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OPTIMIZING UNMANNED AERIAL VEHICLE FOR FOOD DELIVERY THROUGH VEHICLE ROUTING PROBLEM: A COMPARATIVE ANALYSIS OF THREE DELIVERY SYSTEMS

Abstract

In recent times, there has been a notable increase in interest surrounding the integration of Un-manned Aerial Vehicle (UAV) technology and vehicle routing problems (VRP) for package delivery purposes. While existing studies have explored various types of package deliveries utilizing VRP, limited attention has been given to on-demand food delivery. This study aims to develop a VRP model that incorporates practical constraints such as payload capacity and maximum flying range, with the primary objective of minimizing travel distance in food delivery operations. A comparative analysis is conducted among three delivery methods, including UAV delivery, to determine the most effective approach and assess the feasibility of each method. Through a case study analysis focused on a pizza delivery service in Sri Lanka, it was observed that implementing VRP in a motorbike delivery system resulted in reduced travel distance, time, cost, and CO2 emissions compared to the existing delivery system. Furthermore, the utilization of UAVs in conjunction with VRP yielded even greater improvements across all parameters. Based on a comprehensive cost analysis considering long-term operations, the UAV-based delivery system was identified as the most cost-effective method, followed by the VRP-incorporated motorbike delivery method. Although the VRP-incorporated motorbike delivery system exhibited a slightly higher average time per route compared to the existing method, the total travel time required to complete all routes remained lower. Consequently, the study concludes that the VRP-incorporated motorbike delivery system outperforms the existing delivery method for food delivery, with the use of UAVs incorporating VRP identified as the optimal delivery method among the three alternatives. The findings contribute valuable insights to the optimization of food delivery logistics, emphasizing the potential of VRP and exploring the feasibility of UAVs for sustainable and efficient long-term delivery solutions.

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1. INTRODUCTION

The logistics and transportation industry is currently experiencing notable expansion, primarily driven by the widespread adoption of e-commerce and online shopping (Thibbotuwawa et al., 2023). This surge has resulted in a substantial increase in package shipments worldwide. Extensive research indicates that global parcel volume is projected to reach a range of 220 to 262 billion by 2026, underscoring the sustained growth of the industry (Pitney Bowes Inc., 2020). Concurrently, the global food delivery market, a prominent sector within package delivery, is also witnessing rapid growth each year. However, this exponential growth and development in the logistics and transportation industry has given rise to challenges, including the escalation of greenhouse gas (GHG) emissions, road congestion, longer travel time, high operating cost and accidents.

The delivery sector is confronted with a significant and pressing challenge concerning the substantial increase in GHG emissions, particularly carbon dioxide (CO_2). This challenge holds significant importance as the transportation industry is accountable for approximately 25% of the global CO_2 emissions (United Nations, 2021), (Vichova et al., 2021) with road transportation contributing a considerable 75% to this emission profile (Leather, 2009). In addition to emissions, research conducted in countries such as Korea has highlighted the association between the food delivery industry and a considerable number of injuries and fatalities during the delivery process (Lee, 2019).

To address the challenges in logistics and transportation, UAVs, commonly known as drones, are increasingly being utilized for last mile delivery in various industries (Thibbotuwawa et al., 2019; 2020). Due to emerging importance in delivery logistics, extensive global studies have been conducted to assess the feasibility of employing drones for last mile delivery, revealing their effectiveness in reducing travel distance, delivery costs, time, accidents, and CO_2 emissions (Thibbotuwawa et al., 2019; 2020). Notably, prominent organizations have undertaken pilot projects to evaluate the viability of drone-based food delivery (Sorooshian et al., 2022). Building upon these initiatives, this study aims to assess the extent to which drones can significantly minimize travel distance, time, cost, and CO_2 emissions in the context of food delivery. Moreover, it will compare drone delivery with two alternative delivery methods, namely the existing motorbike delivery system and a motorbike delivery system modified with a VRP model. Additionally, the study will evaluate the total cost implications to determine the viability and potential success of drones as an investment in the food delivery industry.

