OPTIMIZATION OF LAST-MILE DELIVERY IN KSA

SABER, D.[1*] – YOUSFI, N.[1] – SELMI, S.[1] – ALOTAIBI, M.[1] – ALOTAIBI, N.[1] – ALHARTHI, R.[1] – ALWGDANI, H.[1] – ALOTAIBI, R.[1]

[1] *Department of Mechanical Engineering, Taif University, Taif, Saudi Arabia.*

**Corresponding author*
e-mail: daliasaber283[at]gmail.com

(Received 22nd October 2024; revised 12th February 2025; accepted 19th February 2025)

Abstract. The rapid growth of e-commerce in Saudi Arabia has intensified the need for efficient last-mile delivery solutions. This study investigates the optimization of last-mile delivery using a mathematical model and a Python-based approach to enhance efficiency, reduce costs, and improve customer satisfaction. A survey conducted among Saudi residents highlighted significant challenges, including delivery delays, high costs, and inefficient routing. The study developed a capacitated vehicle routing problem (CVRP) model, which aimed to minimize total travel distance while meeting customer demands within vehicle capacity constraints. The model, implemented using LINGO software, demonstrated a 17.21% reduction in travel distance, translating into cost and time savings. However, due to computational complexity, a Python-based optimization program was developed as an alternative, reducing the total distance traveled by 31.15% and cutting delivery time by 33.82%. The results indicate that automated route optimization significantly enhances last-mile logistics, ensuring timely deliveries and reducing operational expenses. The findings highlight the importance of integrating mathematical optimization with programming solutions to streamline logistics operations. This study offers practical insights for logistics companies in Saudi Arabia to adopt advanced route-planning technologies, ultimately improving service efficiency and customer experience. Future research should explore integrating real-time traffic data and customer preferences to further optimize last-mile delivery processes.
Keywords: *last-mile delivery, e-commerce, Mathematical model, vehicle route, python programming*

Introduction

Last-mile delivery can be defined as the last step in the delivery process in which packages arrive to customers. It is extremely important part of the supply chain as it is the point of interaction with the customers. The customers expect fast delivery whether it is home delivery or pickup, and whether the delivery service managed internally or by third party supplier. Last-mile delivery is complicated, as many factors contribute to making it costly and ineffective (Vrhovac et al., 2023). The Saudi Arabian economy has experienced unprecedented growth in recent years. This growth returns in support of the National Transformation Program (NTP) and Vision 2030 in the development of a multi-faceted development of the economy. One of the most important parts of Program (NTP) and objectives of Vision 2030 is developing the e-commerce sector that will add further fuel to economic development plans. Different stakeholders define E-commerce in a variety of ways; however, in Saudi Arabia, e-commerce defines as an economic activity that is done wholly or partially through remote connectivity technology using an electronic medium to provide a product or a service (Ministry of commerce (MCI).

Increasing broadband and smartphones penetration rates, large social media penetration and the government's growing focus on e-commerce are key factors that are driving this shift toward and increase online buying in the country. Underpinned by a steady shift from offline shopping to online and mobile shopping, the Saudi e-

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.197

commerce market has experiencing significant growth and development over the past few years, where reached US$ 8.53 Billion in 2022 and it is expected to grow at compound annual growth rate (GAGR) of 20.87% to reach US$ 22.01 billion in 2027. However, there are challenges affect increasing the use of e-commerce; these include logistical challenges related to delivery schedules, costs, and merchandise handling. Where the e-commerce industry relies on an efficient supply chain represented in a sequence of logistics processes, which include the production of raw materials, manufacturing of finished goods, warehousing, inventory management, order fulfillment and last-mile delivery that represents the last step in supply chain. All the stages in the e-commerce supply chain are designed to support and fulfill the success of the last stage of the chain, the last mile. Therefore, this paper focuses on it to ensure the success of the entire process.

Related literature

The growth of the Internet, technology, and the growth of E-commerce in recent years has increased the demand for last-mile mail delivery, and many scholars agree that the most critical logistic process in supply chain is the last-mile delivery. Based on a recent review of the literature that was presented, "last-mile delivery" refers to the activities required for physical delivery to the destination chosen by the recipient (Olsson et al., 2022). Last-mile delivery can be defined as the last stretch of a business-to-customer (B2C) parcel delivery service where goods move from the order penetration point to the final consignee’s preferred destination point (Risher et al., 2020). While Jucha (2021) mentioned that last-mile logistics refers to that part of transit in supply chains, whereas goods are delivered from the last transit point to the final point or place of delivery. Thus, the last point of delivery for the e-commerce supply chain corresponds to the place of residence of the end consumer. As previously stated, the last mile is the most time-consuming and expensive stage of the delivery process, therefore, logistics services providers are always keen to raise the effectiveness of the process to keep pace with customers’ needs while maintaining cost efficiency. Bopage et al. (2019) suggested that the effectiveness of last mile delivery depends heavily on five key decisions. These decisions include facility location decision: number of distribution centers; inventory decision: inventory in each facility; inventory policy; transportation policy: number of vehicles, route planning, capacity of vehicles and scheduling; and distribution decision.

