A Stitch in Time: Capacitated Vehicle Routing of Blinkit Q-commerce for Environmental Savings

by

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Abstract

The evolving landscape of quick commerce (Q-commerce) introduces unique challenges and opportunities for instant grocery delivery enterprises such as Blinkit. Renowned for its swift service in densely populated urban areas like Gurugram, Blinkit relies on a network of 'dark stores' strategically positioned to meet its commitment of delivering within 10 minutes. This study concentrates on two of these stores, strategically situated in both densely and sparsely populated areas, aiming to evaluate the effectiveness and consequences of rapid delivery services. Despite the widespread acceptance and market share enjoyed by ultrafast delivery services, concerns over safety and environmental impact have arisen. Notably, the police's crackdown on traffic violations and subsequent worker strikes led to the temporary closure of over 100 Blinkit stores in the Delhi NCR area.

The sustainability of Q-commerce faces scrutiny, as the rapid delivery model risks undermining the environmental benefits previously associated with traditional e-commerce (Kendall, 2017). Major retailers contribute to escalating carbon emissions through frequent local deliveries . Studies indicate that consumers are willing to extend their wait time up to 4.2 times the typical delivery window when informed about the environmental advantages (Fu et al., 2018). This finding opens avenues for an alternative objective: minimizing emissions while still respecting cost considerations.This project studies the benchmark system of blinkit q-commerce in Gurugram, India and proposes an alternate system for quick commerce deliveries. It aims to achieve CO2 emission reduction by enforcing speed control and optimal batching in a capacitated vehicle routing process. The results show that even though the delivery time increases in the alternate model, the savings for emissions, trips, cost and fuel consumption increase to 30-57% of the benchmark tours.

Keywords

Quick-commerce Deliveries , Sustainability ,Inbound logistics, Environmental impact,Simulation, CO2 emissions, Capacitated Vehicle Routing

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VRP	Vehicle Routing Problem	The Vehicle Routing Problem deals with the design of optimal routes from a warehouse to the different points by considering the following factors (Praveen, 2022).
CVRP	Capacitated Vehicle Routing Problem	CVRP is based on the generalization of the Traveling Salesman Problem and it is a combinatorial optimization problem. It depends on the maximum load capacity and the weight & volume of goods transported. The challenge is to transport a greater number of goods in a single trip without exceeding the maximum capacity (Praveen, 2022).
TSP	Traveling Salesman Problem	Given a list of cities and the distances between each pair of cities, the objective of the TSP is to find the shortest possible tour that visits each city exactly once and returns to the original city. The tour must cover all cities while minimizing the total distance traveled (Praveen, 2022).

1. Introduction

In the fast-paced Q-commerce marketspace of India, Blinkit stands out with its impressive 10-minute order-to-delivery commitment, facilitated by a strategic network of more than 400 'dark stores' (*Dark: Blinkit Strike*, 2023) in India out of which more than 20 serve the diverse urban densities in Gurugram. Examining this model becomes pivotal in understanding the inherent trade-offs of ultrafast delivery. The existing benchmark system employed by Blinkit in Gurugram, a city characterized by a mix of densely packed and sparsely populated areas, serves as an ideal case study for evaluating the inherent trade-offs associated with ultrafast delivery services.While home delivery companies typically offer varying schedules, shorter delivery times pose logistical challenges in fleet management (Fu & Saito, 2018). Extending delivery times presents opportunities to enhance truck utilization and reduce a company's carbon footprint. However, the challenge lies in convincing customers to opt for longer delivery times. Our research explores the feasibility of developing an alternate system focused on reducing environmental emissions by extending delivery times by leveraging environmental incentives obtained by speed control and batching (Fu & Saito, 2018).

2. Literature Review

When we looked at studies done for the exploration of sustainable last-mile home delivery, we found that the escalating consumer demand for swift delivery services has triggered a competitive race among companies, exemplified by the rise of the quick commerce market offering instant delivery. While this trend caters to customer expectations for quick shipping, it leads to underutilized vehicle capacities, necessitating more frequent dispatches and consequently escalating transportation costs. Beyond the financial implications, these inefficient routes are environmentally detrimental due to heightened carbon intensity. The study by Villamizar et. al delves into the environmental ramifications of expedited inbound logistics, examining operational aspects. Employing a discrete-event simulation model, the study investigates the impact of various parameters (e.g., delivery windows, inventory management policies, truck types) on the sustainability of inbound logistics. Validation of the model is conducted with Mexico's largest retailer to discern the actual sustainability of fast shipping and explore strategies for mitigating its environmental impact. Findings from the simulation model reveal a notable increase in CO2 emissions associated with fast shipping, primarily attributable to challenges in cargo consolidation. The study establishes that fast shipping escalates both total CO2 emissions and costs by up to 15% and 68%, respectively (Villamizar & Martinez, 2021).

Another study by Agarwal.et.al revealed that two-wheeler vehicles in developing nations play a pivotal role in transportation, but their emissions pose environmental concerns. Gasoline-fueled engines emit NOx and particulate matter, impacting urban air quality, particularly during stops at traffic lights. This experimental study assesses various two-wheeler vehicles for exhaust emissions, including gravimetric and online measurements at different engine speeds and a simulated traffic junction. Gravimetric assessments reveal slightly higher total particulate mass, BSOF, and trace elements at 2500 rpm. Online measurements show that engines with higher cubic capacity emit more nano-particles, and particle-bound PAH concentration increases with engine speed, albeit notably low at 3000 rpm. Regulated gaseous emissions increase with engine speed (Agarwal, 2015). These findings provide critical insights into two-wheeler emissions, aiding in understanding and mitigating their environmental impact.

Another pivotal discovery emerged from a study by (Fu & Saito, 2018): customers exhibit a willingness to wait, averaging 4-6 times contingent on the incentives provided (no incentive – 4.2 , economic incentive – 5.5 days, and environmental incentive – 4.7 days). Notably, information pertaining to the number of trees saved exerts the most significant influence on a customer's patience. Factors such as education, occupation, and socioeconomic status demonstrate minimal impact on the willingness to wait and the additional days one is willing to wait. While it remains inconclusive that millennials are inherently more patient when environmental incentives are offered, binary logistic regression reveals a general trend where respondents' willingness to wait increases with decreasing age. For instance, millennials display a greater inclination to wait compared to baby boomers. These outcomes prompt further exploration into the relationship between age and patience.

The various studies' insights lay a valuable foundation for crafting an alternative delivery model with reduced emissions. By understanding customers' willingness to wait and the significance of environmental factors, such as trees saved, the study advocates reshaping delivery practices. The identified customer tolerance of 4.2x becomes pivotal for extending the free delivery timeline from 10 minutes to 42 minutes, enhancing vehicle utilization efficiency and reducing carbon emissions. Optimized utilization yields a substantial reduction of CO_2 equivalent (Fu & Saito, 2018). The empirical evidence from these studies supports the implementation of a sustainable delivery approach that aligns with customer expectations and environmental considerations, fostering a greener last-mile delivery system.

3. Study Area

The pursuit of instant gratification in delivery times has inadvertently escalated safety concerns. Blinkit's delivery agents, often found speeding and engaging in risky maneuvers, highlight the dilemma between rapid service and road safety (Rai, 2023). Notably, the stringent measures by the Indian police, which resulted in nearly a thousand legal actions against Q-commerce operatives in one day in metro cities, underscore the tension between industry practices and law enforcement. The environmental footprint of Q-commerce, exacerbated by the frequency of deliveries, has emerged as a critical concern. Contrary to traditional e-commerce models, which benefited from consolidated deliveries, the push for speed in Q-commerce has introduced an environmentally detrimental factor (Sackos, 2021).

Gurugram, often referred to as the "Millennium City," stands out as an ideal study area for Blinkit's Q-commerce operations for several compelling reasons. It is characterized by a mix of densely populated urban areas and sparsely populated regions, providing a diverse landscape for studying Q-commerce. Blinkit's promise of instant delivery within 10 minutes is particularly relevant in dense urban locales, making Gurugram a strategic location to assess the efficiency and implications of rapid delivery services.It is known for its tech-savvy population, which is often more receptive to innovative solutions like Q-commerce.

