulation was utilized to discover which stage in the production process needed additional employees to reduce the production time. In addition, we wanted to determine the effect on the system if new equipment is bought and if suppliers are changed.

3. SMALL AND MEDIUM ENTERPRISE SUPPLY CHAIN MODELLING APPROACH

The modeling approach comprises five different phases, all represented in Figure 3.1. The first step in the modeling process is to identify the problem definition, which indicates the purpose of the study and specifies the system boundaries (Li, Ren, and Wang, 2016). Secondly, the restaurant's supply chain model is developed with data gathered from the restaurant's Point-Of-Sale (POS) System, inventory management, and daily observation. In step 3, the model is tested and validated using Parameter Variability – Sensitivity Analysis. In this technique, the input values and internal parameters are varied, and the effects are analyzed. The results from the model should replicate the impact as in the real system (Sargent, 1991). Finally, in the last step, the model was performed under different scenarios to see the effect on performance measures and the changes in the system behavior over time.

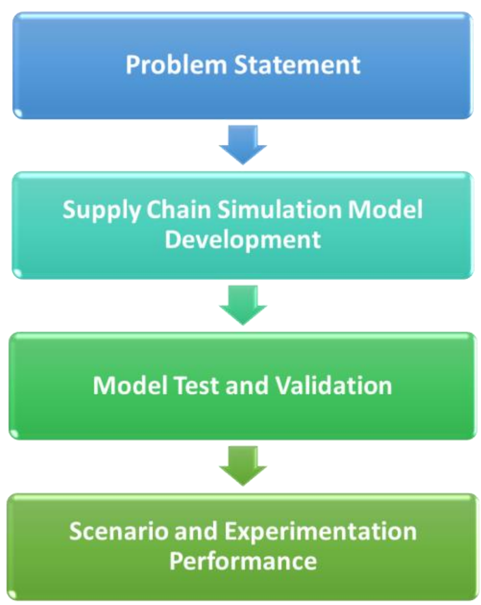

Figure 3.1: Framework of Supply Chain Simulation Modelling Process

3.1 PROBLEM STATEMENT

Worldwide, the food industry has been significantly disrupted by the COVID-19 pandemic. Changes in spending and eating trends, COVID-19 infections among restaurant workers, closure of multiple plants and manufacturers, disruptions in transportation, extreme labor shortage, and a significant increase in food prices are some of the effects of COVID-19 (Hobbs, 2020). With the various disruptions within the food supply chain, SMEs struggled to keep their businesses open. This study examines the case of an SME restaurant from the fast-food industry that faced multiple challenges. The restaurant faced labor shortages and longer lead times from their suppliers. They also encountered a considerable increase in demand for delivery orders and decreased carryout orders.

3.2 SUPPLY CHAIN MODEL SIMULATION DEVELOPMENT

3.2.1 SUPPLY CHAIN STRUCTURE

The restaurant's supply chain simulation model was built using a software called AnyLogic®. AnyLogic is a simulation software used in manufacturing, healthcare, marketing, transportation, warehouse operations, and supply chains. AnyLogic is the leading simulation software for business applications, utilized worldwide by over 40% of Fortune 100 companies (Borschchev, 2013). AnyLogic has all the right tools to make any model elegant, natural, and manageable. The software offers three different types of modeling: agent-based, discrete event, and system dynamics (Borschchev, 2013). Multimethod modeling was used to construct the supply chain using agent-based and discrete event modeling. The supply chain starts with procuring raw material from suppliers to make the product to deliver the customer's final product. An example is depicted below in Figure 3.1.