One of the major challenges in last mile delivery is the transportation and logistics of the goods. The delivery of goods to the end customer must be done in a timely and cost-effective manner, and this can be challenging due to various factors such as traffic congestion, road conditions, and unpredictable weather conditions. In addition, the delivery of goods to remote or rural areas can also pose a significant challenge, as these areas may not be well-connected by transportation networks, making it difficult to reach customers in a timely and cost-effective manner. Another major challenge in last mile delivery is the operational aspect of the delivery process. This includes managing the resources required for the delivery process, such as delivery vehicles, drivers, and delivery schedules. In addition, organizations must also manage the delivery process in a way that ensures that the goods are delivered to the end customer in a safe and secure manner. This can be challenging, particularly in cases where the delivery of goods involves multiple delivery locations or many deliveries in a short period of time. Finally, technological challenges also play a significant role in last mile delivery.

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.197

The use of technology has become increasingly important in managing the delivery process, and organizations must have access to the right tools and technologies to effectively manage the delivery process. This includes the use of GPS tracking, real-time monitoring, and automated delivery systems. However, organizations must also be able to effectively integrate these technologies into their existing systems to effectively Ray et al. (2020). According to Jucha et al. (2021), there are many challenges faced logistics providers regarding overcoming the last mile deliver. Such challenges include high costs of order fulfillment for high price sensitive customers. Strong competitive external pressure on free delivery services, increased customer expectations due to short delivery times, individually scheduled delivery times, ability to track and allocate specific shipments along with the ability to choose an alternative place to deliver shipments in addition to a large number of failed attempts to deliver or return products. The percentage of delivery failure ranges between 15% in the UAE region and 40% in Saudi Arabia (Wanganoo and Patil, 2020). Challenges fall behind the lack of routing network, resource planning, distances, third parties being involved in the distribution, several points of contacts, non-transparent supply chain, and lack of zip code/delivery addresses (Saber et al., 2022). Moreover, there is an internal weakness in the last mile companies, as their delivery models lack responsiveness, flexibility, and operation interactions.

Also, the cultural factors have a negative impact on the success of the process, where GCC and Middle East cultures prefer cash payment over online payment for security reasons, and when they guarantee that the product is in hand (Jamous et al., 2022). Last-mile delivery is a critical phase that delivers on the customer's promise when managed effectively; otherwise, it messes up all supply chain efficiency processes (Miko and Abbas, 2024). As consumers increasingly turn to online shopping, requirements such as on-time delivery and saving on delivery costs are of great importance. Retail and logistics companies are struggling to find strategies that provide a successful and fast last-mile delivery service that meets consumer preferences and expectations. Last mile delivery experience is an important factor to ensure customer satisfaction, which has six dimensions as shown in *Figure 1* cognitive experience, emotional experience, behavioral experience, sensorial experience, physical experience, and social experience (Olsson et al., 2022).

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.197

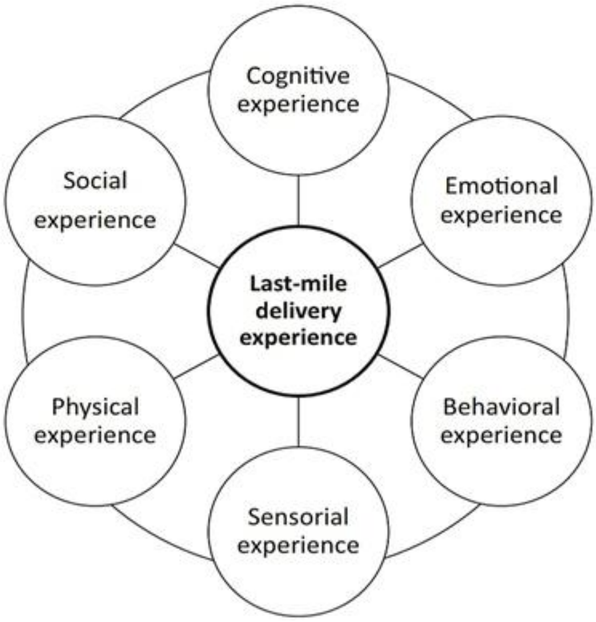

Figure 1. *Last-Mile Delivery Experience Framework: Consumer Experience Dimensions.*

