We-Doo

Revolutionising Delivery Services

Stamatis Karvounis
School of Computing
National College of Ireland
Dublin, Ireland
x18197051@student.ncirl.ie

***Abstract*— The project aims to validate the idea of "We-Doo" to revolutionize delivery services. The main objective is to create a simulation framework for planning and implementing "We-Doo" services in new townships and selecting the most suitable cargo bike for trial runs. The project investigates various average parcel receipt rates (p) and cargo bike ranges (30km, 35km, 40km, and 45km). By generating synthetic data representing real-world delivery demands, the simulation provides valuable insights and recommendations to optimize delivery operations. The rigorous simulations will guide "We-Doo" in data-driven decisions to transform delivery services in commuter townships.**

Keywords—Simulation, Optimization, Model, Services

I. Introduction

"We-Doo" is an ambitious start-up with a groundbreaking vision to transform delivery services in commuter townships across the country. To validate their innovative business idea and strategize for expansion, "We-Doo" has entrusted with a crucial task, to develop a comprehensive simulation solution to model typical evening delivery runs for a small township.

The primary objective of this project is to create a simulation framework that can be effectively utilized to plan and implement "We-Doo" services in new townships and to make informed decisions about selecting the most suitable cargo bike for their trial runs. However, a significant challenge arises as the average number of parcels a customer receives per day (denoted as p) is currently unknown. Therefore, it is important to explore and analyze various p values within the assumed range of $0.2 \leqslant p \leqslant 0.3$, while also considering values beyond this range. This investigation will encompass at least three p values to ensure a comprehensive understanding of the system's performance under different conditions.

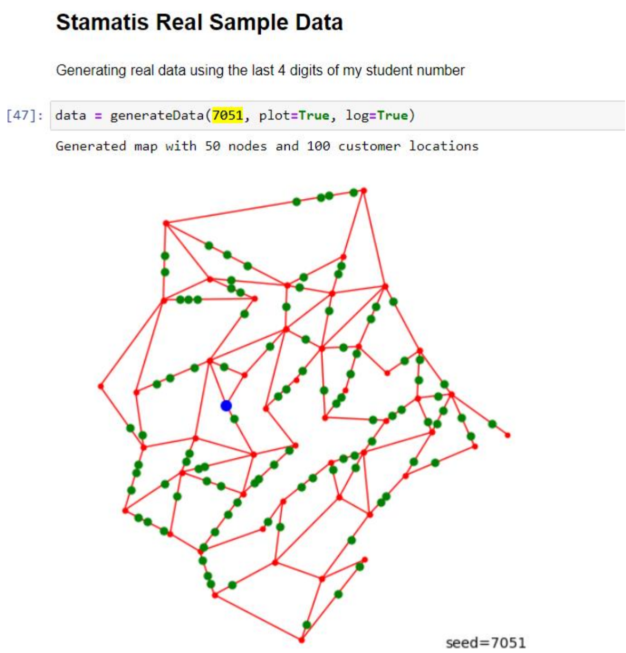
Furthermore, to provide valuable recommendations to "We-Doo," an assessment of the cargo bike's performance for various ranges (r) will be conducted, including 30km, 35km, 40km, and 45km. By conducting an in-depth analysis, "We-Doo" will get well-reasoned and data-driven insights to support their ultimate choice of the optimal cargo bike that aligns with their specific requirements.

The basis of the simulation lies in the generation of synthetic data that accurately replicates the complexities of a real-world bike courier service. This synthetic data comprises crucial components, such as the detailed map layout (M), waypoints (W) representing delivery stops, and comprehensive customer information (C) including their delivery locations and preferences. By incorporating randomization during the data generation process, diverse scenarios can be generated that mirror real-world delivery demands, encompassing varying distances between waypoints, different customer volumes, and unique parcel delivery patterns.

II. Literature Review

For the simulation study presented in this project, different files and data generation methods were utilized, all of which were sourced from the material provided on Moodle [1]. The primary goal of the simulation study was to model the evening delivery runs for a small township, simulating the operations of "We-Doo," a start-up company aiming to revolutionize delivery services in commuter townships.

To facilitate the simulation process, synthetic data have been produced into two essential pickle files: "x18197051.sample.pickle" and "x18197051.data.pickle." The former serves as a representative sample of the entire dataset, allowing to understand its structure and format and conduct preliminary testing and debugging of our simulation code. The latter holds the complete dataset, acting as the primary input for the simulation code in the subsequent stages of the project. The "generateData()" method was used and the 4 last digits of my student number (7051) was used (_ = generateData(7051, plot=True, log=True)).