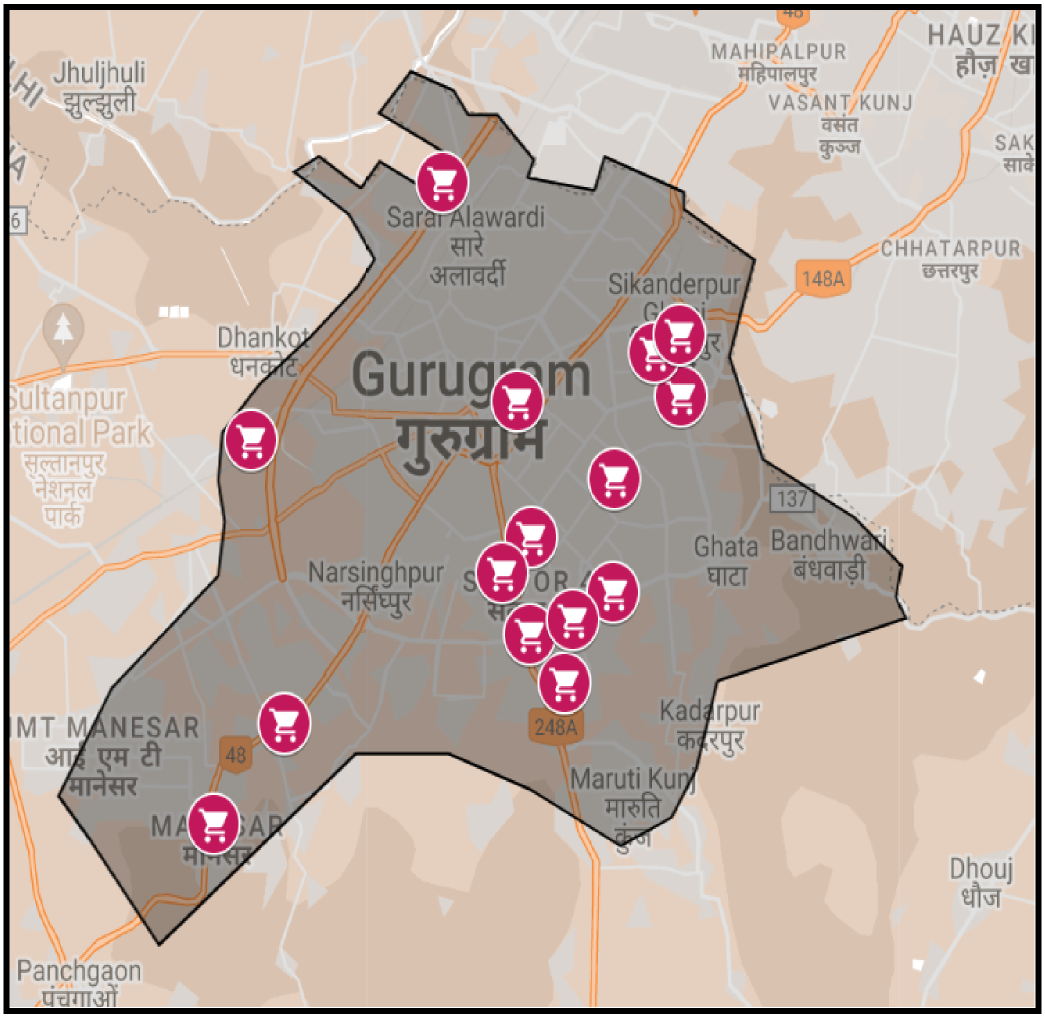

Figure 1: Blinkit Dark Store Locations Gurugram

Gurugram already has about 20 blinkit dark stores setup for its delivery system (**Figure 1**). It hosts a competitive market environment with various players in the e-commerce and quick commerce sectors. Analyzing Blinkit's performance in a competitive landscape allows for benchmarking against other service providers, aiding in identifying areas for improvement and differentiation. It faces notorious traffic congestion and infrastructure challenges, common in rapidly growing urban areas. This presents an opportunity to evaluate Blinkit's operational efficiency, particularly in navigating traffic and optimizing delivery routes, crucial aspects for quick and reliable last-mile delivery. Gurugram's diverse demographic composition, including a mix of young professionals, families, and urban dwellers, allows for a comprehensive understanding of various consumer segments.

4. Model Formulation

VRP models are employed to optimize various aspects of the delivery process, such as cost, time, and environmental impact. We are going to discuss two different models: the current Benchmark System, which is the existing delivery framework for Blinkit, and the Alternative Model, which is a proposed alternative designed to improve upon the current system.There are different types of routing problems which are solved using so many algorithms. Among those types, one of the best known problems is the Capacitated Vehicle Routing Problem(CVRP). The Capacitated Vehicle Routing Problem deals with the total distance traveled, total cost and some other special parameters on a demand basis.

4.1 Benchmark System

CVRP depends on the maximum load capacity and the weight & volume of goods transported. The challenge is to transport a greater number of goods in a single trip without exceeding the maximum capacity. The additional complications are that multi depots can be used. The vehicle has a different capacity and a multi compartment can be used. In this article, the CVRP is discussed in detail with the recent solutions published by the different set of authors. The sample route optimization is given in **Figure 2**.

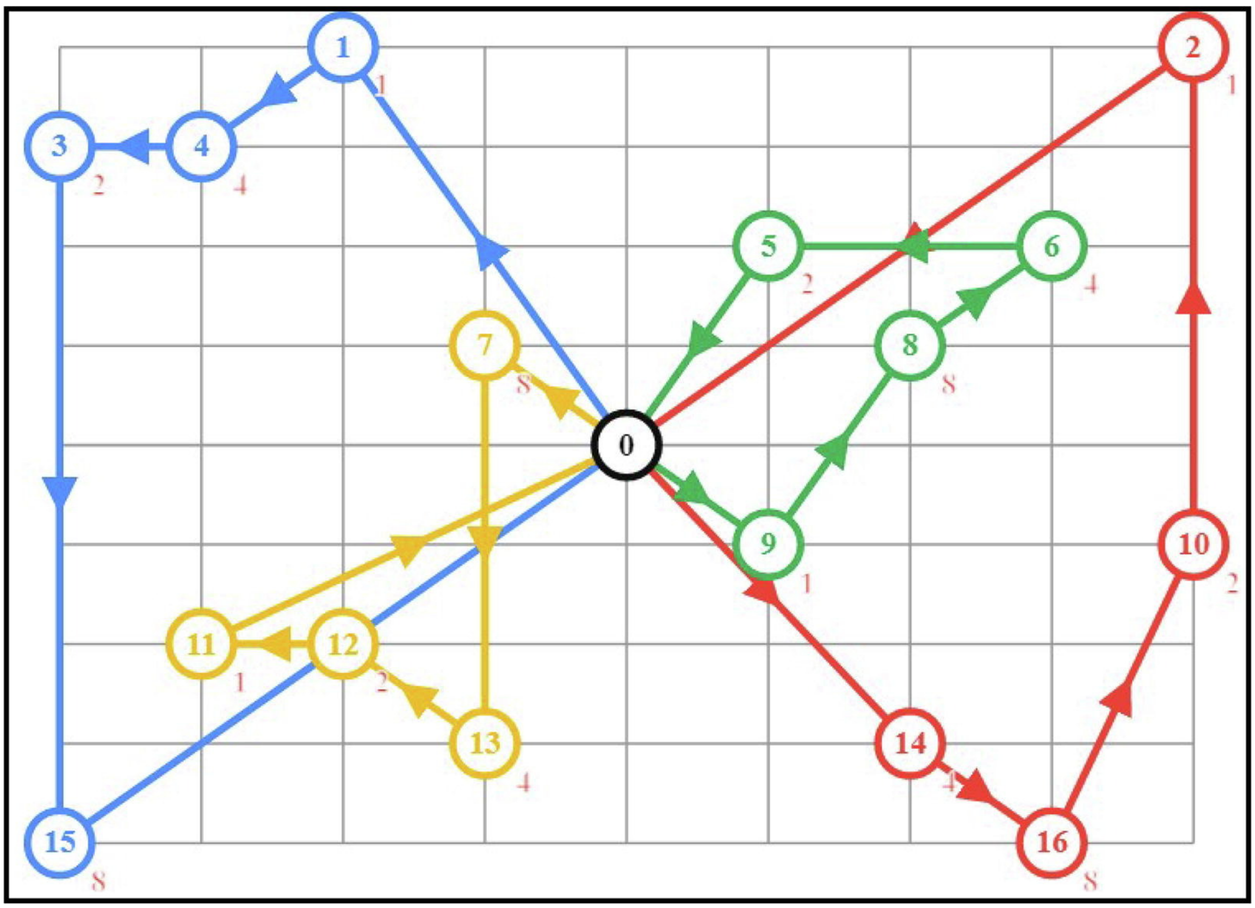

Figure 2: Capacitated Vehicle Routing Network

4.2 Data Collection:Primary Survey

The formulation of the optimization model above was based on key parameters obtained from a primary survey conducted with Blinkit delivery executives (DE). The survey sought insights into essential aspects of the delivery process, shaping the decision variables, parameters, and constraints of the mathematical model. Here's a breakdown of how the survey findings aligned with the model components:

Batching: The survey included questions about batching, with the provided information suggesting a maximum of two orders per batch ($k \leq 2$). This aligned with the model's constraint indicating that the maximum orders a delivery executive could carry per route was 2.