There are many e-commerce delivery options, also known as "last mile delivery options," such as pick-up from the store and home delivery. According to research studies and analyses, a high percentage of customers prefer the traditional home delivery method. As per Zhou et al. (2020) the main factors that make the traditional home delivery service mostly preferable are: (1) social influence; (2) effort expectancy; (3) performance expectancy. The literature lacks a holistic view of the customer experience with last-mile delivery in Saudi Arabia. Florio et al. (2021) propose a machine learning framework that combines multiple algorithms to address the complex and dynamic nature of last-mile delivery operations. The framework consists of three main components: data preprocessing, model training, and model deployment. The data preprocessing component is responsible for collecting and preparing the relevant data, such as delivery time, route, and delivery cost. The model training component uses the processed data to train a machine learning model that predicts the optimal delivery routes and schedules. The model deployment component integrates the trained model into the delivery operations to optimize the delivery processes in real-time.

Since the last-mile delivery process has a significant impact on the overall logistics costs there have been many articles discussing ways and inventions to optimize it. One of these articles, Jucha (2021) discussed how artificial intelligence can affect and solve existing problems in last-mile delivery. The ways in which artificial intelligence can aid in the resolution of challenges in last-mile delivery. Vehicle Routing Optimization (VRO), for example, is represented by many AI applications with the goal of designing the lowest-cost routes to meet customer demand. Another example is the Last Mile Platform (LaMP), which uses AI to automate courier routes based on a variety of factors. And the last example he mentioned is autonomous things, which are physical devices that use artificial intelligence to automate various tasks. Robots, drones, and various autonomous vehicles are examples of such autonomous devices; these devices can deliver orders to difficult-to-reach locations. While in other article Huang et al. (2022) implement an Adaptive Large Neighborhood Search (ALNS) algorithm to optimize the last mile delivery by focusing on the demand of market distribution

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.197

methods. Moreover, demonstrate the effectiveness of this approach. However, this approach cannot guarantee that the solution is the best possible solution. Also take into consideration that the algorithm has difficulties considering multiple criteria, as well as considering dynamic changes to increase the accuracy of the solution. Bayliss et al. (2023) designed and implemented a framework of a multi-modal and variable-echelon delivery system that utilizes multiple modes of transportation and has the ability to adapt to change in demand. However, this system requires a high level of coordination and collaboration between various stakeholders, such as transportation providers, delivery companies, and costumers. The key conclusions agreed upon by all researchers in their articles were customer satisfaction and cost savings through optimizing the entire delivery process.

Problem statement

The last-mile delivery in Saudi Arabia has been increasing over the recent years and so, as it's increased, the operation costs increased to meet the demands. On the other hand, logistics companies are suffering to meet the growing demand on-time and fulfill delivery deadlines. This directly negatively affects the customer experience and erosion trust between the company and the customer. Hence, this is a major challenge for logistics companies to meet customers demand on-time while maintaining cost efficiency. According to market statistics the last-mile delivery account for more than 50% of the total shipping cost by Allied Market Research. In addition, based on a survey study conducted by the Communications and Information Technology Commission (CITC) in 2021, 17% of customers mentioned that they encountered a problem receiving orders, which is delays in receiving orders, i.e., failure to fulfill delivery deadlines. Therefore, to confirm these findings and to quantify the current scale and impact of the problem, we conducted another survey targets the residents of Saudi Arabia those who have at least one experience with logistics companies. The Sample size was calculated in line with the literature review regarding similar previous customer satisfaction surveys.

The sample size of the survey was a total of 385 responses. The sample size is calculated based on a 50% population proportion, a confidence level of 95%, and with a 5% margin of error. Initially, a total of 794 responses were received, but only 735 responses were fully completed, i.e., more than required based on the calculations .The results showed explicitly that the 97% of participants preferred home delivery, this is evidence that the demand for last-mile delivery is high. Over half of those surveyed (66%) indicated that the most important problem they encountered is delays in receiving orders, i.e., failure to fulfill delivery deadlines. That is, they felt let down by the company in its commitment to on-time delivery. Overall, less than a third of those who responded (32%) indicated that not at all satisfied about their last whole experience, while 6% slightly satisfied. The results of the survey contributed to exploring the factors due to which customers select a specific logistics company, delivery time/ speed is considered to be the most important factor for 92% of participants, and previous customers' experiences are important for 23% of participants. This reflects the importance of the customer experience in raising customer loyalty and is a key indicator that the last mile delivery experience mediates the relationship between the customer's perception of the online shopping experience and customer satisfaction. This work aims to optimize the last-mile delivery for one of the logistics companies in Saudi Arabia by:

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.197

(1) Reducing costs related to last-mile delivery; (2) Upgrading the quality of service by speeding up the delivery process; and (3) Improving customers' experience.