This study aims to fill a significant research gap by focusing on the optimization of delivery routes for fast food meal services using drones during peak hours (Benarbia & Kyamakya, 2022). Specifically, it aims to develop a customized VRP model tailored for UAV-based food delivery, with a specific emphasis on serving customers within a restricted geographical area during peak hours. The study further evaluates the impact of VRP techniques and UAVs on crucial variables, including travel distance, time, cost, and emission reduction. To assess the cost effectiveness of the proposed method, it is compared to existing approaches, enabling a comprehensive evaluation of its effectiveness and practicality. Accordingly, the study has two main objectives,

1. Testing the research hypothesis,

– UAVs and motorbikes in VRP settings for food delivery will reduce travel distance, time, cost, and emissions in transportation planning.

2. Evaluating the viability of implementing UAV food delivery concerning its total cost implications.

2. LITERATURE REVIEW

This chapter provides an overview of the previous studies conducted on UAV package delivery, emphasizing the need for additional research, and investigating the extant knowledge in this field.

In recent years, there has been rapid advancement in drone technology, with frequent development and integration of new features into UAVs. These UAVs come in various specifications tailored for different applications, and their potential to over-come challenges associated with traditional delivery methods has made them a valuable tool in modern logistics (Ghelichi et al., 2021). Originally designed for military purposes, including surveillance and espionage, drones are increasingly being explored for civilian applications by businesses (Mathew et al., 2021). With their versatile nature, drones find utility in diverse fields such as agriculture, firefighting, national defense, search and rescue operations, medical applications, and delivery logistics (Hwang et al., 2019; Li et al., 2023). Delivery logistics applications of drones can be categorized into four main areas: retail and e-commerce, postal services and mail delivery, food and beverage delivery, and healthcare and emergency services, as identified by Moshref-Javadi and Winkenbach (2021). Each of these categories has numerous real-world examples in current practice.

The optimization of the VRP has emerged as a central focus in the transportation and logistics sector. With the introduction of UAVs, researchers have turned their attention towards investigating the adaptability of VRP variants to address UAV routing challenges. UAVs have presented the delivery industry with a compelling opportunity, offering a more efficient, cost-effective, and environmentally sustainable alternative to conventional ground-based transportation methods. Consequently, there has been a noticeable surge in interest surrounding the development of practical routing algorithms specifically tailored for UAVs. Previous studies have predominantly centered on the examination of various VRP types that can be suitably modified to address UAV routing concerns.

In a study by Yadav and Narasimhamurthy (2018), the focus was on developing an efficient delivery schedule for UAVs in a UAV delivery system. The primary objective was to minimize the completion time for a given set of delivery orders. The problem encompassed specific characteristics of the VRP, requiring the utilization of heuristic-based techniques for solving due to its large-scale nature. Another investigation conducted by Sundar and Rathinam (2014) presented a problem related to the Unmanned Aerial Vehicle Routing Problem (UAVRP) for a single UAV. The objective of this challenge was to determine an optimized route that ensures each location is visited at least once, while satisfying the fuel constraint and minimizing fuel consumption. Addressing the issue of perishability in the distribution network, Zhang and Li (2023) introduced the Collaborative Vehicle Drone Distribution Network (CVDDN) optimization problem. Their study proposed a bi-objective model that aims to minimize the total cost of product distribution while reducing the loss of value.

Tab. 1. Summary of literature focused on the application of UAV routing problem for delivery logistics

Citation	Research Objective	Key Contributions
(Yadav & Narasimhamurthy, 2018)	Minimize the completion time for a given set of delivery orders.	Two heuristic based techniques (Cost Optimized Scheduling Heuristic (COSH) and Cost Optimized Intermediate Replenishment Scheduling Heuristic (COIRSH)) with look ahead mechanisms and appropriately defined costs.
(Sundar & Rathinam, 2014)	Determining an optimized route that ensures each location is visited at least once, while satisfying the fuel constraint and minimizing fuel consumption.	Develop an approximation algorithm for the problem and propose fast construction and improvement heuristics to solve.
(Zhang & Li, 2023)	Minimizing the total cost of product distribution while reducing the loss of value.	Two-phase hybrid heuristic algorithm based on the improved K-means clustering and the extended Non-dominated Sorting Genetic Algorithm-II is proposed to solve the investigated CVDDN optimization problem

The existing body of literature on the VRP and drone delivery has predominantly focused on optimizing delivery time, cost, and fuel consumption. However, there is a noticeable research gap when it comes to the application of these concepts specifically to perishable items and fast-food delivery. This study aims to fill these research voids by exploring the unique challenges and potential optimization opportunities in the context of drone-based delivery for perishable and fast-food items. Consequently, this research holds significant academic importance in advancing the understanding and practical implementation of efficient and effective drone delivery systems for perishable and fast-food items.