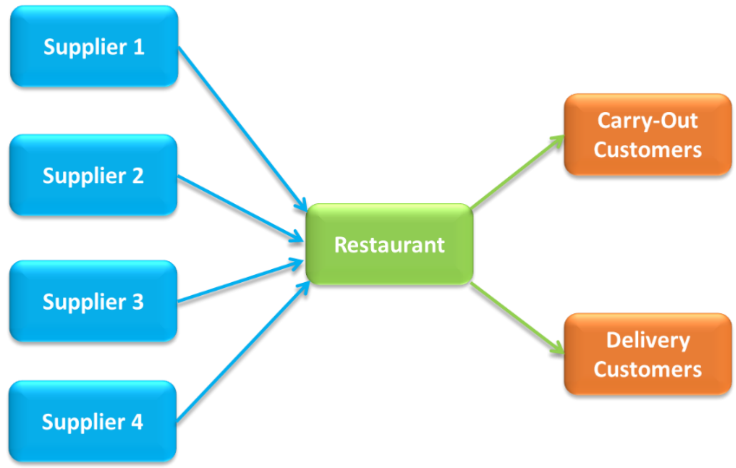

Figure 3.2: Supply Chain Structure of Restaurant

Agent-based modeling is used to demonstrate the behavior of the delivery system between suppliers, restaurants, and customers. This type of modeling is defined as “the set of techniques [in which] relations and descriptions of global variables are replaced by an explicit representation of the microscopic features of the system, typically in the form of microscopic (‘agents’) that interact with each other and their environment according to (often very simple) rules in a discrete space-time” (Nicholls et al., 2016, p. 3). Agents may represent very diverse things: projects, products, ideas, people, vehicles. They are a unit of model design that can have behavior, memory, and timing by having defined variables, events, stock and flow diagrams, and process flowcharts. The design of an agent typically starts with identifying its attributes, behavior, and interface with the external world (Borschchev, 2013). In this case, the agents represent the delivery trucks used to deliver the supplies to the restaurant and the employees with automobiles to deliver to the customers who chose delivery.

Discrete event modeling was used to build the sequence of operations performed to finish an order placed by the customer. The term discrete refers to the fact that discrete event modeling jumps from one event’s time to the following (Karnon et al., 2012). Figure 3.3 represents the series of events that the order must go through before handing it off to the customer. The processes inside the restaurant include taking orders, preparing orders, cooking orders, packing orders, and deliver of hand-out orders.

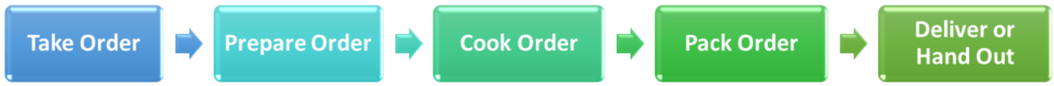

Figure 3.3: Sequence Structure of Operations to Produce a Customer Order

3.2.2 The Restaurant Process

The process transforms into the AnyLogic model depicted in Figure 3.4. First, agents are generated by the source, which is the starting point of the process. Agents represent objects that move through the system; in this case, they stand for the customer orders. The source, "CarryOutOrders," defines how many agents should be generated and the schedule of exact arrival times and quantities. Because the restaurant has peaked in demand during lunch and dinner times and has certain working hours, we used an arrival table with the number of orders per hour. The information can be found in Table 3.1.

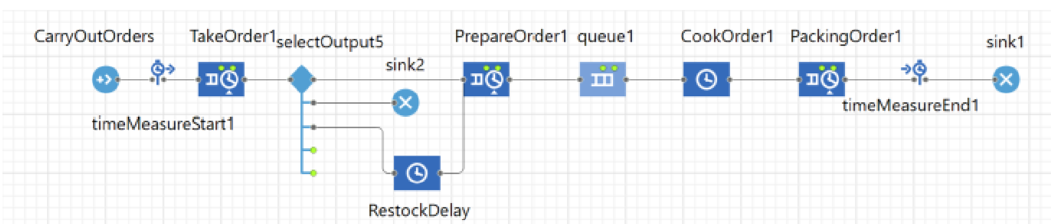

Figure 3.4: Restaurant's Discrete Modeling Process for Carry Out Orders

Table 3.1: Carry Out Arrival Times

Start	*End*	*Value*
10:00:00 AM	11:00:00 AM	3
11:00:00 AM	12:00:00 PM	2

12:00:00 PM	1:00:00 PM	6
1:00:00 PM	2:00:00 PM	7
2:00:00 PM	3:00:00 PM	8
3:00:00 PM	4:00:00 PM	14
4:00:00 PM	5:00:00 PM	15
5:00:00 PM	6:00:00 PM	10
6:00:00 PM	7:00:00 PM	11
7:00:00 PM	8:00:00 PM	9
8:00:00 PM	9:00:00 PM	7
9:00:00 PM	10:00:00 PM	5
10:00:00 PM	11:00:00 PM	3

The orders enter the first step, “TakeOrder1,” where the employee takes the order and sends it to the kitchen. The duration of this process is represented by the pert distribution, which is a continuous distribution with three inputs, Minimum, Most Likely, and Maximum (pert (min, mode, max)). It was noted that 80% of customers already knew their order. In comparison, the other 20% had to be assisted with their options which delayed the process. In this step, the employee is represented as a resource. Resources are objects that agents use to perform a given action. Examples of resources include employees, doctors, nurses, vehicles, and forklift trucks. Resources or employees can also serve one or more agents simultaneously (Banks, 2000).