Materials and Methods

Mathematical model design

The model was designed as Capacitated Vehicle Routing Problem (CVRP) that involves finding the most efficient way to deliver goods from a central depot to a set of customers using a fleet of vehicles that have limited capacity. the goal is to minimize the total distance traveled by all the vehicles while ensuring that each customer's demand is satisfied, and the capacity of each vehicle is not exceeded. Several factors need to be taken into consideration in building the model shows in the *Figure 2*, include distance, demand, and vehicle capacity. The objective of the model is to minimize the total travel distance. To obtain the following outputs: number of vehicles, total distance, and vehicle route.

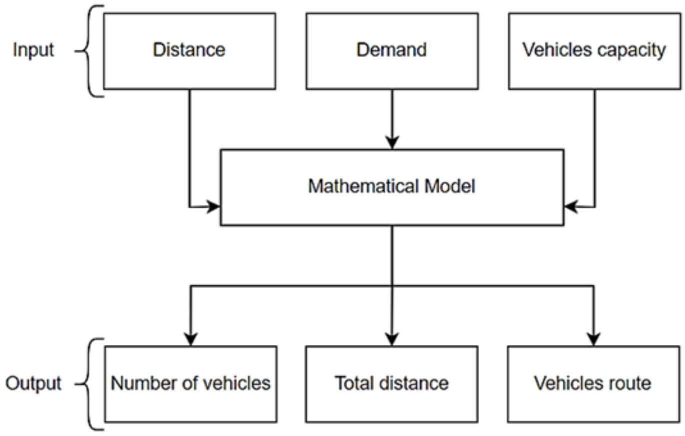

Figure 2. *Flowchart of Optimization Model by LINGO.*

Sets: C is the set of nodes (customer locations), including a depot (warehouse).
Parameters: Q_i represent the amount required at node i, $\forall\ i\ \in\ C$; $VCAP$ is the capacity of a vehicle; U_i represent the accumulated deliveries at node i, $\forall\ i\ \in C$; $DIST_{ij}$ represent the distance from node i to node j $\forall\ i,j\ \in\ C$, there are n nodes $(\ depot\ = 1)$.
Decision variables: x_{ij} is a binary variable that takes the value 1 if a vehicle travels from node i to node j, and 0 otherwise, $\forall\ i,j\ \in\ C$.
Objective: Minimize the total travel distance (Eq. (1):

$$Min\ Z = \sum_{i=1}^{n}\sum_{j=1}^{n} DIST_{ij}x_{ij} \qquad \text{Eq. (1)}$$

Constraints:
A vehicle does not travel inside itself:

$$x_{ij} = 0\ \forall\ i \in C \qquad \text{Eq. (2)}$$

Each node (except the depot) must be entered and left by exactly one vehicle:

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.197

$\sum_{i=1}^{n} x_{ij} = 1 \; \forall \; j \epsilon \, C, j \neq Depot$ Eq. (3)

$\sum_{j=1}^{n} x_{ij} = 1 \; \forall \; i \, \epsilon \, C, i \neq Depot$ Eq. (4)

The depot node must be left by the same number of vehicles as it is entered:
$\sum_{j=1}^{n} x_{1j} = \sum_{i=1}^{n} x_{i1}$ Eq. (5)

The total demand served by a vehicle must not exceed its capacity:
$\sum_{j=1}^{n} Q_j \, x_{ij} \; \leq VCAP \; \forall \; i \, \epsilon \, C$ Eq. (6)

Subtour elimination constraints to prevent subtours (cycles) in the solution:
$U_i - U_j + Q_i x_{ij} \; \leq VCAP - Q_j \; \forall \; i,j \, \epsilon \, C, i \neq Depot, j \neq Depot, i \neq j$

Eq. (7)

$U_i \geq Q_i \; \forall \; i \, \epsilon \, C$ Eq. (8)

The decision variables must be binary:
$x_{ij} \, \epsilon \, \{ 0, 1\} \; \forall \; i,j \, \epsilon \, C$ Eq. (9)

The minimum number of vehicles required, fractional and rounded:
$\text{VEHCLF} = \sum_{i=2}^{n} \frac{Q_i}{VCAP} \; , \forall \; i \, \epsilon \, C$ Eq. (10)

$\text{VEHCLR} = \text{Ceil (VEHCLF)}$ Eq. (11)