3. METHOD

In this study, the existing pizza delivery system of a prominent pizza delivery service in Sri Lanka is utilized as an application for food delivery. The process is then modified to incorporate the use of VRP and UAVs to calculate and compare the effectiveness of different delivery methods.

3.1. Pizza delivery – existing process

The primary mode of transportation in this process involves using motorbikes to deliver pizzas within a specified geographic area. The pizza delivery service operates at multiple locations across various regions, with a significant focus on urban areas. Additionally, the company strategically establishes outlets in sparsely populated areas to ensure broad accessibility and nationwide coverage of its services.

Customers have three options to place their pizza orders: through the official website, via telephone, or by visiting a physical retail location. Orders within an 8-kilometer radius are accepted or directed to the nearest outlet. However, this range may vary for certain outlets based on the level of traffic congestion in the area, as it directly impacts on the delivery time. In such cases, the range is determined by considering the distance that can be covered at an average speed of 40 kilometers per hour.

During each delivery, only one package is allowed to be transported by a single motorbike rider. However, there is an exception where two packages can be delivered together if the addresses are close to each other and located on the same route and street. In all other cases, packages are delivered individually to ensure timely delivery. The current operational procedure allocates approximately 30 minutes for the delivery of each package to the customer.

It is imperative to construct a robust VRP model that efficiently enables UAVs to accomplish deliveries within a designated timeline while minimizing the overall distance traveled.

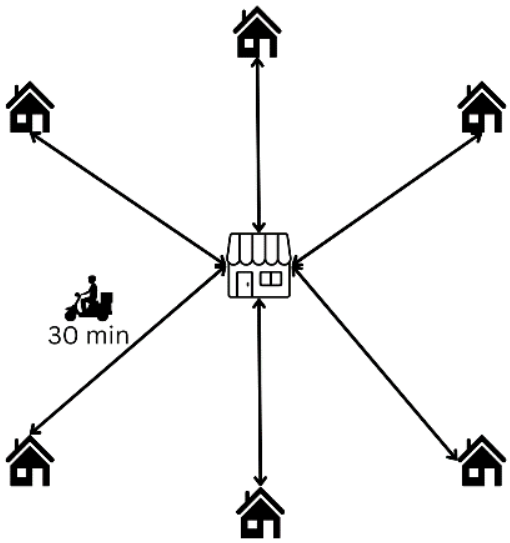

Fig. 1. Existing pizza delivery process

3.2. VRP development for UAVs and motorbike delivery system

One of the primary objectives of this study is to develop a dedicated VRP model that aims to minimize the total travel distance in the context of food delivery. The model's practical applicability is taken into consideration by incorporating various constraints, such as limited range and payload capacity, for both UAVs and motorbikes. To achieve this, a modified version of the capacitated vehicle routing problem (CVRP) is formulated to determine the optimal set of routes for the delivery vehicles.

3.2.1. Assumptions and limitations

- All the UAVs are identical.
- The battery is fully charged in every UAV before the start of each trip.
- The effect of weather on travel speed and travel time is not considered.
- The UAV can carry a maximum payload of (p_d), indicating the number of packages per trip.
- The maximum delivery range (r_d) of the UAV is decided based on the payload (p_d) and the payload is assumed to be fully occupied throughout the route.
- The average speed of the UAV is decided based on the maximum speed of the UAV.
- UAVs travel at constant speeds.
- The exact location can deploy more than one UAV at the same time.
- Service time for delivery, including UAV landing and takeoff time, is constant at every customer location and the depot.
- UAVs can carry more than one package at once.
- A single UAV services each customer on a single visit.

3.2.2. Decision variables

- x_n^d is a binary decision variable that equals 1 if delivery location n is assigned to drone d and 0 otherwise. Drone travels from node i to n.
- y_n^d is a binary decision variable that equals 1 if drone d travels to delivery location n and 0 otherwise.
- w_n^d is a decision variable that gives the distance travelled by drone d from node i to node n.

3.2.3. Objective function

Z: Objective function for minimizing travel distance.

$$\text{Minimize Z } = \sum_{i \in N} \sum_{n \in N} x_n^d w_n^d \tag{1}$$

The primary aim is to optimize the routing of drones with the objective of minimizing travel distance while accounting for constraints related to payload capacity and range. The objective function encompasses a variable, denoted as Z, which represents the cumulative distance traveled by all UAVs. The distance calculation is based on the Euclidean distance method, which captures the movement of UAVs. For motorbike movement road distance is used.

