Enhancing logistics by optimizing operational efficiency through simulation for 'We-Doo'

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Abstract — **The project aims at enhancing logistics by optimizing operational efficiency through simulation for 'We-Doo', a recent startup company. The primary objective of this project is to recommend an optimal delivery warehouse location in the commuter township map with the lowest cost base. The methodology for this project involves developing a simulation model to evaluate candidate warehouse locations through heuristics by incorporating factors such as customer location, route length, and operational cost of the delivery. The workload data is generated by using the seed number 8268 to simulate daily delivery operations, considering parameters such as length of delivery route, count of parcels delivered, and working time of the driver. Through thorough investigation, analysis, and simulation runs for multiple days, valuable insights are obtained regarding the performance of different warehouse locations and their respective cost base. Evaluation of the simulation involves histograms for visualisation and statistical significance is investigated by using ANOVA. The sample size was increased to 50 days in the longer simulation run to discover valuable insights for strategic decision making, which highlight the significance of strategic location selection in enhancing operational efficiency and customer satisfaction.**

Keywords—Optimization, Heuristics, Linear Programming, Simulation, Last-mile delivery, Warehouse location, Operational efficiency, ANOVA.

I. INTRODUCTION

In the dynamically evolving domain of e-commerce and logistics, efficient delivery system has emerged as the most important contributing factor for ensuring customer satisfaction and maintaining minimum operational efficiency for the logistic companies. By addressing this challenge, 'We-Doo', a recent promising startup, aims to transform operational delivery systems by optimizing delivery centre locations in commuter township locations with the lowest cost base, thereby enhancing the robustness and reliability of parcel delivery services for the company. 'We-Doo' recognized the crucial aspect of the supply chain and management which aligned with the company's ethics in the concept of improving customer convenience through reliability and sustainability for the end-to-end delivery process while simultaneously resolving the logistical operations.

The fundamental principle of 'We-Doo's' business model is to establish a local optimal delivery warehouse within the commuter township location, where packages from other outsourced logistics companies are stored during the day. During subsequent evenings, employed drivers use electric cargo bikes to distribute the parcels to the end customer location in the township. By decentralizing the delivery process and bringing it closer to the end customers, 'We-Doo' aims to modernize logistic operations, reduce the time of delivery to the end customer, and ensure a personalized, safe, and secure delivery experience for subscribed customers paying monthly instalments.

Effective identification of warehouses is the most significant aspect for this project as these strategically located delivery warehouses determine the shortest delivery route, thereby reducing fuel consumption and carbon emission for the electric bikes used by delivery personnels, thereby contributing to environmental sustainability. Moreover, the optimal delivery warehouse location allows 'We-Doo' to capitalize on economies of scale by merging the count of parcels and shortest delivery route. Through careful identification of optimal warehouse location, the company could improve its distribution network system by integrating with local infrastructure in the township to improve overall service reliability.

The solution of 'We-Doo's' innovative plan depends on the strategic selection of optimal delivery centre location within each township. The decision requires critical investigation of various contributing factors such as length of delivery route, count of parcels delivered, and working time of the driver. The main objective of this project is to determine the most suitable delivery centre locations across multiple commuter townships through simulation and to evaluate the potential warehouse locations through quantitative performance metrics and qualitative factors.

A. Input parameters

The project incorporates the given parameters for the development of the simulation model. The values assigned to the input parameters have been systematically generated by assigning the last four digits from the author's student identification number which is '22228268' to ensure reproducibility, consistency, and integrity in the project analysis. The seed number '8268' is critical for the development of the simulated environment as it has influence over the project analysis and result. The following are the key input parameters and their respective values:
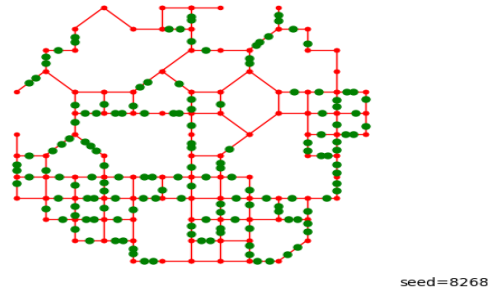

Figure 1: x22228268_C17. Sample street map with customer locations (green) generated from seed number 8268.