Start Point: The survey indicated that the start point for delivery executives was always the depot. This was reflected in the model's formulation, where the constraints implied that each delivery executive traveled from the depot.

Packing Time: According to the survey, the packing time at the store was reported to be 2 minutes ($T_{pack} = 2$). This value was incorporated into the model as a constraint limiting the packing time to less than 2 minutes.

Number of Delivery Executives: The survey included questions about the number of delivery executives working at every station, limited to a maximum of 15 DEs.

The primary survey, therefore, served as a foundational source for gathering real-world data and insights that directly influenced the formulation of the optimization model. By incorporating these survey findings, the model was tailored to Blinkit's specific operational characteristics and constraints, providing a systematic approach to improving the efficiency of last-mile home delivery.

4.3 Benchmark CVRP Model Formulation

Sets and Indices:

$O = \{O_1, O_2, O_3, O_4, ...\}: set\ of\ customer\ orders$

$DE = \{DE_1, DE_2, DE_3, DE_4, ...\}: set\ of\ available\ delivery\ executives$

$C = \{C_1, C_2, C_3, C_4, ...\}: set\ of\ customer\ locations$

Parameters:

$W: maximum\ weight\ each\ DE\ can\ carry = 60\ kg$

$k: number\ of\ orders\ each\ DE\ carry$

$T_{pack}: packing\ time\ at\ the\ store = 2\ min$

$T_{delivery}: maximum\ delivery\ time = 8\ min$

$Cost_{fuel}: fuel\ cost\ per\ delivery$

$Cost_{fixed}: fixed\ cost\ per\ delivery$

Decision Variables:

$x_{ij}^{k}: binary\ variable\ that\ equals\ 1\ if\ DE\ k\ travels\ from\ location\ i\ to\ location\ j,\ and\ 0$

Objective function:
Minimize the total delivery cost.

$$min \sum_{k \in DE} \sum_{j \in C} (Cost_{fuel} + Cost_{fixed}) \cdot x_{ij}^{k}$$

s.t constraints:

- each customer is visited exactly once by exactly one vehicle:

$$\sum_{k \in DE} \sum_{j \in C \cup \{0\}, j \neq i} x_{ij}^{k} = 1 \qquad \forall i = C$$

-

- weight constraints for each DE:

$$\sum_{j \in C} w_j \bullet x_{ij}^{k} \leq 60 \qquad \forall k \in DE$$

- Single order cannot exceed 15kg:

$$\frac{w}{k} < 15 \qquad \forall i \in O$$

- Delivery time constraints for each order:

$$\sum_{j \in C} T_j \cdot x_{ij}^{k} \leq 8 \qquad \forall k \in DE$$

- Pack time constraints:

$$T_{pack} < 2$$

- Maximum orders that DE can carry per route:

$$\sum_{j \in C} x_{ij}^{k} \leq 2 \qquad \forall i \in S, \forall k \in DE$$

- Dynamic: The model is dynamic, implying that it accounts for changing conditions or real-time adjustments in the delivery process.

The Benchmark System is structured around a set of customer orders O and a fleet of available delivery executives DE, each assigned to various customer locations C. The model's objective is to minimize total delivery costs, accounting for both fuel costs and fixed costs associated with each delivery. Decisions in the model are binary, represented by x_{ij}^{k}, indicating whether a delivery executive k travels from one location i to another location j. The system is subject to several constraints, including a limit on the weight each executive can carry, which is 60 kg, the number of orders per route, packing time at the store, and a maximum delivery time of 8 minutes for each order. Each customer must be visited exactly once, and the number of orders per delivery executive route is capped at 2.

4.4 Alternate System

The alternative system proposed by our study aims to realign the objectives of Q-commerce with environmental sustainability. The primary decision variable, delivery time, is dissected into two components: the batching assignment to delivery executives and the minimization of emissions during order delivery. By optimizing batch assignments, the model seeks to reduce the number of trips to similar areas, consequently lowering emissions. Additionally, by extending the delivery window to 42 minutes, in alignment with customer willingness to wait, the model aims to strike a balance between operational efficiency and ecological responsibility.

4.5 Alternate Model Formulation

Sets and Indices:

I: $set\ of\ customer\ orders\ and\ locations$

DE: $set\ of\ available\ delivery\ executives$

Parameters:

c_k: $maximum\ weight\ each\ DE\ can\ carry\ =\ 60\ kg$

q_i: $demand\ for\ customer\ i\ (order\ weight)$

T: $maximum\ route\ time\ (pack\ time\ and\ delivery)$

s_i: $packing\ time\ at\ the\ store\ =\ 2\ min$

$d_{ij}(t)$: $travel\ time\ from\ customer\ i\ to\ customer\ j\ at\ time\ t,\ considering\ congestion$

$Cost_{fuel}$: $fuel\ cost\ per\ delivery$

$Cost_{fixed}$: $fixed\ cost\ per\ delivery$

M: $A\ large\ number\ for\ logical\ constraints$

v: $speed\ of\ the\ vehicle$

e_k: $CO_2 emissions\ rate\ per\ unit\ distance\ for\ vehicle\ k$

Decision Variables:

x_{ij}^k: $binary\ variable\ that\ equals\ 1\ if\ DE\ k\ travels\ from\ location\ i\ to\ location\ j,\ and\ 0$

a_i^k: $arrival\ time\ of\ vehicle\ k\ at\ customer\ i$

Objective function:

Minimize the total cost.

$$min \sum_{k\in DE} \sum_{i\in I\cup\{0\}} \sum_{j\in I\cup\{0\}, j\neq i} d_{ij}(a_i^k)\cdot x_{ij}^k + Cost_{fuel} + Cost_{fixed} + e_k$$

s.t constraints

- each customer is visited exactly once by exactly one vehicle:

$$\sum_{k\in V} \sum_{j\in I\cup\{0\}, j\neq i} x_{ij}^k = 1 \qquad \forall\ i\ =\ I$$

- The total demand of each vehicle route must not exceed its capacity:

$$\sum_{i \in I} q_i \bullet \sum_{j \in I \cup \{0\}, j \neq i} x_{ij}^k \leq c_k \qquad \forall k \in V$$

- The arrival times should respect the travel times and service times (M is a big number):

$$a_j^k \geq \left(a_i^k + s_i + d_{ij}\left(a_i^k\right)\right) \cdot x_{ij}^k - M\left(1 - x_{ij}^k\right) \qquad \forall i,\ j \in I \cup \{0\},\ i{\neq}j,\ k \in V$$

- Vehicle speed constraints (emission formula)

$$30 \leq v \leq 50$$

- Weight constraints for each DE:

$$\sum_{j \in C} w_j \bullet x_j^k \leq 60 \qquad \forall k \in V$$

- Single order cannot exceed 15 kg:

$$\frac{w}{k} < 15 \qquad \forall j \in I$$

- Delivery time constraints for each order:

$$\sum_{j \in C} T_j \cdot x_j^k \leq 42 \qquad \forall k \in V$$

- Pack time constraints:

$$T_{pack} < 2$$

- Emission constraint related to speed:

$$e_k = 0.11337(v) \qquad \forall k \in V$$

- Dynamic:The model is dynamic, implying that it accounts for changing conditions or real-time adjustments in the delivery process.

The transition from Blinkit's current Benchmark System to the alternative Model marks a pivotal evolution in delivery strategy, integrating advanced parameters to enhance cost-efficiency and environmental responsibility. The alternative Model consolidates customer orders and locations into a single set I, emphasizing the maximum load a delivery executive can manage alongside the demand for each order and a comprehensive maximum route time, inclusive of packing durations at the store and variable travel times due to congestion. A salient feature of this model is the inclusion of e_k, representing the CO2 emissions rate per unit distance for each vehicle, thereby weaving an environmental dimension into the fabric of the delivery optimization problem. This model's core objective transcends cost considerations to encompass emission reduction, incorporating fuel costs, fixed costs, and the environmental cost quantified by emissions over the distance traveled. The constraints are meticulously crafted to assure single visits to customers, like the Benchmark System, but with augmented attention to each vehicle's capacity and emission output correlated to vehicular speed.