3.2.4. Constraints

Payload Constraint:

For each drone d ∈ D and each delivery location n ∈ N, the total payload of items assigned to drone d should not exceed its maximum payload.

$$\sum\_(n \in N)\ [x_n^d] \le p_d \text{ for all } d \in D \quad (2)$$

The cumulative payload of all delivery locations assigned to a UAV must be less than or equal to the drone's maximum payload. In this case, the payload is defined by the number of packages a UAV can carry.

Range Constraint:

For each drone d ∈ D, the total distance travelled by drone d should not exceed its maximum range:

$$\sum\_(n \in N)\ [y_n^d * w_n^d)] \le r_d \text{ for all } d \in D \quad (3)$$

The range restriction ensures that the cumulative distance traversed by each UAV does not exceed its maximum range. It is the aggregate of the distances travelled by each UAV to the designated delivery locations multiplied by the binary decision variable y_n^d, which indicates whether a UAV has been assigned a particular delivery location.

A specialized version of the VRP was devised specifically for a pizza delivery system that operates using motorbikes. The purpose was to assess the feasibility of this system compared to the existing delivery method, which lacks proper routing strategies. Although there are similarities between this problem and the UAVRP, there are notable differences as well.

The primary objective remains the reduction of the total travel distance. However, the model in this study considers only the constraint of payload capacity, while disregarding the range limitation associated with motorbikes due to their ample fuel capacity and range capabilities.

3.3. Model implementation

3.3.1. Programming language and tools

The implementation made use of the subsequent software tools and libraries:

1. Programming Language: Python 3.7.9
2. Libraries:

- NumPy (version 1.19.5) for numerical computations and array operations.
- Pandas (version 1.3.0) for data manipulation and analysis.
- Requests (version 2.26.0) for making HTTP requests to external APIs.
- Geographiclib (version 1.52) for geodesic calculations and distance computations.
- OSRM API for road distance computations.
- OR-Tools (version 9.1.9490) for solving the CVRP.

3.3.2. Distance between locations

The primary input required for the VRP model is a distance matrix encompassing the distances between all locations or nodes, aiming to optimize the selection of routes with minimal travel distance. This study computed the distances between locations using two different APIs. Firstly, the GeographicLib API (Karney, 2022) was utilized to calculate the

Euclidean distance between locations for UAV routing. Secondly, the OSRM API (Fernando et al., 2022a) was employed to determine the road distance between locations for motorbike routing and to assess distances within the existing delivery system.

3.3.3. Optimization algorithm

Using hybrid algorithms for optimization produce near optimal solutions within a reasonable computational time, adaptability to a variety of problem types and the potential to improve solution quality and computational efficiency (Fernando et al., 2022b, 2024).

Based on the results of the study conducted by Abdirad, Krishnan and Gupta (2020) the initial solution method used in the designed VRP model is "Global cheapest arc", and the improvement algorithm selected is "Guided local search". According to the empirical observations, the combination of algorithms yields the most favorable computational outcomes.

3.4. Sensitivity analysis

A sensitivity analysis is performed to evaluate the influence of vehicle capacity and vehicle speed on the performance of the VRP models. This analysis aims to enhance the overall efficiency of the models and furnish decision makers in the food delivery system with valuable insights by examining the effects of alterations in these variables.

Tab. 2. Available sensitivity analysis variables and their effect

Variable	Test on how it affects
Vehicle capacity	Total travel distance/ Total travel time
Vehicle speed	Total travel time

3.5. Scenario comparison

This comparative study examines three scenarios to assess the feasibility of integrating VRP and UAVs in food delivery logistics. The aim is to validate research hypothesis by comparing the travel distance, travel time, CO_2 emissions and travel cost for three scenarios. The three scenarios are as follows:

– The existing pizza delivery system in which a Motorbike serves a single location at once to ensure timely delivery, hereafter referred to as a Motorbike delivery system (MB-DS).
– Use VRP to deliver pizza using a motorbike by modifying the existing system to serve multiple locations per motorbike, hereafter referred to as the Motorbike VRP delivery system (MBVRP-DS).
– Use of UAVs for pizza delivery applying the VRP to reduce the total distance travelled, hereafter referred to as the UAVRP delivery system (UAVRP-DS).