1) Map of township (M):

The above encoded graph consists of vertices which represent the intersections. The edges present in the graph represent road segments. The vertices in the graph are the pairs of (x, y)-coordinates and the edges are encoded as pairs of vertices.

2) Customers delivery addresses (C):

The above graph represents the customer delivery targets across the map in the plane. These are the potential customer locations in the township.

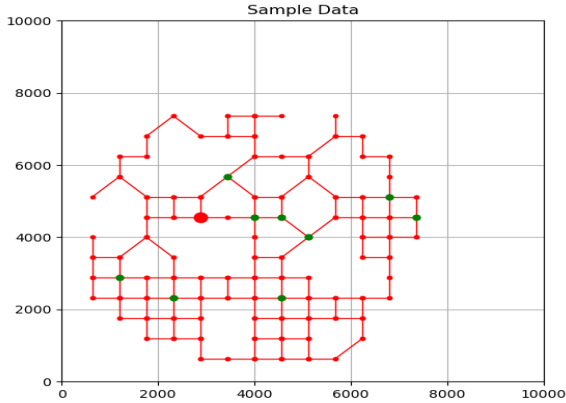### 3) Warehouse Locations (W):

Figure 2: x22228268_C52. Ten warehouse locations in the town generated from seed number 8268.

The above ten warehouse locations represent the set of potential development sites for establishing new delivery centres within the township which are generated on the map using seed number '8268'.

4) Average Number of Parcels (p):

The mean count of parcels which are expected to be delivered to the end customer each day has been defined as a constant value of 0.15, which indicates the volume of anticipated parcel per customer each day and the overall demand for operational services. This input parameter determines whether the workload distribution is normal or expovariate.

B. Simulation constraints

The simulation generated must incorporate time handling and best base cost to enhance the project outcome. To address this, the following simulation constraints are provided:

- The maximum range of the cargo bike is given to be 40 km.
- The average driving speed of the cargo bike is given to be 15km/h.
- The time for handing over the parcel to the customer is given in an expovariate distribution, the cumulative preparation time for each parcel is assumed to be 50 seconds for each parcel.
- The time taken for end day procedures is given to be 10 minutes or 600 seconds.
- The operational cost which includes maintenance of the electric cargo bike is given to be 8 cents for each kilometre travelled.
- The delivery personnel are paid at the rate of 30 euros for each hour with a constraint of 60 euro for each working day.

A cost function was formulated to capture the daily cost incurred by the warehouse which is given below:

Let the daily driver wage in Euros be **D**.
Let the daily distance travelled on bike by delivery personnel be **d**.
Let the daily working time for parcel delivery personnel be **t**.
Let the daily bike operational cost be **B**.
Then,

$$D = min(60, t \times 30)$$

$$B = \frac{8}{100} \times d$$

$$W = D + B$$

Here, **W** represents the cost function, which has aided in determining the best warehouse location based on minimal mean warehouse cost over the entire simulation period among different warehouses.

II. LITERATURE REVIEW

In the vast domain of delivery optimization, continuous development and research studies have contributed valuable insights in the sphere of delivery path optimization, customer demand forecasting, and best cost base location analysis. [1] had conducted a comprehensive investigation in the dynamic vehicle routing problem which enhanced the contribution of better route planning for best delivery operations. [2] applied the application of unsupervised machine learning approaches to forecast customer demand and delivery path optimization, displaying the untapped potential for predictive analytics for the enhancement of logistic optimisation. [3] contributed a review of location-allocation based models for facility planning which displayed insights into abstract methodologies for identifying potential warehouse locations. Similarly, [11] discussed different algorithms for location-based problems which are substantial to the identification of optimal delivery warehouse locations.