The orders then have the option to enter a “ReStockDelay” or “PepareOrder1” based on multiple conditions. Orders can only enter the “ReStockDelay” if any product from the inventory has reached 0. Once orders are in this process, they can wait until the product is restocked or canceled. The waiting time will be determined by the time it takes for the supplier to arrive at the restaurant. This delay does not require any employees. Suppose none of the products reach an inventory of 0. In that case, orders will go directly to “PrepareOrder1”.

Once the order has been prepared, it enters the process of cooking. This step doesn’t require any employees; however, it does have a capacity of 6 orders cooking at a time. If the capacity is full, the orders will wait in “queue1” until the capacity is available. The final step is “PackingOrder,” which requires employees who have a work schedule, also found in the Appendix Section. Finally, the orders are handed to the customers and then exit through the “Sink” block for their disposal.

3.2.3 Delivery to Customers

If the orders are requested for delivery, a few more steps must be added to the process. After the order has been packed, a delivery driver or resource is commanded to grab a truck in the “seize block” and drive 25 mph to the customer from the restaurant, as demonstrated in the block “toCustomer” in Figure 3.5. Once the driver arrives, it unpacks and hands the order to the customer in the “unpacking” block with a processing time of a uniform distribution. The uniform distribution is also continuous with two inputs (min, max). Finally, the driver navigates back to the restaurant represented in the “moveTo” block, releasing the truck.

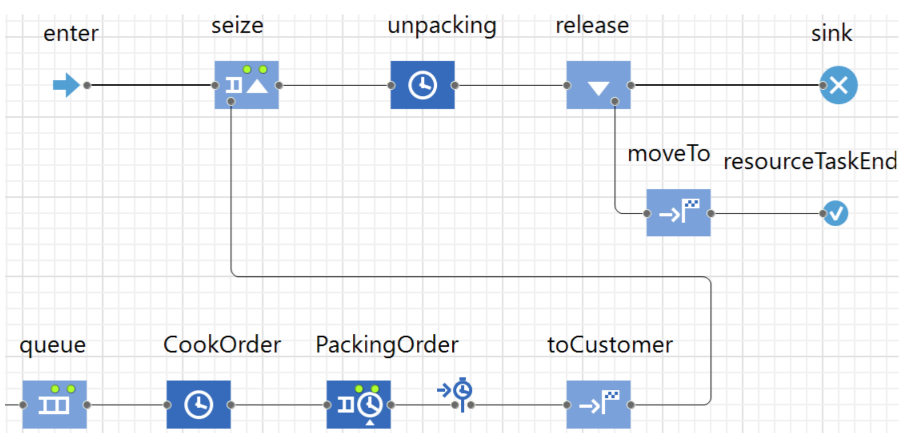

Figure 3.5: Restaurant’s Discrete Modeling Process for Delivery Orders

3.2.4 Inventory and Suppliers

The restaurant’s supply chain includes four different suppliers: Supplier 1, Supplier 2, Supplier 3, and Supplier 4. Supplier 1 is responsible for sending Product A to the restaurant, Supplier 2 supplies with Product B and Product C, Supplier 3 with Product D and Product E, and

Supplier 4 with Product F. All products in stock decrease at a daily usage rate, and it is reflected as Stock such as the one in Figure 3.6 as "PepsStock." Suppose the supply of any product reaches a low number between 0 and 5. In that case, it will send an order to the corresponding supplier. The supplier will seize a truck, drive to the restaurant, unpack the order with a processing time, and return it to the supplier.