To ensure accuracy in the comparison, the study utilizes the same dataset comprising customer orders, including their locations and demand, for all three scenarios. The VRP model is employed in these scenarios to determine optimal and feasible routes, and the evaluation of total distance, time, cost, and CO_2 emissions is conducted for each route and dataset. There are slight variations in parameter values between the two VRP models. The data and information pertaining to the existing system are primarily gathered through discussions with industry professionals involved in the pizza delivery process. Essential data types include average demand, motorbike capacity, delivery time allocation, and preferred delivery speed. Parameters associated with UAVs are established based on an available UAV specifically designed for package delivery, as per the information provided by Edel (2020). The service time for delivery, including the landing and takeoff time for UAVs, is assumed to be consistent for both motorbikes and UAVs. The delivery speed of motorbikes and UAVs is employed to calculate the delivery time for each route.

The selection of batch order deliveries is determined by considering the average hourly customer order rate observed during peak periods. To facilitate the delivery process, both motorbikes and UAVs are deployed at 15-minute intervals, wherein VRP models are applied to determine the most optimal routes for delivering packages to designated locations.

The comparison of scenarios consists of two distinct components. The first part entails evaluating the scenarios based on travel distance, travel time, travel cost, and emissions to assess their feasibility for food delivery. The main objective is to examine how each scenario optimally utilizes vehicle capacity and minimizes total travel distance. The second part of the comparison focuses on assessing the overall cost associated with package delivery in the three scenarios. This assessment considers various cost components such as capital expenses, vehicle maintenance and service, operational costs, and travel expenses. By calculating the cost per package, considering these factors, the aim is to analyze the feasibility of implementing the scenarios in terms of their long-term cost implications over the lifespan of the vehicles.

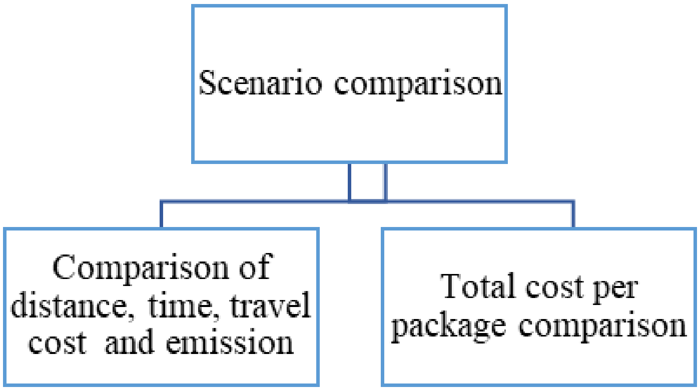

Fig. 2. Senario comparision breakdown

3.6. Calculations

3.6.1. CO_2 emissions calculation

In calculating CO_2 emission for motorbikes and UAVs, two approaches are used depending on the vehicle's energy source. Since here we consider battery-powered UAVs, the energy consumption of the UAV battery in kilo-watt hours per kilometer and CO_2 emission during the electricity production in kilograms per kilowatt hour is used to calculate the CO_2 emission per km from UAVs during the delivery process.

$$UAV\ energy\ consumption = \frac{Battery\ capacity\ (kwh)}{Range\ (km)} \tag{4}$$

$$\begin{aligned} CO_2\ emission\ per\ kilometer = {} & UAV\ energy\ consumption\ (kwh/km) \\ & \times CO_2\ emission\ for\ electricity\ production\ (kg/kwh) \end{aligned} \tag{5}$$

CO_2 emission calculation for the motorbike involved fuel efficiency of the motorbike and CO_2 emission per one liter of gasoline combustion during the motorbike journey. The CO_2 emission per km is calculated.

$$Motorbike\ fuel\ consumption\ (l/kg) = \frac{1}{Fuel\ efficiency\ (km/l)} \tag{6}$$

$$\begin{aligned} CO_2\ emission\ per\ kilometer = {} & Motorbike\ fuel\ consumption\ (l/km) \\ & \times CO_2\ emission\ by\ gasoline\ combustion\ (kg/l) \end{aligned} \tag{7}$$

3.6.2. Travel cost calculation

The travel cost analysis for each mode of transportation in this study focuses solely on fuel and energy expenses associated with the operations. Other operational costs, including rider charges, drone operator charges, and vehicle maintenance costs, are not considered in this part of the calculation.