For evaluation of complex routes for key decision making in logistics and supply chain management, [4] and [5] provided various simulation methods such as discrete-event simulation and other optimization algorithms which served as the basis for the development of this simulation model to evaluate warehouse locations. In the sphere of supply chain management, [6] and [7] provided useful guidance in supply chain strategy, planning, operations, and overall management whilst [8] provided information on statistical design of routes and analysis of models. Additionally, research by [10] explored the ripple effect in supply chains, displaying the trade-offs between efficiency, resilience, and disruptions management. Furthermore, handbook [9] helped in research on applied optimization methodologies in the manufacturing systems.

Traditional optimisation algorithms like ant colony optimization (ACO) are useful but has the disadvantage of local optima traps. Recently, research proposed augmenting ACO with particle swarm optimization (PSO) algorithm [13]. This fusion improved global path exploration and balanced between flexibility and stability by incorporating other contributing factors such as recharge cost and total time travelled. [17] research proposed a cluster-based method for delivery optimization which focused on optimizing vehicle delivery routing based on customer time windows which

demonstrated a 22% reduction in overall delivery costs and a decrease in the count of vehicles and delayed delivery parcels. [18] employed the traveling salesman's algorithm to optimize route length which resulted in a decrease in delivery time and route length. The proposed solution displayed the transformative potential of software to achieve customer satisfaction. By considering simultaneous first pickup and last delivery [15] investigated the optimization of delivery operations in logistics for minimum transportation cost and delivery routes which demonstrated significant cost reductions and improved operation efficiency. [19] redesigned the optimisation as a quantum alternating operator ansatz (QAOA) in the quantum approximate optimization algorithm by developing mixers as constraints which confined the search space to feasible solutions.

The shortest delivery route is critical for urban logistics for the normalization of epidemic prevention measures [12]. The study had designed a more efficient delivery route using multi-task logistic unmanned ground vehicles (UGVs). The role of delivery robots in enhancing shortest delivery route during the pandemic highlighted the use of robots which offered a feasible solution. [14] reviewed the operational techniques of delivery robots in three-dimensional space operations. It emphasized the environmental conditions required for the widespread adoption of electric autonomous vehicles and robots. The transformative potential of delivery robots for logistics requires certain system considerations to overcome existing limitations such as battery problems. [16] introduced the NSGA-II optimization algorithm for urban transportation to determine the optimal parameters for drivetrain components and transmission systems. The research explores input parameters such as electric motor power, battery capacity, transmission ratios, and shift speed schedules. The framework reduced energy consumption, drivetrain costs, and acceleration time by combining a forward-facing vehicle, scalable component models, and a control algorithm.

III. METHODOLOGY

The sequence of processes followed in this project included numerous steps for the fabrication of synthetic data and validation of the simulation model for optimizing delivery operations for 'We-Doo' by aiding in the process of best warehouse location's selection. The course of steps followed in this project are mentioned as below:

A. Generation of data.

The first step involves generating demographic data which includes map of the township, customer locations, and candidate warehouse locations based on the author's seed number **8268**, the last four digits of the student id. To generate the data, the generateData() function has been utilized.

B. The Simulation Model Development

Appropriate classes for different elements in the simulation such as **Customer**, **Driver**, **Parcel**, **Delivery Centre** were developed. A **recorder** class was deployed which makes use of the mentioned classes to capture datapoints. The recorder class consists of utilities for statistical visualization which aided in validation of the model.

The simulation process used algorithms like the A* and Floyd-Warshall to find the shortest path between different locations on the map. Later, iterative integer programming was used to generate the roundtrip for the driver personnel.

Another strategy to generate the roundtrip using Heuristic function was developed to fasten the process of simulation, because finding the optimal solution for roundtrips is not always feasible due to time constraints.