There must be enough vehicles leaving the depot:
$\sum_{j=2}^{n} x_{1j} \; \geq VEHCLR$ Eq. (12)

The given model is a mixed integer programming formulation for the CVRP, which is a classic optimization problem in the field of operations research. The goal of the CVRP is to find an optimal set of routes for a fleet of vehicles to serve a set of customers, where each customer has a demand for a certain amount of goods. The model defines several sets, including the set of customers (1 to 61). The set of amounts required at each customer (Q), the set of accumulated deliveries at each customer (U), the set of distances between customer locations (DIST), and the set of binary decision variables (X) that are equal to 1 if a vehicle travels from node I to node J, and 0 otherwise. The objective of the model is to minimize the total travel distance, which is calculated as the sum of the distances between each pair of nodes multiplied by the corresponding binary decision variable. The model includes several constraints that ensure that the vehicles visit all the customer locations and do not exceed their capacity. These constraints include ensuring that each customer locations are visited by exactly one vehicle, that the accumulated deliveries at each node do not exceed the vehicle

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.197

capacity, and that the vehicles leave each location after servicing it. The model also includes several bounds and logical constraints to ensure that the accumulated deliveries at each location are calculated correctly and that the binary decision variables are properly defined. Finally, the model calculates the minimum number of vehicles required to serve all the customers and ensures that enough vehicles are sent out of the depot to meet this requirement.

Python programming

Python is a popular programming language that is widely used for solving optimization problems, including CVRP. It plays a significant role in CVRP by providing a flexible and efficient platform for modeling and solving complex optimization problems. There are several libraries and packages available in Python that can be used to model and solve CVRP. In addition, it enables users to build and solve sophisticated optimization models efficiently, visualize the results, and integrate with other tools and platforms. To solve the problem using Python programming, the flowchart shown in Figure 3 illustrates the required inputs, including customer ID, location, demand, number of vehicles, and vehicle capacity. The model optimizes the vehicle route sequence and calculates the total distance traveled.

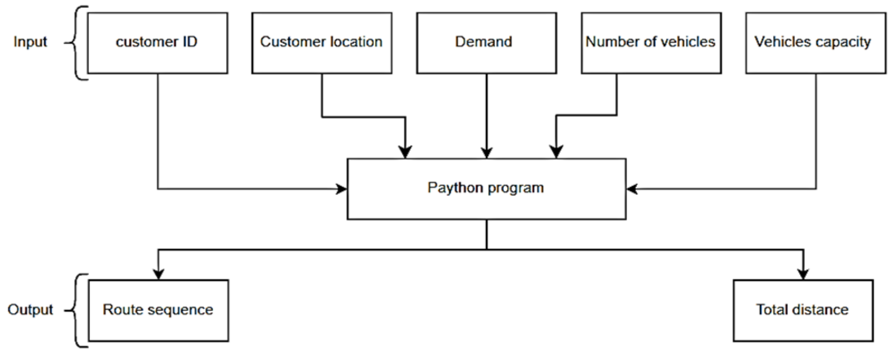

Figure 3. *Flowchart of Optimization Model by Python Programming.*

Program codes

Data Model Function: [a] The ‘create_data_model ()’ function is to return a dictionary ‘data’ containing the following keys: (1) ‘distance_matrix’: a 2D array of distances between all pairs of locations, including the depot and the customers. (2) ‘demands’: a 1D array of demands for each customer. (3) ‘vehicle_capacities’: the capacity of each vehicle. [b] ‘num_vehicles’: the number of vehicles available: (1) ‘depot’: the index of the depot location.

Index Manager: The ‘pywrapcp.RoutingIndexManager’ class is used to manage the indices of the locations and vehicles in the routing model. It takes as input the number of locations, the number of vehicles, and the index of the depot.

Routing Model: The ‘pywrapcp.RoutingModel’ class is used to define the routing model. It takes as input the ‘Routing Index Manager’ object and sets up the routing model with the appropriate number of vehicles.

Distance Callback: The ‘distance_callback’ function is a callback that is used by the routing model to compute the distance between two locations. It takes as input the indices of the starting and ending locations and returns the distance between them.

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.197

Demand Callback: The ‘demand_ callback’ function is a callback that is used by the routing model to retrieve the demand of a location. It takes as input the index of the location and returns its demand.

Capacity Constraint: The ‘routing .Add Dimension With Vehicle Capacity’ function is used to add a capacity dimension to the routing model. It takes as input the demand callback, the lower bound (0), the upper bound (the vehicle capacities), a boolean indicating whether to enforce the capacity constraint at every step of the route, and a name for the dimension.