A significant alteration in the alternative Model is the elimination of the restrictive two-order cap per delivery route, a limitation in the Benchmark System that frequently necessitated return trips to the store or depot. Abolishing this cap unleashes the potential for delivery executives to transport more than two orders per journey, subject to capacity and demand, thereby diminishing the frequency of depot returns, yielding cost reductions, and enhancing customer satisfaction through expedited deliveries.

Another key modification in the proposed model was the removal of the constraint on the number of orders per route, allowing batching up to the full 60 kg capacity of the delivery bikes. Additionally, the rigid 10-minute delivery window was discarded, enabling a dynamic calculation of costs based on actual fuel consumption along the routes. This adjustment not only reflects a more realistic operational model but also underscores the environmental benefits, as total emissions were calculated in line with the fuel economy specifics of the two-wheelers utilized.

Route optimization in the alternative Model is refined to support multiple deliveries within a singular expedition, leveraging economies of scale to diminish delivery costs and operational time, further abetted by the positive environmental ramification of reduced CO_2 emissions from fewer trips. Such enhancements in the model resonate with modern delivery and logistics methodologies that prioritize not only efficiency but also sustainability.

4.6 Fuel Economy and Emission Calculations

After going through multiple reviews of commonly used delivery bikes in India, it was found that 100-125 cc or class 1 bikes were the most common for Q-commerce platforms. In various models of these bikes, it was found that the optimal fuel economy is achieved within a speed range of 30-50 km/h as shown in **Figure 3.**.

Figure 3: Commonly used delivery bikes in Gurugram, 2023

The incorporation of vehicle speed constraints, mandating maintenance of speeds between 30 km/h and 50 km/h, underscores a commitment to optimized fuel economy and, consequently, minimized CO2 emissions. This operational parameter aims to curtail fuel expenditure—a significant delivery cost element, while contributing to global emission reduction goals and sustainability ethos. Additionally, the speed constraints promise to bolster road safety, potentially align with urban regulatory frameworks, and bolster operational predictability, thereby enhancing the accuracy of dynamic routing and overall service dependability.

Parameters		Fleet	Class 1	Class 2	Class 3
Market share		100%	85.0%	13.9%	1.0%
Engine size (cc)	Min	69.9	69.9	124	149.5
	Max	2,294	125	1,811	2,294
	Avg	123.5	106.7	215.2	276
Curb weight (kg)	Min	55	55	114	143
	Max	431	150	421	431
	Avg	116.1	109.2	155.0	160.6
Engine power (kW)	Min	0.18	0.18	7.1	12.5
	Max	154	8.7	74.7	154
	Avg	7.1	6.1	12.2	19.6
Fuel consumption (l/100 km)	Min	1.25	1.25	1.64	2.39
	Max	5.43	2.06	3.33	5.43
	Avg	1.74	1.66	2.18	2.61
CO_2 emissions (g/km)	Min	29.64	29.64	38.87	56.73
	Max	128.87	48.89	79.04	128.87
	Avg	41.19	39.31	51.68	61.97

Table 1: Fuel Consumption of Delivery Bikes

In essence, the alternative Model represents not merely an incremental upgrade but a comprehensive overhaul of delivery mechanism, one that acknowledges and addresses the multifaceted nature of fuel dynamics and the urgent need to curtail emissions within the logistics domain. As shown in **Table 1,** fuel consumption of Class 1 type bikes was accounted for. The average values were considered for economy speed and max value was considered for speeds above economy.

To calculate the emissions for the bikes average values of bike size were assumed and the emission value was taken in kg of CO2 from **Table 2**.

Size of bike	kg of CO2e, per km	kg of CO2e, per mile
Small	0.08277kg	0.13321kg
Medium	0.10086kg	0.16230kg
Large	0.13237kg	0.21302kg
Average	0.11337kg	0.18245kg

Table 2: Average kg CO_2 Emission of Delivery Bikes

This gave us the average emission coefficient of 0.11337 kg CO_2/Km for economy speed range and 0.136044 kg CO_2/Km for speeds above the economy range.

5. Model Implementation

The coding and analysis process revealed that enforcing speed controls and applying the Clarke-Wright Heuristic within the CVRP framework in Blinkit's delivery system offers significant advantages in terms of cost, time, and environmental impact. Compared to the current system, this alternative approach presents a compelling case for operational changes and demonstrates the potential for data-driven, algorithmic optimization to revolutionize the efficiency and sustainability of Q-commerce delivery platforms.

To develop and test the Benchmark System and Alternative Model, we utilized a diverse range of technologies: Google My Maps (GMM) facilitated the definition of our study area, OpenStreetMap (OSM) provided geospatial data and network visualization, Google Distance Matrix API calculated travel distances between delivery points, Google OR-Tools implemented the CVRP optimization algorithm and Bing Maps API in conjunction with Excel served as a secondary tool for CVRP implementation. The model implementation process unfolded in two distinct phases: the experiment setup phase defined the research framework and prepared delivery data, while the model development phase implemented both systems and produced performance reports across cost, time, and environmental metrics.

5.1 Experiment Setup

Defining Study Areas and Order Locations:

The initial step in constructing our experimental framework involved establishing the study area. While **Figure 1** depicts the geographical distribution of Blinkit's dark stores, our experiment required a single depot per simulation. Therefore, we meticulously selected two distinct areas representing contrasting densities within Blinkit's operational landscape. Leveraging Google My Maps, we delineated these areas and exported their shapes and associated dark store locations as CSV files.

Next, we needed to define the target locations for order deliveries. Manually selecting these locations would impede the generation of diverse, real-world scenarios. Thus, we devised a system to randomly generate 15 order locations within the boundaries of the defined study areas. **Figure 4** shows the entire Gurugram network retrieved by OpenStreetMap while **Figure 5** visualizes our focused network, including dark stores, study areas, and generated order locations.