For smaller simulations the author has used iterative integer programming approach to generate roundtrips daily drivers corresponding to a particular warehouse location whereas in longer simulations heuristic approach was preferred to save computational time.
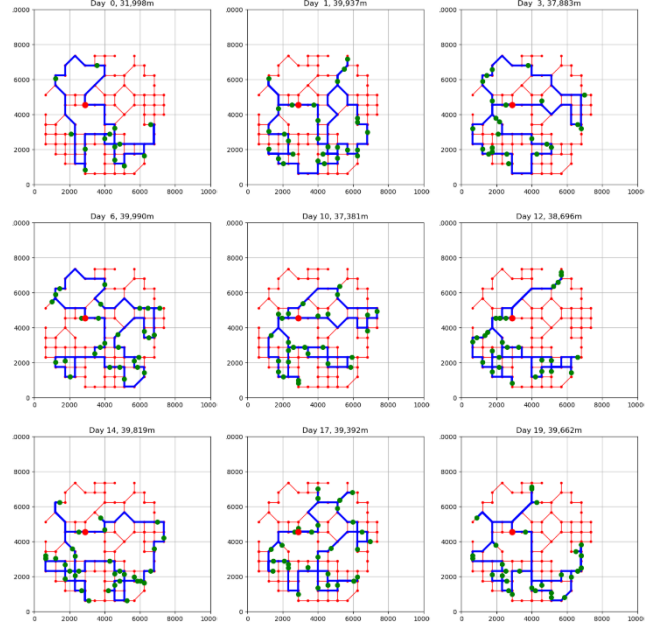
C. Simulation Runs

Figure 3: x22228268_C55. Simulation runs for 20 days.

The optimal warehouse was finalized after running the simulation on the optimal warehouses using heuristic approach and comparing them based on the cost function defined in section I.
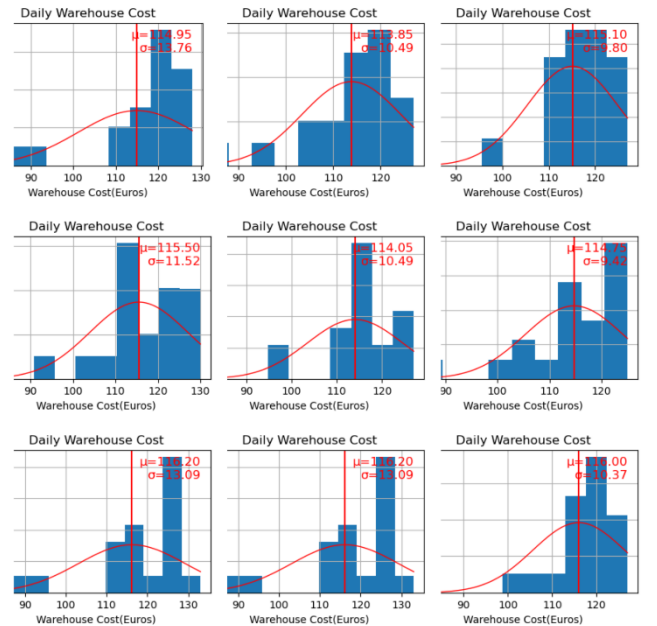

Figure 4: x22228268_1C94. Different warehouse location cost.

The author ran a relatively longer simulation (50 days) with ten different seeds on the chosen best warehouse location (2880,4560) and combined the results ensuring that data is consistent with the smaller simulation run conducted for 20 days and further used the results to verify statistical significance.

IV. RESULTS AND INTEREPRETATION

The conducted project generated key insights for 'We-Doo' which contributed to the selection of the optimal delivery warehouse location, and the shortest delivery route. The operational cost of the selected warehouse location was calculated by the author by considering the driver's daily wage, bike operational cost and the warehouse operational cost.