The data used for the simulation study was stored in two pickle files: "x18197051.sampleData.pickled" and "x18197051.data.pickled." These files were generated using the "GenerateData.ipynb" Jupyter Notebook provided on Moodle. The notebook contained a method called "generateData," which allowed the generation of sample data for model verification and early test runs.

To create personalized data for the simulation, the "generateData()" method was called with specific parameters. The seed number used for data generation was set to 7051, corresponding to the last four digits of the student number "x18197051." This ensured reproducibility and consistency in the generated data for future simulations. The resulting data was then stored in the "x18197051.sampleData.pickled" file, representing a representative sample of the synthetic data, and the "x18197051.data.pickled" file, containing the complete dataset required for the simulation.

In the simulation code, the algorithms and procedures used were adapted from Step 9: Multiple Simulations, which was provided on the Moodle page. The code was tailored to accommodate different values of "p" (parcels per customer) and "r" (range of distance that the cargo bikes can travel). This enabled the simulation to explore a range of delivery demand scenarios and bike range options, allowing for a comprehensive evaluation of the delivery system's performance under varying conditions.

III. Methodology

A. *p Values*

In this project, four different values of p (parcels per customer) were tested, 0.1 and 0.4 outside the $0.2 \leqslant p \leqslant 0.3$ range and 0.2, 0.3 within the range. The analysis involved investigating the mean and standard deviation for the number of parcels per customer and the number of parcels per day for each scenario.

For this study, four different scenarios were examined with varying average parcel demands (p) per customer, addressing the problem of selecting the most suitable cargo bike range for "We-Doo's" delivery operations. The objective was to identify a bike range that can efficiently handle the majority of delivery demands in each scenario.

The results of the analysis indicate that all bike range options are capable of effectively handling the delivery demands for each scenario. Specifically:

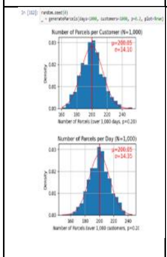
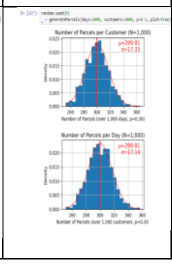
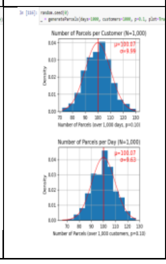
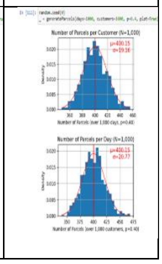
p = 0.2	p = 0.3	p = 0.1	p = 0.4
			

Figure 1. Graphs of the different p values

Scenario 1 (p = 0.2) and Scenario 3 (p = 0.1) both represent lower delivery demands. While these scenarios demonstrate that the cargo bikes can handle lower delivery demands with ease, they do not fully challenge the capabilities of the bike fleet. On the other hand, Scenario 2 (p = 0.3) and Scenario 4 (p = 0.4) represent moderate to higher delivery demands. Despite the higher demands, all bike range options could remain capable of accommodating the delivery requirements effectively. These scenarios presented a more challenging test for the cargo bikes, especially during days with increased delivery demands.

For each value of p, we will further explore the impact of different bike range options (r) on the delivery process. The bike range options considered are r = 30km, r = 35km, r = 40km, and r = 45km, representing different maximum distances that the cargo bikes can travel on a single charge. This range of bike options allows us to evaluate the system's performance under various bike capabilities, considering both shorter and longer delivery ranges.

B. *Parameters*

Furthermore, several crucial parameters affect the time and operational aspects of the delivery process. These parameters play a vital role in defining the efficiency and performance of the bike courier service.

AVERAGE_SPEED: represents the average speed of the cargo bike while driving between waypoints. The value is calculated as 15 km/h converted to meters per second (15/3.6) to ensure consistency in the simulation units. The average speed determines the time required to cover the distance between waypoints during the delivery process.

PREP_TIME_PER_PARCEL: represents the cumulative preparation time includes route planning, sorting parcels in the delivery order, and packing the cargo bike. For each parcel to be delivered, an assumed time of 50 seconds is required for the preparation process.