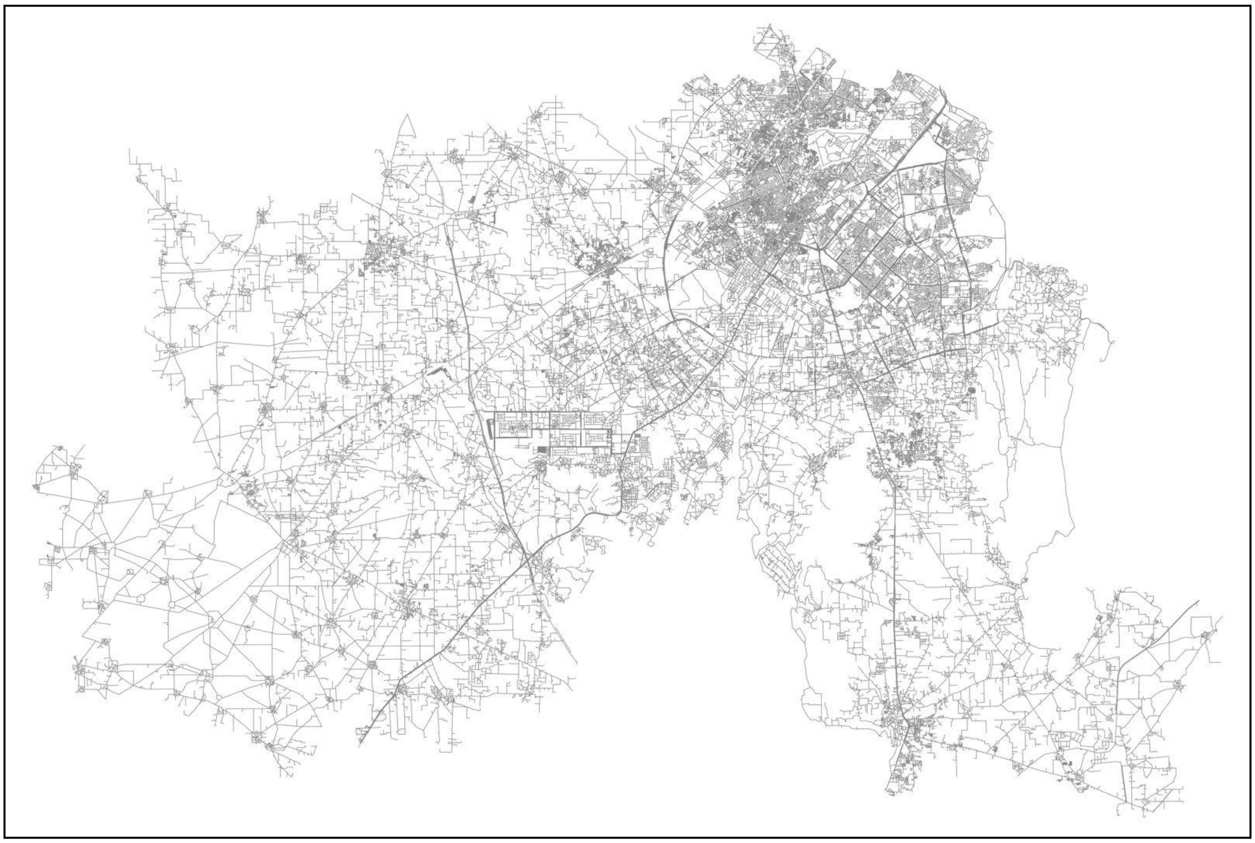

Figure 4: Open Street Map Network Gurugram, India 2023

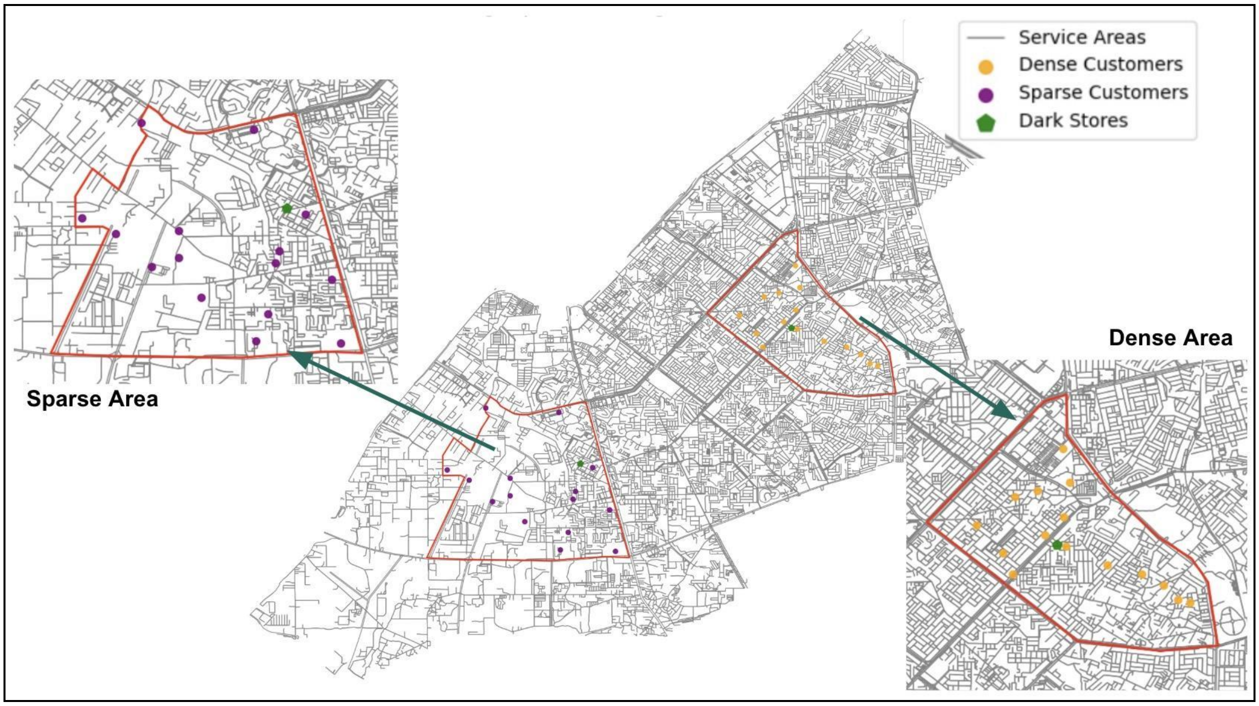

Figure 5: Subgraph of Study Area

Constructing Distance and Time Matrices:

The final step in experiment setup involved creating distance and time matrices for the established networks. We prioritized actual road travel distances over Euclidean approximations due to their incompatibility with real-world road networks. To obtain these matrices, we utilized the Google Distance Matrix API, as illustrated in **Table 3**. However, the API-generated travel times significantly underestimated the average speeds observed in practice. Consequently, we derived independent time matrices for both the benchmark and proposed models by dividing the distance matrix by their respective average travel speeds.

Modular Code Design and Simulation Limitations:

Our experiment setup code infrastructure was designed for flexible parameter generation to facilitate multiple simulations. While we initially aimed for 30 simulations, limitations in our Google Cloud budget and computational resources necessitated reducing the number to 5.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	0.000	2.400	1.686	1.391	1.556	1.349	1.800	2.718	2.953	0.512	1.364	1.615	1.495	2.451	1.485	1.778
1	1.852	0.000	4.017	2.060	0.989	2.527	2.764	0.807	3.547	2.333	2.824	1.998	1.591	2.722	2.704	0.269
2	1.686	3.393	0.000	2.744	3.759	2.610	1.595	4.123	1.549	1.393	1.159	3.105	2.985	3.675	1.280	3.500
3	0.746	1.582	2.910	0.000	1.218	2.064	3.360	1.900	4.841	1.227	2.924	2.040	1.920	2.876	3.045	0.960
4	1.862	0.879	3.538	1.419	0.000	3.180	3.566	1.155	4.349	2.343	3.551	1.110	0.703	2.207	3.505	0.516
5	1.745	2.317	3.018	1.668	2.682	0.000	1.799	3.046	2.582	1.245	1.859	3.710	3.591	4.415	1.738	2.424
6	2.274	2.174	1.595	1.525	2.539	1.391	0.000	2.903	1.989	0.819	0.436	3.568	3.448	4.272	0.288	2.281
7	2.484	0.731	4.648	2.040	1.118	3.180	3.417	0.000	4.200	2.964	3.478	1.915	1.705	2.141	3.357	1.138
8	3.063	2.963	1.549	2.315	3.329	2.180	1.961	3.693	0.000	2.447	2.021	4.357	4.237	5.062	1.900	3.071
9	0.534	2.210	1.405	1.561	2.059	0.871	0.819	2.939	2.475	0.000	1.025	2.117	1.998	2.954	1.146	2.281
10	1.317	2.234	1.159	1.585	2.599	1.451	0.436	2.963	2.049	0.449	0.000	3.628	3.508	4.332	0.192	2.341
11	2.251	1.889	3.091	2.450	1.110	3.569	3.540	2.182	5.022	2.732	3.104	0.000	0.408	0.702	3.226	1.526
12	1.981	1.481	3.087	2.021	0.703	3.299	3.536	1.972	5.017	2.462	3.100	0.408	0.000	1.150	3.221	1.118
13	1.855	3.702	2.696	2.693	1.890	3.173	3.145	2.610	4.627	2.336	2.709	1.251	0.605	0.000	2.830	3.080
14	2.213	2.113	1.280	1.464	2.478	1.330	0.288	2.842	1.928	1.134	0.192	3.507	3.387	4.212	0.000	2.220
15	1.585	0.269	3.749	1.141	0.527	2.796	3.033	0.926	3.816	2.066	3.093	1.536	1.129	2.260	2.972	0.000

Table 3: Distance Matrix of Simulated Random Order Locations

5.2 Model Development

Route Optimization with Embedded Time Constraints:

The core of our alternative model utilized Google OR-Tools, a robust optimization framework capable of handling the complexities of our delivery system. To account for realistic delivery scenarios, we embedded time constraints reflecting the maximum allowable wait time at each customer location. To find efficient, feasible routes under these constraints, we employed the Clarke-Wright Savings Method within the solver. This heuristic iteratively identifies profitable route combinations by merging nearby customers, aiming to minimize overall distance traveled.

Leveraging Clarke-Wright for Efficiency and Sustainability:

Recognizing its efficiency in routing problems, we integrated the Clarke-Wright heuristic to specifically target improved delivery times and lower emissions. The model's optimized routes yielded promising results, which were reported to the console (**Figure 7**) and analyzed (**Table 4**). To analyze the impact of speed control in isolation, we simultaneously built a secondary model that adhered to the existing benchmark system's constraints without the Clarke-Wright heuristic. This parallel comparison clearly highlighted the benefits of enforced speed control, showcasing tangible reductions in delivery times and fuel consumption.