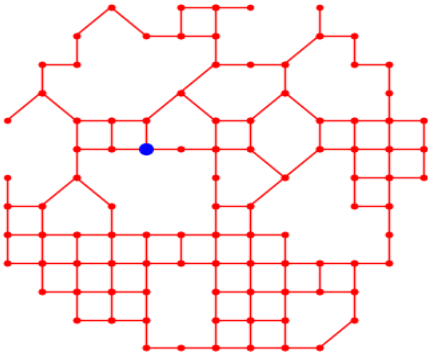### A. Optimal Delivery Center Location

Figure 5: x22228268_C55. Optimal delivery location. (2880,4560)

According to the simulation results, the optimal delivery warehouse location is chosen to be [2880,4560]. This warehouse location showcased exceeding performance in terms of optimizing the length of delivery route, parcel distribution, and reduced operational costs in comparison to other candidate warehouse locations generated by the author's seed number.

B. Interpretation of Results

The simulation run for both 20 days and 50 days revealed valuable information regarding the trends and patterns incurred during delivery operations. Therefore, the project highlighted the use of simulation and optimisation for the delivery of more efficient logistic services. The analysis of the shortest delivery path, count of parcels, and driver's daily working time discovered strategic information into the operational problems and future opportunities for the company.
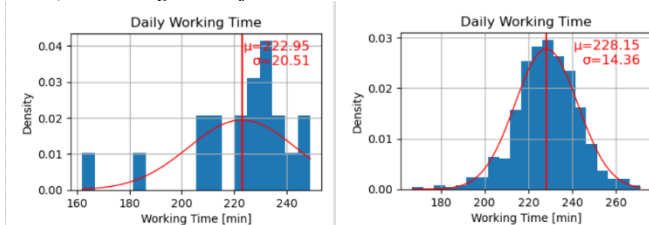
1) Working time of driver

Figure 6: x22228268_C59&C87. Daily working time of driver.

The above plot demonstrates the working time of the driving personnel. The average working time of the driver is 228.15 minutes which is 3 hours and 48 minutes with a variance of approximately 15 minutes.
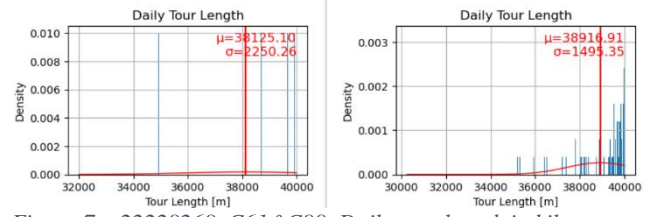
2) Daily tour length

Figure 7: x22228268_C61&C88. Daily tour length in kilometers.

The optimal tour length for the selected warehouse location was measured up to be 38,916.91 kilometers with a variance of approximately 2000 kilometers.
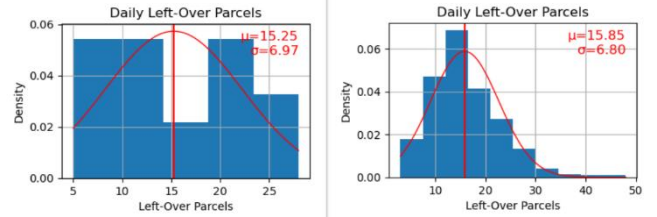
3) Leftover parcels

Figure 8: x22228268_C63&C89. Daily leftover parcels count.

The unreceived parcels which could not be delivered to the customer were calculated to be approximately 15 parcels with a variance of 6 parcels.

4) Daily delay incurred in parcel delivery

Simulation	**50 days**		Simulation	**20 days**	
Delivery (Day)	Delay (minutes)	Parcels (11191)	Delivery (Day)	Delay (minutes)	Parcels (11191)
Day 0	6126	54.7%	Day 0	248	55.2%
Day 1	3434	30.7%	Day 1	139	31.0%
Day 2	1061	9.5%	Day 2	44	9.8%
Day 3	375	3.4%	Day 3	13	2.9%
Day 4	132	1.2%	Day 4	5	1.1%
Day 5	35	0.3%			
Day 6	17	0.2%			
Day 7	7	0.1%			
Day 8	3	0.0%			
Day 9	1	0.0%			

The above table displays the time taken by the warehouse to deliver leftover packages. The table displays the summary for both simulation runs. It can be concluded that the delay incurred during parcel delivery is most likely to be resolved within 10 working days. Through efficient planning and proper execution, the count of leftover parcels can be decreased by the company.