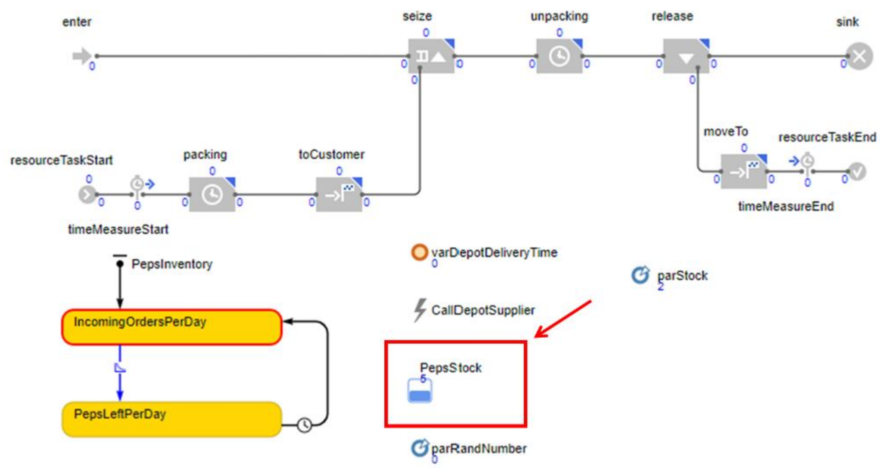

Figure 3.6: Inventory Unit of One Material

3.3 Model Validation

A model should be developed for a specific purpose or application and its validity determined concerning that purpose. Tests and evaluations are conducted until sufficient confidence is obtained that a model can be considered for its intended application (Sargent, 1991). As previously discussed, several parameters within the model were varied to verify if the model was working correctly and could be utilized to find solutions. The employees for each station inside the restaurant were decreased, and it was found that the time to finish an order increased by approximately 15%. The processing times for the stations inside the restaurant were increased by 2 minutes in the same form. It was established again that finishing an order increased by 10% - 20%. Product A hit a stock of 0, and this caused half of the customers to leave the system while others chose to wait until the product was restocked. The restocking was validated when the Stock was filled to its maximum number. The lead time for getting a supply was recorded to about 2-4 hours for each supplier. Additionally, the performance measurements of the current system were compared to the process of the in real-life and it was determined that the model was very accurate.

4. MODEL RESULTS, SCENARIOS, AND EXPERIMENTATION

4.1 CURRENT SYSTEM

The model is launched with the processing times and the number of incoming orders of a typical day. A typical day consists of four shifts for each processing station. On a normal working day, the ideal due time for carryout orders is 40 minutes, and the scheduled time for deliveries is 55 minutes. The orders enter the "TakeOrder1" block and process at a processing distribution time of pert (2, 5, 3) minutes. The order-taking process has one employee for shifts 1, 2, and 4 and 2 employees for the 3rd shift. If units in the inventory reach 0, 95% will cancel while the other 5% will decide to wait until restocked. Otherwise, the orders will proceed to the next block, "PrepareOrder1," and are processed at a distribution time of pert (2, 5, 3.5) minutes. Employees are positioned in the same way as the first station, "TakeOrder1". The orders then continue to the next station, "CookOrder1", and this task is completed with a time of pert (6, 12, 9.5) minutes without employees being present. The orders are then prepared in the next step, "PackingOrder1," with a time of pert (2, 5, 3) minutes, and if the order must be delivered, the processing time increases to pert (3, 6, 5) minutes. This station has one1 employee for each shift. A summary of the employee shifts is detailed below in Table 4.1.

Table 4.1 Employee Shifts for Each Processing Station

	Order Employees		Prepare Employees		Pack Employees		Delivery Drivers	
Shift 1	10:00 - 14:00	1	10:00 - 14:00	1	10:00 - 14:00	1	10:00 - 12:00	1
Shift 2	14:00 - 16:00	1	14:00 - 16:00	1	14:00 - 16:00	1	12:00 - 16:00	1
Shift 3	16:00 - 22:00	2	16:00 - 21:00	2	16:00 - 22:00	1	16:00 - 22:00	2
Shift 4	22:00 - 23:00	1	21:00 - 23:00	1	22:00 - 23:00	1	22:00 - 23:00	1

If the orders are for delivery, the drivers will seize the order and navigate to the customers at an average speed of 25 MPH. Once the driver arrives, it unpacks the order at a processing time with a uniform distribution of (5, 10) minutes and then drives back to the restaurant. The shifts for the drivers are also mentioned in Table 4.1. The model was run for 648 hours or 27 days, and the results are listed in Table 4.2.