Search Parameters: The ‘pywrapcp Default Routing Search Parameters’ class is used to set the search parameters for the routing model. In this script, the search strategy is set to ‘PATH_CHEAPEST_ARC’, which starts by selecting the cheapest arc (shortest path) between two nodes and builds a path from there. The local search metaheuristic is set to ‘GUIDED_LOCAL_SEARCH’, which performs a search guided by a heuristic function. The time limit is set to a large number (900 seconds) to ensure that the search does not terminate prematurely.

Solution Printing: The ‘print_solution’ function takes as input the data, manager, routing, and solution objects, and prints out information about the solution. It first prints the objective value (total distance traveled), and then iterates over each vehicle and prints out its route, including the load at each step. Finally, it prints out the total distance and load for all routes.

Main Function: The ‘main’ function is the entry point of the script. It creates the data model, sets up the routing model, adds the capacity constraint, sets the search parameters, and solves the problem using the ‘SolveWithParameters’ function. If a solution is found, it calls the ‘print_solution’ function to print out the solution details.

Results and Discussion

This section presented the results of both mathematical model and python program that were developed to optimize the delivery routes for a fleet of delivery vehicles. The objective of the analysis was to minimize the total distance traveled by the vehicles, while ensuring that all customer demand was met, and the capacity of each vehicle was not exceeded. *Table 1* presents a summary of the key findings from the analysis of the Linear Programming (LP) model, including the minimum number of vehicles should be used, the route for each vehicle, demand for each route, the total distance traveled in Km, total travel time in hours and the total fuel cost in SAR. The results of the analysis of the mathematical model indicate that the feasible solution that resulted from running time is about 6 hours and 53 minutes involves the use of 5 delivery vehicles, with each vehicle following a specific route to deliver goods to customers. As shown in *Table 2*, the total distance traveled by the vehicles was reduced by 17.21 % compared to the current delivery system, resulting in significant cost savings for the company of 29.27 SAR, and significant time saving by 17.36%. These savings are significant and suggest that the LP model could be a valuable tool for optimizing the logistics company's delivery routes and improving efficiency. By using the LP model, the logistics company could potentially reduce costs, save time, and improve customer satisfaction by delivering orders more quickly and accurately.

Table 1. *Route by Linear Programming Model.*

Vehicle	Route	Demand	Total distance (km)	Time (hours)	Total Fuel Cost (SAR)

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.197

1	1-3-27-42-61-49-10-20-48-26-7-53-39-44-1	39	82.4	2.20	26.94
2	1-13-17-51-25-52-45-60-33-34-1	30	67	1.66	21.91
3	1-16-28-6-12-56-4-29-9-22-21-14-35-32-1	39	110.6	2.96	36.17
4	1-23-46-57-31-19-37-30-58-8-38-43-47-24-1	39	80	2.48	26.16
5	1-59-36-40-55-11-41-50-54-18-15-5-1	33	90.5	2.27	29.59
	Total	180	430.5	11.57	140.77

***Table 2**. Comparison between Actual route and LP model.*

Category	Actual route	Route by LP Model	Deviation	Percentage
Total Distance (KM)	520	430.5	89.5	17.21%
Total Time (hours)	14	11.57	2.43	17.36%
Total Fuel Cost (SAR)	170.04	140.77	29.27	17.21%

However, there are limitations when using LINGO which occur in calculation processing is running hours (6 hours and 53 minutes) because of the complexity of the model. Based on the characteristic of LP model that increasing the size of the problem will increase the level of difficulty in computing and problem solving. As a result, we decided to use a Python program that was faster and more effective in addressing the higher level of complexity. *Table 3* presents a summary of the key findings from the analysis of python program as LP summery, which including the minimum number of vehicles should be used, the route for each vehicle starting from depot (node 0), demand for each route, the total distance traveled in Km, total travel time in hours and the total fuel cost in SAR. Based on the results, we can see in *Table 4* that the total distance traveled by the logistics company's vehicles was 520 km, while the python program suggested a route with a total distance of 358 km, resulting in a saving of 162 km or 31.15%. Similarly, the actual delivery time was 14 hours, while the python program suggested a delivery time of 9 hours, resulting in a saving of 5 hours or 33.82%. The total travel cost for the actual route was 170.04 SAR, while the python program suggested a fuel cost of 117.07 SAR, resulting in a saving of 52.97 or 31.15%.