Figure 8 showcases the data in table 1 in the form of a bar plot for better understanding through visualization.
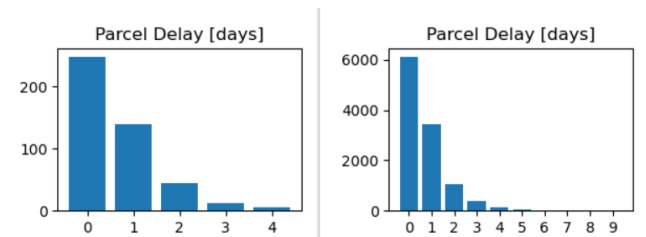

Figure 9: x22228268_C66&C91. Parcel delay in days.

The delay in parcel delivery was found to be resolved within the allocated timeframe, which contributes to customer satisfaction and retention as well.
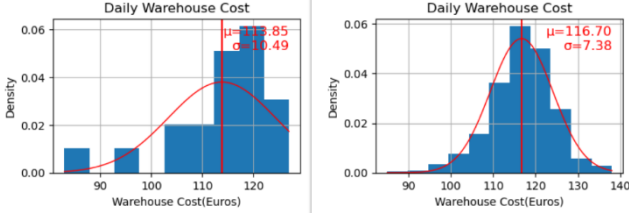
5) Daily Warehouse Cost

Figure 10: x22228268_C70&C94. Daily Warehouse Cost (Euros).

The daily warehouse operational cost was calculated as per the equations mentioned earlier, and the 95-confidence interval revealed that the optimally selected warehouse expects a daily expenditure on operations to be between 116-117 euros with a standard deviation of 10 euros.
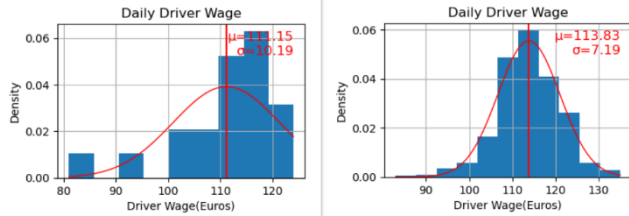
6) Daily Driver Wage

Figure 11: x22228268_C68&C92. Daily Driver Wage (Euros).

The total expenditure incurred by the company to employ the driving personnel was estimated to be between 113 euros with a standard deviation of 10 euros.

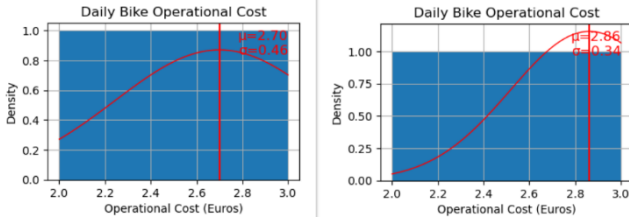### 7) Daily Bike Operational Cost

Figure 12: x22228268_C69&93. Daily Bike Operational Cost.

Similarly, the operational cost for the operation and maintenance of the electric bikes used by the driving personnel was calculated to be below 3 euros for each working day. This adds up to the company's motive for a more sustainable ecosystem and prevents environmental degradation through less carbon emissions.

C. Statistical Significance and Implications

The author conducted ANOVA test on the simulation model for evaluation based on the mean daily cost incurred by the selected warehouse (2880,4560) to determine the choice of warehouse is statistically significant or not. Based on the cost metric the author also utilised visual aids such as histograms and line plot to compare the different warehouse involved in the simulation, the results for which are shown in figure 4.

To conduct the F-Test, the author created a new data frame of cost related data by reading all previously stored recorder files. Furthermore, the following hypothesis was developed; Null Hypothesis (H0): The mean cost of the chosen warehouse is not significantly different from the mean costs of other warehouses. Alternative Hypothesis (H1): The mean cost of the chosen warehouse is significantly different from the mean costs of other warehouses.