Table 4.2 Performance Measurements for Current System

Average Production Time	34.3 minutes
Percentage of Late Carry Out Orders	26.09%
Percentage of Late Delivery Orders	10.33%
Percentage of Total Late Orders	23.35%
Number of Customers Waiting for Restock	7
Number of Customers Leaving	97
Percentage of Customers Leaving	3.06%

Figure 4.1 represents the production time in hours, where the highest points were reached due to the seven customers that were willing to wait 2-3 hours until the inventory was restocked.

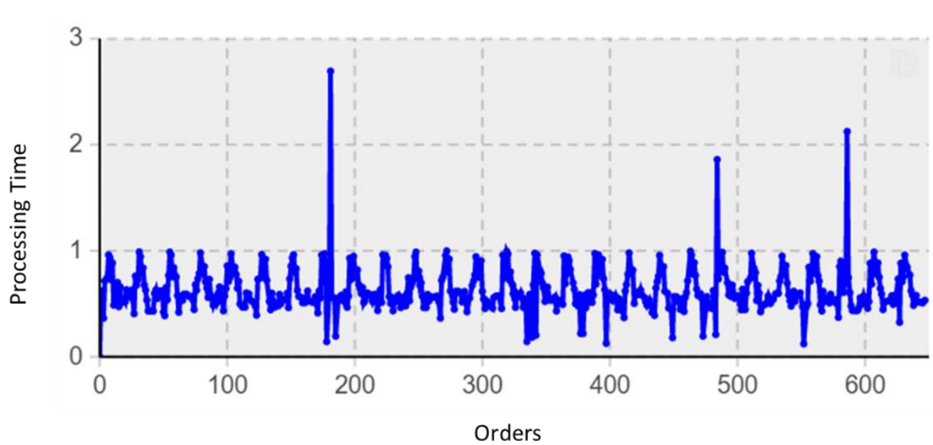

Figure 4.1: Production Time for Carry Out and Delivery

4.2 Scenarios and Experiments on the current system

Different Scenarios were tested with the same processing times of each station and same order arrival rate. As a starting point, the number of employees for shifts 2 and 3 were configured for each station. However, due to a limited budget, the restaurant only had the allowance to hire a maximum of two employees. Therefore, different combinations of placing one or two employees in each shift were made, and the effects on the performance measurements were analyzed.

After testing many combinations, it was noted that placing more employees in the third station, Packing, had a significant effect on the variables. For example, in one scenario, one employee was added to the third shift of the Packing station, and another one was added to the second shift of Prepare station. As a result, the average production time decreased to 30.9 minutes, and the percentage of late orders decreased to 11.45%. Similarly, one employee was added to the third shift of the Packing station and another one to the third shift of Prepare station, and the average production time was reduced to 31.1 minutes. The percentage of late orders also resulted in 11.45%. Below is a summary of the performance measurements of both scenarios in Table 4.3.

Table 4.3 Performance Measurements of Two Scenarios with Additional Employees Hired

Scenario 1		**Scenario 2**	
Average Production Time	30.9 mins	**Average Production Time**	31.1 mins
Percentage of Late Carry Out Orders	12.06%	**Percentage of Late Carry Out Orders**	12.41%
Percentage of Late Delivery Orders	8.50%	**Percentage of Late Delivery Orders**	6.98%

Percentage of Total Late Orders	11.45%	**Percentage of Total Late Orders**	11.45%
Number of Customers Waiting for Restock	6	**Number of Customers Waiting for Restock**	8
Number of Customers Leaving	104	**Number of Customers Leaving**	98
Percentage of Customers Leaving	3.30%	**Percentage of Customers Leaving**	3.09%

In the next step, additional equipment was added to increase the capacity of the cooking station from 6 to 8. Again, the same processing times and order arrival rates were used. However, the two employees added from the previous scenarios were used. With the additional oven in the first scenario, the average production time remained the same, but the percentage of late orders decreased to 11.08%. In the second scenario, the average production time was slightly reduced to 30.7 minutes, and the rate of late orders decreased to 10.75%. Table 4.4 states all performance measurements for this experiment.