Navigating Algorithmic Challenges:

While the Clarke-Wright heuristic proved effective, scaling up the model presented challenges. We observed a significant increase in solver runtime when exceeding three vehicles, regardless of the employed heuristic (Clarke-Wright or Christofides). Attempts to improve performance with Guided Local Search, a metaheuristic optimization technique, yielded no significant advantage.

Consequently, our OR-Tools implementation of the Benchmark Model, which operates with more delivery executives than the proposed system, failed to run in a reasonable amount of time. As a result, we pivoted to the VRP Spreadsheet Solver developed by Güneş Erdoğan at the School of Management, University of Bath. This solver utilizes Bing Maps API to determine the distance matrix and an insertion heuristic to determine the optimal delivery routes (**Figure 6**).

Figure 6: Benchmark Model Discrepancy

Metrics and Implications:

By aligning optimal routes with the established fuel economy range for delivery motorcycles, we calculated key performance metrics under enforced speed control. These included average delivery times, delivery costs, and fuel consumption. Our findings demonstrate that the proposed model not only enhances operational efficiency but also contributes to environmental sustainability by reducing fuel usage and associated emissions.

6. Results

6.1 Performance of Alternate Model

To analyze the performance of the alternate model, random simulations of order locations were generated and the average value after n simulations was taken into account for delivery time, emissions, fuel consumption and total tour time. A sample output of a single routing query has been shown in **Figure 7**. It shows the time elapsed on route, the route sequence, the travel time and distance between the nodes in the route, emissions and fuel cost of teh route. At the end of the query, the model gives the total time taken across all routes, total emission, fuel consumption and total operations cost.

```
Distance travelled: 1.503 km
Travel time between Node 0 and Node 6: 2.2544999999999997 min
Distance travelled: 1.387 km
Travel time between Node 6 and Node 2: 2.0805 min
Distance travelled: 1.638 km
Travel time between Node 2 and Node 13: 2.457 min
Distance travelled: 0.512 km
Travel time between Node 13 and Node 10: 0.768 min
Distance travelled: 1.645 km
Travel time between Node 10 and Node 0: 2.4675000000000002 min
Route for vehicle 0:
 0 ->  6 ->  2 ->  13 ->  10 -> 0
Time elapsed on route: 10.0275 min
Distance travelled on route: 6.684999999999999 km
Emissions of the route: 0.7579 kg CO2
Fuel cost of the route: $0.1298

Distance travelled: 1.989 km
Travel time between Node 0 and Node 7: 2.9835000000000003 min
Distance travelled: 0.451 km
Travel time between Node 7 and Node 1: 0.6765 min
Distance travelled: 0.748 km
Travel time between Node 1 and Node 3: 1.122 min
Distance travelled: 1.183 km
Travel time between Node 3 and Node 15: 1.7745 min
Distance travelled: 0.742 km
Travel time between Node 15 and Node 12: 1.113 min
Distance travelled: 1.611 km
Travel time between Node 12 and Node 0: 2.4165 min
Route for vehicle 1:
 0 ->  7 ->  1 ->  3 ->  15 ->  12 -> 0
Time elapsed on route: 10.085999999999999 min
Distance travelled on route: 6.723999999999999 km
Emissions of the route: 0.7623 kg CO2
Fuel cost of the route: $0.1306

Distance travelled: 1.004 km
Travel time between Node 0 and Node 9: 1.506 min
Distance travelled: 0.96 km
Travel time between Node 9 and Node 8: 1.44 min
Distance travelled: 0.561 km
Travel time between Node 8 and Node 11: 0.8415 min
Distance travelled: 1.49 km
Travel time between Node 11 and Node 14: 2.235 min
Distance travelled: 0.269 km
Travel time between Node 14 and Node 5: 0.4035 min
Distance travelled: 0.141 km
Travel time between Node 5 and Node 4: 0.21149999999999997 min
Distance travelled: 1.677 km
Travel time between Node 4 and Node 0: 2.5155000000000003 min
Route for vehicle 2:
 0 ->  9 ->  8 ->  11 ->  14 ->  5 ->  4 -> 0
Time elapsed on route: 9.152999999999999 min
Distance travelled on route: 6.102 km
Emissions of the route: 0.6918 kg CO2
Fuel cost of the route: $0.1185

----------------------------------------
Maximum time spent on a delivery run: 10.085999999999999 min

Total time spent on road by all delivery executives: 29.266499999999997
Total emissions from operations: 2.2119620700000002 kg CO2
Total cost of operations: $0.379
```

Figure 7: Alternate Model - Solver report for a simulation

Such random order queries when simulated multiple times in the proposed system yielded promising results, aligning with the objective to keep time elapsed on each route under 42 minutes. The simulations not only ascertained adherence to this time constraint but also facilitated the computation of average CO_2 emissions for individual links and entire tours. The calculated values of each iteration were stored together (**Table 4**) to later compute the averages.

	Maximum Wait Time for Order	Total Distance for all Orders	Total Emissions Produced	Total Fuel Burned	Total Monetary Cost
0	10.8465	21.085	2.390406	0.350011	0.409513
1	10.086	19.511	2.211962	0.323883	0.378943
2	9.978	17.578	1.992818	0.291795	0.3414
3	9.435	16.189	1.835347	0.268737	0.314423
4	8.007	14.928	1.692387	0.247805	0.289932

Table 4:Results of Simulated Random Order Locations for Proposed Model

To ensure a robust analysis, 30 simulations were conducted, encompassing varying order combinations. This approach was instrumental in deducing average values for emissions, link times, and delivery costs.

6.2 Performance of BenchMark Model

To study the performance of the benchmark model, excel based VRP solver was utilized since the python model was running into prolonged runtimes. A set of random coordinates was first put into the distance matrix and was visualized via excel's bing maps (**Figure 8**). After setting the batching, speed and capacity constraints, the solution was run. On an average the best solution was found after 600 iterations of the solver.

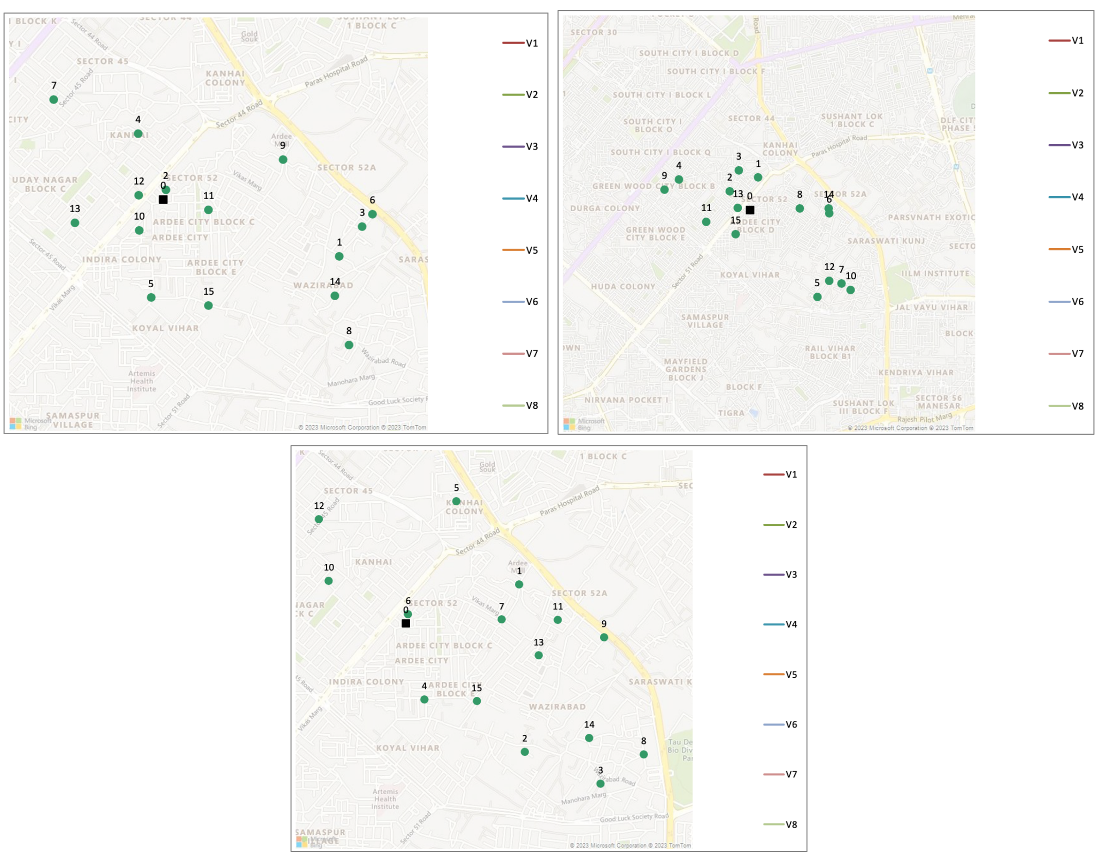

Figure 8: Simulated Random Order Locations in Excel for Sample Simulations

The CVRP routes obtained from the excel VRP solver were then visualized on the map. The benchmark model utilized almost double the no. of vehicles than the proposed model(**Figure 9**).