The result for the first test generated a p-value of 0.99 because the synthetic data had less variance. Therefore, the author conducted another test on the selected warehouse (2880,4560) and another warehouse (1200,2800), identified considering the total cost and location displayed in figures 2 and 4 respectively.

The result displayed that the null hypothesis was rejected and since the p-value for the hypothesis is greater than 0.05, the author concludes that the selected best warehouse is not statistically significant. Further, the author generated a statistical summary of the two warehouses by comparing the total cost of the warehouse using the function **warehouseCost(daily).** In the further sections, the author increased the simulation size to 50 days for a better understanding based on visual aids related to cost and driver wage to finalize if the selected warehouse can be considered best.

The statistical analysis discovered that the selected delivery warehouse location (2880,4560) was statistically superior in terms of total expenditure and logistic operations when compared to alternative warehouse delivery locations. These results have provided major insights into the operations at 'We-Doo' as they assist in developing strategic decisions influencing resource allocation and future endeavors. Thus, through simulation and optimization, 'We-Doo' has the potential to modernize the logistics industry by enhancing its operational capabilities by leveraging technology to business.

V. REFLECTION AND FUTURE WORK

The advantages and limitations of this project's ability to make use of real-world data to drive key decision making is necessary for further analysis and evaluation of the result. These are important for improving the general predictive ability of the model and its application in the logistics industry. The following are the reflection for further development of the model.

A. Strenghts

1) Comprehensive Approach

This project followed a systematic approach to design, simulate and optimize a model to resolve the issue of the optimal warehouse location in the commuter township map. The methodology involves creating a simulation routine for the selected warehouse selection, data analysis, and statistical evaluation. This project generated a vast apprehension of the operational functions and the contributing factors influencing delivery operations along with customer retention.

2) Heuristic Application

Incorporating heuristic techniques to this approach ensured the simulation model saves on computational time. This strategy can be well applied to real time data to influence key decision making pertaining to the shortest delivery route depending upon the count of packages arrived for a particular day, and then ultimately, selection of the most optimal warehouse delivery location.

3) Cost reduction function

The author created a function mentioned in section 1 to calculate the total cost incurred by the company for a particular warehouse. This approach allows for the selection of an optimal warehouse location derived from the simulation runs. This provides the company with real world insights and decision-making strategies to improve its operational efficiency by minimizing total warehouse expenditure.

B. Limitations

1) Synthetic Data

The simulation model relied on synthetic data generated and considered various assumptions regarding the distribution of various paramerters involved which makes it less suited for real world scenarios as it fails to quantify unceratinties involved in the process. The model has the ability to work on real world data.

2) Limited Scope

The use of heuristic in finding the optimal delivery path may not always generate the most optimal path which can impact the company's essential resources such as revenue and customer satisfaction index.

C. Future Work

1) Dynamic Modeling

The use of dynamic simulation models could enhance the accuracy, responsiveness and robustness of the model. It would incorporate input parameters such as real-time variance in customer demand, traffic signals and road infrastructure, and other external factors.

2) Multi-Objective Optimization

Future analysis could include multiple objective optimization which enables the author to evaluate trade-offs between objectives by providing a set of optimal warehouse locations. This approach would enable 'We-Doo' to pursue a more holistic approach to delivery operations.

3) Alternate heuristic approaches

The author can also develop a more sustainable and robust model using different heuristic algorithms for simulation and optimisation susch as ant colony optimisation and genetic algorithm.

In conclusion, this project's primary goal was achieved by enhancing logistics and optimizing operational efficiency through simulation for 'We-Doo' and selecting an optimal warehouse delivery location within the provided commuter township map. Subsequently, utilization of ANOVA and other statistical tests including visual aids generated valuable information regarding the cost efficiency of the optimum warehouse over other alternatives.

Further research could make use of additional input parameters, such as environmental impact caused due to carbon emissions, road infrastructure and customer location preferences for the refinement of the optimal warehouse location selection and overall delivery performance.

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