***Table 3**. Route by Python program.*

Vehicle	Route	Demand	Total distance (km)	Time (hours)	Total Fuel Cost (SAR)
1	0-4-27-3-11-55-28-8-37-7-57-20-21-58-0	39	102	2.38	33.35
2	0-2-26-12-54-10-39-6-35-16-38-52-43-0	36	75	1.79	24.53
3	0-1-50-9-31-19-48-41-60-34-13-25-47-40-0	39	63	1.82	20.60
4	0-15-14-33-51-44-59-32-53-17-0	27	54	1	17.66
5	0-22-45-24-56-18-36-46-42-29-5-30-23-49-0	39	64	1.8	20.93
	Total	180	358	9	117.07

***Table 4**. Comparison between Actual route and Python Program.*

Category	Actual route	Route by LP Model	Deviation	Percentage
Total Distance (KM)	520	358	162	31.15%
Total Time (hours)	14.00	9	5	33.82%
Total Fuel Cost (SAR)	170.04	117.07	52.97	31.15%

The results of the python program seem better than the results of LP model as shown in *Figure 4*. However, both of solutions considered as feasible solution and not the optimal, because the complexity of the problem the running of both methods will takes long time to reach the optimal solution, however, the python program took only 15 minutes to generate the solution which is less than LP model. In addition, one of the advantages of using Python programming is the ability to visualize results, as illustrated in *Figure 5* that shows the route of one of vehicles. By the end, the results of the analysis demonstrate that implementing strategies and technologies to optimize the delivery process can have a significant impact on the efficiency and reliability of operations. By reducing delivery times, optimizing delivery routes, and improving the delivery experience for customers, we were able to improve the overall quality of the delivery process and reduce fuel costs. These findings provide valuable insights for future supply chain management strategies and initiatives.

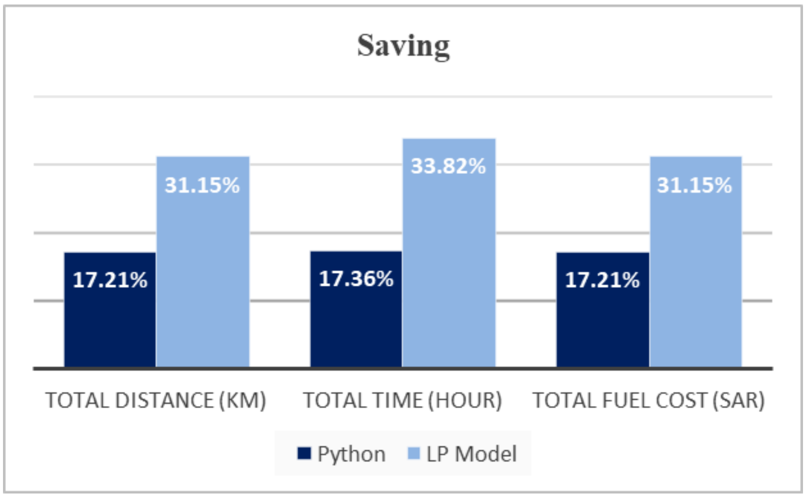

Figure 4. *Comparison between LP model and Python.*

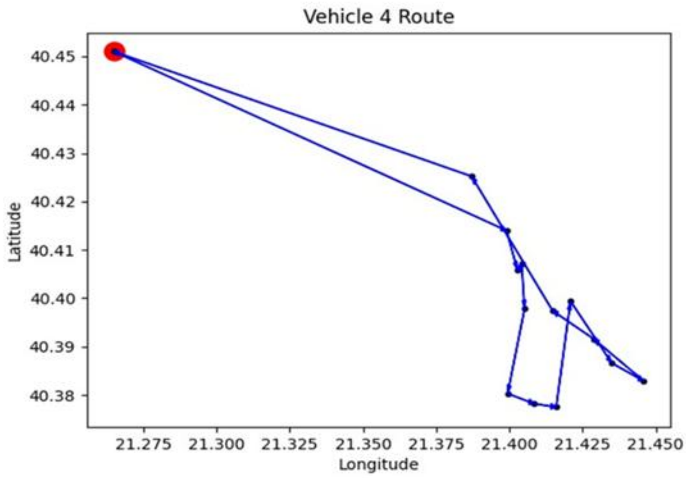

Figure 5. *Route of Vehicle 4.*

Conclusion

In this study we have successfully achieved the following: Firstly, the survey results revealed that the last-mile delivery process in Saudi Arabia was facing significant challenges, including delays, high transportation costs, and inefficient route planning. Secondly, we analyzed the current state of logistics company in Taif city and found that there was room for improvement in terms of optimizing the last-mile delivery process. To overcome these challenges, we proposed a mathematical model and Python programming to optimize the route planning process and decrease the distance traveled by delivery vehicles. By implementing these solutions, we were able to find feasible

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.197

solutions to the challenges faced by logistics companies, including optimizing the delivery routes and reducing transportation costs. We hope that our findings will be helpful for the logistics companies and enhance their competitiveness and meet the growing demand for fast and reliable last-mile delivery services.