RETURN_TIME_PER_PARCEL: When parcels are returned to the delivery center, there is a processing time associated with each parcel. The parameter specifies that it takes 30 seconds to process each returned parcel in the delivery center.

AVERAGE_TIME_ANSWER_DOOR, AVERAGE_TIME_HANDOVER, AVERAGE_TIME_SIGNOFF: These parameters represent the average time taken for different customer interactions during the delivery process.

END_OF_DAY_TIME: represents the time allocated for the end-of-day closing procedure. At the end of the delivery day, the delivery center goes through a closing process that takes 600 seconds (10 minutes). The parameters help in managing the simulation and ensures that the delivery process concludes appropriately.

C. *Simulation*

The first step of the simulation involves generating parcel data for each day based on the specified parameters. This is done using the generateParcels function, which creates parcel lists for each day and each customer. These parcels represent the daily delivery demands that need to be fulfilled by the bike courier service.

A Recorder object (rec) is created to record and store the simulation data. This allows us to capture important metrics and statistics during the simulation process, enabling us to analyze and visualize the results later.

The core of the simulation process is represented by the generatorProcess function. This function simulates the delivery process over multiple days. It starts by creating a

DeliveryCentre object (DC) and a Driver object (D). The DeliveryCentre acts as the central hub for parcel storage and distribution, while the Driver represents the courier responsible for delivering parcels to customers.

Throughout the simulation, the system records various events, such as parcel delivery, customer interactions, and delivery center activities. The Recorder object (rec) captures these events and stores relevant data for analysis.

Once the simulation runs for the 50 days, the Recorder object is finalized, and the simulation ends. Finally, the function returns the Recorder object (rec) containing the recorded simulation data.

By running multiple simulations with different parameter settings, we can explore various scenarios and make data-driven decisions to optimize the delivery operations and plan for the rollout of the service in new townships. The simulations are run using the same set of seed values (7051) to ensure consistency in the results. The goal of these simulations is to analyze and compare the performance of the bike courier service for each bike range under different delivery demand scenarios.

IV. Results and Visualizations

The results of the simulations reveal valuable insights into the performance of different bike ranges for delivery operations. The impact of varying bike ranges was investigated on daily working time, tour length, left-over parcels, and parcel delays. By analyzing these key metrics, we aim to identify the most efficient bike range that optimizes delivery efficiency while minimizing delays.

The results of the simulations can be seen in the table below, which shows the “Daily working time”, “Daily tour length”, “Daily left-over parcels”, and “Parcel delays”, and will be discussed in more detail later.

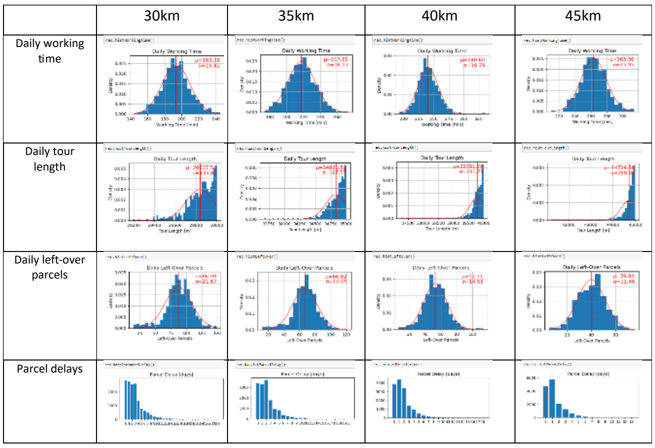


Figure 2 Visualization of the bike range

Parcel Delays

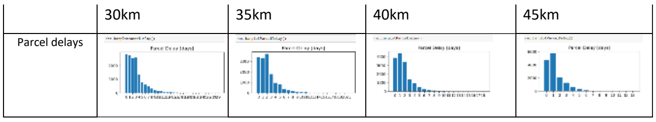
The results of the Delivery delay table (figure 3) for each simulation shows that the 30km bike range has the highest percentage of parcels with more than 2 days delay (45.6%), followed by 35km (30.8%), 40km (15.8%), and 45km (9.5%). The 45km bike range has the highest percentage of parcels delivered on the same day (31.6%), followed by 35km (22.4%), 40km (25.9%), and 30km (19.0%). The 1-day delay percentage is highest for the 35km bike range (38.4%), followed by 40km (29.3%), 30km (18.4%), and 45km (38.4%).