Table 4.4 Performance Measurements of Two Scenarios with Additional Employees Hired and Increase in Cooking Capacity

Scenario 1		**Scenario 2**	
Average Production Time	30.9 mins	**Average Production Time**	30.7 mins
Percentage of Late Carry Out Orders	11.91%	**Percentage of Late Carry Out Orders**	11.81%
Percentage of Late Delivery Orders	7.30%	**Percentage of Late Delivery Orders**	5.97%

Percentage of Total Late Orders	11.08%	**Percentage of Total Late Orders**	10.75%
Number of Customers Waiting for Restock	6	**Number of Customers Waiting for Restock**	5
Number of Customers Leaving	97	**Number of Customers Leaving**	96
Percentage of Customers Leaving	3.04%	**Percentage of Customers Leaving**	2.99%

The following step was to experiment if switching suppliers would make a difference in the performance measurements. It was established that Supplier 2 and Supplier 3 offer the same raw material as Supplier 1, and Supplier 3 has the same raw material that Supplier 4 has. Using the same processing times, arrival rate orders, and the two additional employees hired, we tested the combinations of switching suppliers. From the results of each combination, it was concluded that switching from Supplier 1 to Supplier 2 and Supplier 4 to Supplier gave the best numbers. In the 1st scenario, the average production time remained the same, the percentage of customers leaving decreased to 1.99%, and the percentage of late orders also reduced to 11.29%. The second scenario revealed a reduction in average production time to 30.8 minutes, a drop in the percentage of customers leaving to 2.18%, and a decrease in late orders to 10.70%, as shown below in Table 4.5.

Table 4.5 Performance Measurements of Two Scenarios with Additional Employees Hired and Change in Suppliers

Scenario 1		**Scenario 2**	
Average Production Time	30.9 mins	**Average Production Time**	30.8 mins
Percentage of Late Carry Out Orders	12.03%	**Percentage of Late Carry Out Orders**	11.70%

Percentage of Late Delivery Orders	7.85%	**Percentage of Late Delivery Orders**	6.11%
Percentage of Total Late Orders	11.29%	**Percentage of Total Late Orders**	10.70%
Number of Customers Waiting for Restock	5	**Number of Customers Waiting for Restock**	2
Number of Customers Leaving	64	**Number of Customers Leaving**	70
Percentage of Customers Leaving	1.99%	**Percentage of Customers Leaving**	2.18%

4.3 FINDINGS AND RECOMMENDATIONS

Analyzing the results, we found that the packing station's 3rd shift and the prepare order station needed at least one more employee each. Adding one employee to the packing station's 3rd shift and another to the prepare order station's second or third shift reduced the average production time by almost 5 minutes. The percentage of late orders decreased by 12%. If another oven is added to the cooking station to increase the capacity to eight, then we see a decrease of 1% in the number of late orders. With suppliers, if we switch from Supplier 1 to Supplier 2 and from Supplier 4 to Supplier 3, we will see a decrease of 1% in the number of late orders and a 1% reduction in the number of canceled orders.

Based on the results, we recommend the restaurant hire two more employees since it will significantly impact the processing times. However, we do not recommend increasing the cooking capacity since the price to buy the equipment can range from $20,000 to $35,000 to keep the same average production time and decrease the number of late orders by only 1%. Moreover, if Supplier 2 has the same prices as Supplier 1 and Supplier 3 as Supplier 4, we recommend the switch since the number of canceled orders dropped from 97 to 64.

5. CONCLUSIONS, LIMITATIONS, AND FUTURE WORK

In this study, we developed a simulation model that mimics the operations of a small restaurant's supply chain to explore alternatives that will improve their production time and delivery times. Additionally, the model demonstrated the impact on the overall system if suppliers were changed. The most important performance measurements were analyzed to find the best implementations that will improve the restaurant's service and give them the ability to become a resilient supply chain that can overcome any situation such as the COVID-19 pandemic. The model can be used as a Decision Support System that allows the customer to use and compare scenarios to generate new ideas and innovative decisions.

The major limitation of this research is that the model lacked small details that a restaurant faces typically. For example, in a restaurant of a fast-food industry, there are situations where employees are absent to work, leave shifts early, take long breaks during their shifts, or have rough days, and their performance decreases significantly. In addition, there are many cases where the orders are never picked up, that must be remade, or delivery orders that never make it to the customer because the wrong address was given, or the door is never answered. Another limitation is that the model doesn't include expenses and an analysis of costs that can be saved with changing suppliers or processes.

There is still a need for future work on this simulation model. An exciting application that the model could be fundamental is the demonstration of sharing resources between the restaurant's franchise chain. This case only analyzed one location. However, there are currently nine locations in the area that share the same suppliers. The model could also be improved by adding characteristics of the suppliers and determining the amount of time it would take to recover the cost that was made to hire new employees. Another future research could examine the impact on sites if a new site is built.

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