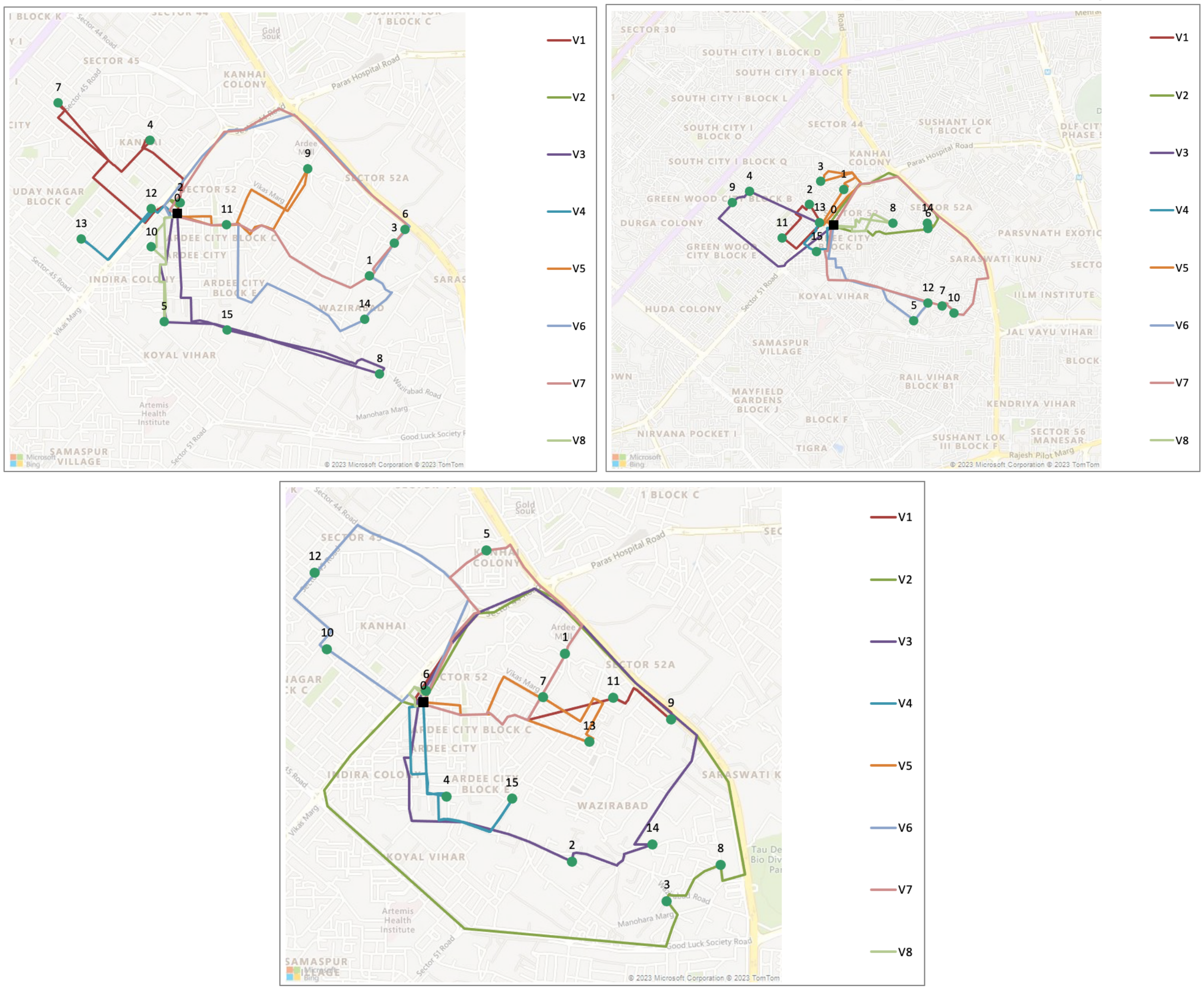

Figure 9: Simulated CVRP routes in Excel for Sample Simulations

After visualizing the CVRP routes, we calculated the values for Distance in Route (km), Time in Route (mins), Delivery time in route (mins), Emissions in route (kgCO2), Distance between depot the last visited node in route and Maximum delivery time taken to visit the last node for each tour in the CVRP solution. The cumulative values for these were also obtained as shown in **Table 5-6-7.**

Route	0-2-11-0	0-6-14-0	0-4-9-0	0-13-15-0	0-1-3-0	0-12-5-0	0-7-10-0	0-8-0	Total
Distance in Rout	2.21	3.57	3.82	1.46	3	4.09	5.9	1.78	25.83
Time in Route	2.410909091	3.894545455	4.1672727	1.5927273	3.272727273	4.46181818	6.436363636	1.941818182	28.1781818
Delivery Time in Route (includes 2 min packing time)	4.410909091	5.894545455	6.1672727	3.5927273	5.272727273	6.46181818	8.436363636	3.941818182	30.1781818
Emissions in Rou	0.30065724	0.48567708	0.5196881	0.1986242	0.408132	0.55641996	0.8026596	0.24215832	3.51401652
depot -last node	1.36	1.54	1.79	0.98	1.64	2.23	2.38	0.89	2.38
Max Delivery Tin	1.483636364	1.68	1.9527273	1.0690909	1.789090909	2.43272727	2.596363636	0.970909091	2.59636364

Table 5: Sample CVRP Simulation 1 in Excel

Route	0-7-4-0	0-2-0	0-8-15-0	0-12-13-0	0-9-11-0	0-14-3-0	0-1-6-0	0-5-10-0	Total
Distance in Route	3.11	0.59	4.28	1.86	2.32	4.78	4.16	1.69	22.79
Time in Route	3.392727273	0.643636364	4.6690909	2.0290909	2.530909091	5.21454545	4.538181818	1.843636364	24.8618182
Delivery Time in Route (includes 2 min packing time)	5.392727273	2.643636364	6.6690909	4.0290909	4.530909091	7.21454545	6.538181818	3.843636364	50.8618182
Emissions in Route	0.42309684	0.08026596	0.5822683	0.2530418	0.31562208	0.65029032	0.56594304	0.22991436	3.10044276
depot -last node	2.24	0.29	3.2	1.01	1.96	2.51	2.01	1.37	3.2
Max Delivery Time of links	2.443636364	0.316363636	3.4909091	1.1018182	2.138181818	2.73818182	2.192727273	1.494545455	3.49090909

Table 6: Sample CVRP Simulation 2 in Excel

Route	0-11-9-0	0-3-8-0	0-2-14-0	0-4-15-0	0-13-7-0	0-10-12-0	0-1-5-0	0-6-0	Total
Distance in Route	4	7.22	5.39	2.87	2.97	3.33	3.34	0.59	29.71
Time in Route	4.363636364	7.876363636	5.88	3.1309091	3.24	3.63272727	3.643636364	0.643636364	32.4109091
Delivery Time in Route (includes 2 min packing time)	6.363636364	9.876363636	7.88	5.1309091	5.24	5.63272727	5.643636364	2.643636364	58.4109091
Emissions in Route	0.544176	0.98223768	0.7332772	0.3904463	0.40405068	0.45302652	0.45438696	0.08026596	4.04186724
depot -last node	1.85	3.88	2.29	1.50	2.08	1.41	2.10	0.29	3.881
Max Delivery Time of links	2.016	4.233818182	2.4927273	1.6407273	2.264727273	1.53818182	2.287636364	0.319636364	4.23381818

Table 7: Sample CVRP Simulation 3 in Excel

From the individual results of running such simulations in excel multiple times, we calculated the average values of all the parameters as shown in **Table 8** for a sample of 3 simulations.