Delivery Delay (15010 parcels)								
Delivery Delay	30km		35km		40km		45km	
None	2849	19.00%	3367	31.60%	3886	25.90%	4737	31.6%
1 Day	2768	18.40%	3294	38.40%	4394	29.30%	5762	38.4%
2 Days	2537	16.90%	3716	13.90%	3356	22.40%	2086	13.9%
>2 Days	6856	45.70%	3716	30.90%	3374	22.40%	2425	16.10%

Figure 3 Delivery delay for each bike range

Based on the simulation results, it appears that the 40 km bike range performs the best in terms of minimizing delivery delays. The percentage of parcels with no delay (None) is the second highest at 25.9%, indicating that a significant portion of deliveries is completed on time without any delay, even though 45km bike range is higher. Additionally, the percentage of parcels with a delay of one day is 29.3%, which is also relatively low compared to other bike ranges.

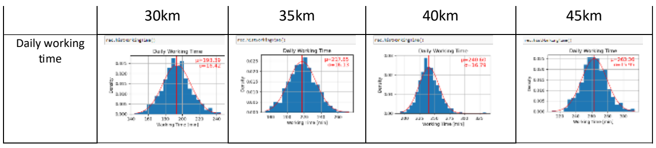
On the other hand, the 45 km bike range has the highest percentage of parcels with no delay (None) at 31.6% but experiences a significant increase in delivery delays of one day (38.4%). This indicates that while the 45 km range can cover a larger distance, it may not necessarily lead to improved overall performance in terms of minimizing delays.



Daily Working Time

As the bike range increases from 30km to 45km, the mean daily working time also increases, indicating that more time is spent on deliveries each day.

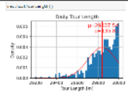
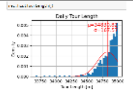
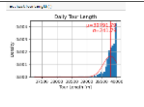
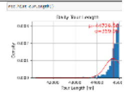
The standard deviation shows the variability in daily working time. The 45km range has the lowest σ, meaning the daily working time is relatively consistent compared to other ranges..



Daily Tour Length

As the bike range increases from 30km to 45km, the mean daily working time also increases, indicating that more time is spent on deliveries each day.

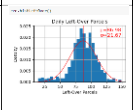
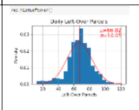
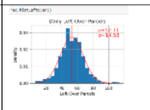
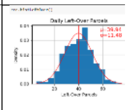
The standard deviation shows the variability in daily working time. The 45km range has the lowest σ, meaning the daily working time is relatively consistent compared to other ranges.

	30km	35km	40km	45km
Daily tour length				

Daily left-over parcels

As The number of daily left-over parcels decreases as the bike range increases. Longer-range bikes can likely cover more deliveries without leaving parcels for the next day.

The standard deviation for left-over parcels also decreases with the bike range, indicating less variability in the number of left-over parcels for longer-range bikes.

	30km	35km	40km	45km
Daily left-over parcels				

In summary, longer bike ranges (e.g., 40km and 45km) generally result in longer daily working times and tour lengths. Longer bike ranges also tend to have fewer left-over parcels, suggesting better delivery efficiency. As the bike range increases, the variability in daily working time and tour length generally increases, indicating less predictable work patterns for longer-range bikes.

V. Conclusion and Future Work

Throughout this research, the efficiency and effectiveness of a bike courier service was investigated considering different bike ranges (30 km, 35 km, 40 km, and 45 km). The simulation was created to model the delivery process and explore various scenarios with different parameters. The analysis focused on metrics such as delivery delays, working time, tour length, and left-over parcels. While the results provide valuable insights, there are several aspects that could be improved, and potential areas for future research can be identified.

In conclusion, while this research sheds light on the performance of a bike courier service in a commuter township, there are several avenues for improvement and potential directions for future research. By incorporating real-world data, exploring dynamic demand models, and optimizing routing algorithms, we can enhance the accuracy and applicability of the simulation results. Additionally, addressing customer behavior, sustainability, and user satisfaction aspects would contribute to designing more efficient and customer-centric last-mile delivery solutions. The continuous improvement of such models and the consideration of new challenges and emerging technologies will be crucial in shaping the future of urban logistics and sustainable delivery services.

VI. References

[1] "Moodle," 08 2023. [Online]. Available: https://mymoodle.ncirl.ie/course/view.php?id=1714#section-12.