In recommendation, it is considered that: (1) Adopt automated route planning and scheduling tools: Our study found that automated route planning and scheduling tools can significantly improve delivery efficiency and reduce transportation costs. We recommend that package delivery companies adopt these tools to optimize delivery routes and streamline the delivery process. (2) Conduct ongoing evaluation and optimization of delivery processes: Our study highlights the importance of ongoing evaluation and optimization of delivery processes to ensure continuous improvement. We recommend that package delivery companies conduct regular evaluations of their delivery processes and implement changes based on feedback and data analysis. In conclusion, the results of the analysis indicate that an optimized delivery system can lead to significant cost savings for the company. However, it is important to consider the limitations of the analysis and to conduct further research to fully understand the implications of the results. Future research could focus on incorporating additional factors, such as delivery time windows and customer preferences, into the model to further optimize the delivery system.

Acknowledgement

This research is self-funded.

Conflict of interest

The authors confirm that there is no conflict of interest involve with any parties in this research study.

REFERENCES

[1] Bayliss, C., Bektaş, T., Tjon-Soei-Len, V., Rohner, R. (2023): Designing a multi-modal and variable-echelon delivery system for last-mile logistics. – European Journal of Operational Research 307(2): 645-662.

[2] Bopage, G., Nanayakkara, J., Vidanagamachchi, K. (2019): A strategic model to improve the last mile delivery performance in e-commerce parcel delivery. – In Proceedings of the International Conference on Industrial Engineering and Operations Management 2p.

[3] Florio, A., Da Costa, P., Özarik, S.S. (2021): A machine learning framework for last-mile delivery optimization. – Technical Proceeding of the 2021 Last Mile Routing Research Challenge 20p.

[4] Huang, Q.L., Wang, W.J., Liang, X.J., Xu, L., Niu, X.Y., Yang, X.Y. (2022): Last-mile delivery optimization considering the demand of market distribution methods: A case studies using Adaptive Large Neighborhood Search algorithm. – Advances in Production Engineering & Management 17(3): 350-366.

[5] Jamous, R., Kerbache, L., Al Omari, A. (2022): Bridging the parcel delivery last mile gap in qatar: Challenges and enhancements. – IFAC-PapersOnLine 55(10): 822-829.

[6] Jucha, P. (2021): Use of artificial intelligence in last mile delivery. – In SHS Web of Conferences, EDP Sciences 92: 9p.

[7] Miko, N.U., Abbas, U. (2024): Determinants of efficient last-mile delivery: evidence from health facilities and Kaduna Health Supplies Management Agency. – Journal of Humanitarian Logistics and Supply Chain Management 14(1): 4-16.
[8] Olsson, J., Hellström, D., Vakulenko, Y. (2022): Customer experience dimensions in last-mile delivery: an empirical study on unattended home delivery. – International Journal of Physical Distribution & Logistics Management 53(2): 184-205.
[9] Ray, P., Duraipandian, R.G.V., Harsh, H.O. (2020): Exploration of the challenges in the last mile delivery in supply chain. – Test Engineering Management 83: 14524-14532.
[10] Risher, J.J., Harrison, D.E., LeMay, S.A. (2020): Last mile non-delivery: consumer investment in last mile infrastructure. – Journal of Marketing Theory and Practice 28(4): 484-496.
[11] Saber, D., Alharthi, L., Alghamdi, D., Alharthi, S., Alsufyani, L. (2022): Improvement in Taif Roses' Perfume Manufacturing Process by Using Work Study Methods: A Case Study. – Asian Journal of Applied Science and Technology (AJAST) 6(4): 66-80.
[12] Vrhovac, V., Vasić, S., Milisavljević, S., Dudić, B., Štarchoň, P., Žižakov, M. (2023): Measuring E-commerce user experience in the last-mile delivery. – Mathematics 11(6): 21p.
[13] Wanganoo, L., Patil, A. (2020): Preparing for the smart cities: IoT enabled last-mile delivery. – In 2020 Advances in Science and Engineering Technology International Conferences (ASET), IEEE 6p.
[14] Zhou, M., Zhao, L., Kong, N., Campy, K.S., Xu, G., Zhu, G., Cao, X., Wang, S. (2020): Understanding consumers' behavior to adopt self-service parcel services for last-mile delivery. – Journal of Retailing and Consumer Services 52: 12p.

eISSN: 2716-6341
https://doi.org/10.55197/qjoest.v6i1.197