Route	sim 3	sim 2	sim 1	Average
Distance in Route	29.71	25.83	22.79	26.11
Time in Route	32.41090909	28.17818182	24.8618182	28.4836364
Delivery Time in Route (includes 2 min packing time)	58.41090909	54.17818182	50.8618182	54.4836364
Emissions in Route	4.04186724	3.51401652	3.10044276	3.55210884
depot -last node	7.876363636	2.38	3.2	4.48545455
Max Delivery Time of links	8.592396694	2.596363636	3.49090909	4.89322314

Table 8: Average Results of Benchmark Model

6.3 Comparative Results

	Avg.Delivery Time for Order (mins)	Avg Distance for All Orders(Km)	Avg Emissions (Kg CO2)	Avg Fuel Consumed (l)	Avg Cost of Delivery ($)	Avg No. of Trips
Benchmark System	4.89	26.11	3.55210884	0.537866	0.62930322	8
Alternate Proposed System	9.6705	17.8582	2.024584134	0.29644612	0.34684196	3
Savings/Reductions	-4.7805	8.2518	1.527524706	0.24141988	0.28246126	5
Savings/Reductions (%)	-98%	32%	43%	45%	45%	63%

Table 9: Comparative Results of the Two Systems

While delivery times in the alternate system were observed to be almost double than that of the benchmark system,they were still within the 10 mins on average and way under the acceptable limit of 42 mins. More importantly, this increase is counterbalanced by the significant reductions in emissions(43%) and costs(45%). A salient outcome from the proposed model was the average emission reduction that almost halved while bringing down the costs by half also. The alternate model also reduced the number of trips by 63% and the distance traveled for deliveries by 32%. This shows that keeping minimized emissions as an objective will help sustainable delivery systems overall.

6.4 Recommendations

Based on the promising results obtained from our model, we feel its necessary to take initiatives to start bringing more people onboard in opting for greener sustainable delivery. We suggest that the Co2 emission savings time be flexed on the delivery app to encourage more users to choose a greener delivery time as shown in **Figure 10**.

Benchmark Model UI

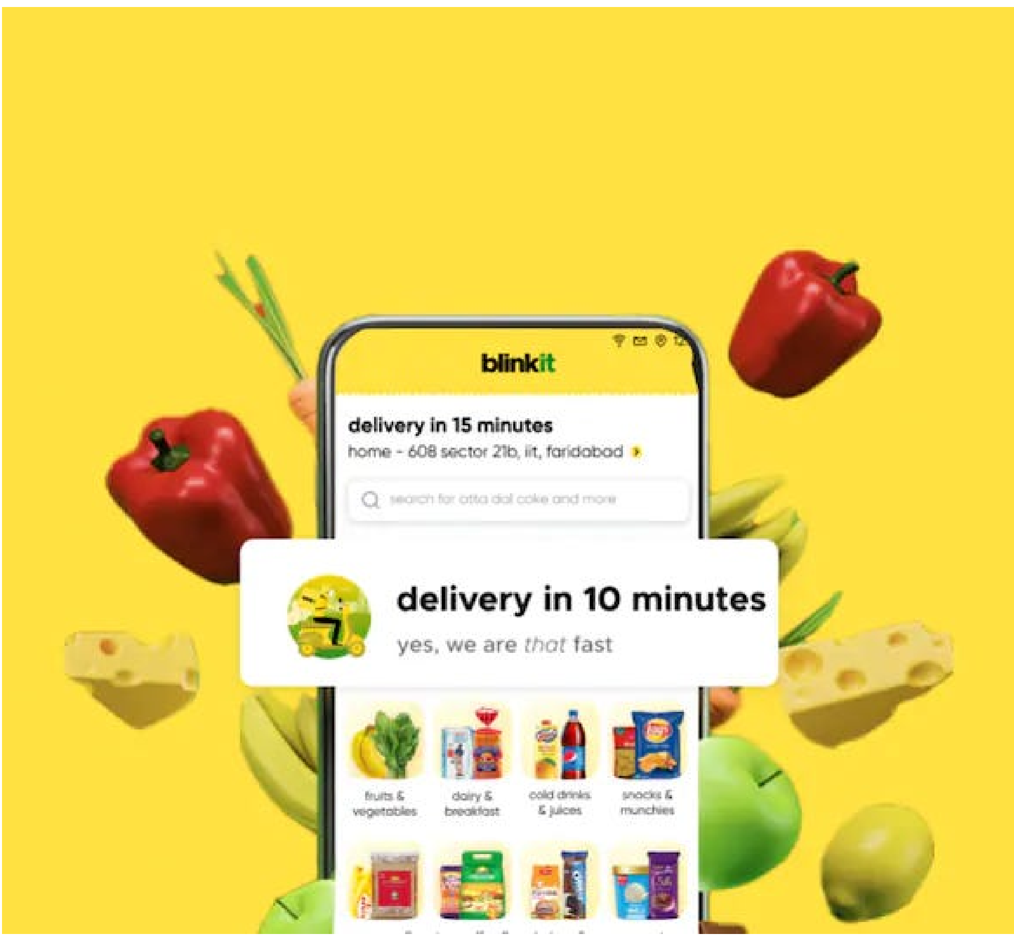

Figure 10:Benchmark Model UI Design

Proposed Model UI

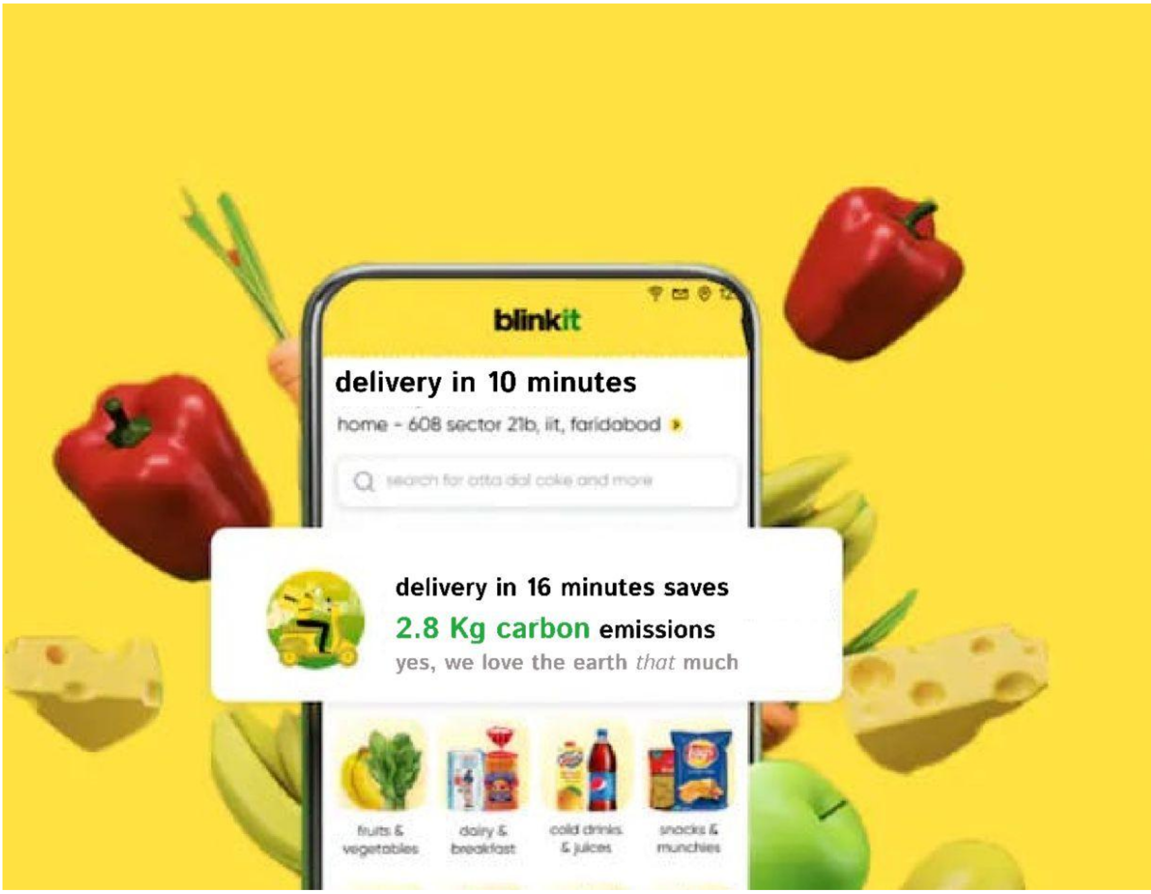

Figure 11: Proposed UI Design for Alternate Model

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