To determine the travel cost for UAVs, the energy consumption, and the electricity cost per kilowatt hour for battery charging are considered.

$$\begin{aligned} Travel\ cost\ for\ UAV\ (LKR) = {} & \text{UAV energy consumption(kWh/km)} \\ & \times \text{electricity charge (LKR/kWh)} \\ & \times \text{Travel distance (km)} \end{aligned} \tag{8}$$

In calculating motorbike travel costs, the analysis considers the motorbike's fuel consumption and the price per liter of gasoline (petrol) in Sri Lanka.

$$\begin{aligned} \text{Travel cost for Motorbike (LKR)} = {} & \text{Motorbike fuel consumption (l/km)} \times \\ & \text{Gasoline price (LKR/l)} \times \text{Travel distance (km)} \end{aligned} \tag{9}$$

3.7. Total cost comparison

The pricing of each package delivery is determined through the consideration of multiple factors, including initial vehicle investment, maintenance costs, operator or driver wages, and travel expenses encompassing fuel or energy consumption associated with the delivery process.

3.7.1. Vehicle (UAV and motorbike) requirement

The determination of the required number of vehicles is based on the average travel time per route. Considering that orders are dispatched at regular 15-minute intervals, the decision regarding the number of vehicles is influenced by the time it takes for dispatched vehicles to return during peak hours. The calculation of the number of vehicles entails multiplying the minimum requirement to serve a single set by the ratio of the average route time to the dispatching time interval. In cases where the resulting value is a decimal, it is rounded to the nearest whole number.

$$\text{Number of vehicles required} = \text{Minimum requirement to serve single set } \times \\ (\text{Average route time}/\text{Dispatching time interval}) \tag{10}$$

3.7.2. Per package cost for UAV deliveries

The determination of capital investment in the delivery service is based on the required fleet size of vehicles. The primary objective of investment costs is to cover expenses associated with acquiring the vehicles. In the case of UAVs there are additional factors to consider, including costs related to software, maintenance, and operations. It is assumed that a single operator can manage and supervising the required number of UAVs.

$$Packages\ per\ day \times Operating\ days\ per\ year\ \times Drone\ lifetime = \text{No: of } Packages \tag{11}$$

$$\frac{\text{Capital cost} \times \text{\#Drones} + \text{Operating cost} \times \text{\#Drones}}{\text{\#Packages}} + \text{Travel cost per package} = \frac{\text{Cost}}{\text{Package}} \tag{12}$$

$$\frac{Average\ peak\ hour\ travel\ cost}{Average\ peak\ hour\ packages} = \ Travel\ cost\ per\ package \tag{13}$$

3.7.3. Per package cost for Motorbike deliveries

The cost calculations for motorbike deliveries follow the same methodology as that used for UAV deliveries. However, there is a differentiation in the calculation of operating costs. For motorbike deliveries, the operating cost includes not only motorbike maintenance and service costs but also rider wages. Unlike UAVs, each motorbike is assigned a dedicated rider for the purpose of its operation.

4. RESULTS AND DISCUSSION

4.1. Sensitivity analysis

4.1.1. Sensitivity to capacity

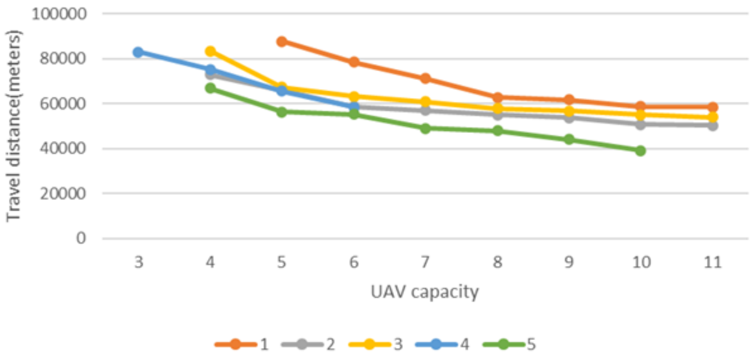

Fig. 3. Changes of distance with UAV capacity

As capacity increases, there is a consistent reduction in travel distance. This indicates that the availability of greater transportation capacity allows for the planning of more efficient routes, leading to shorter distances traveled. However, it is important to note that there exists a point of diminishing returns, where the decrease in distance becomes less significant beyond a specific capacity threshold.

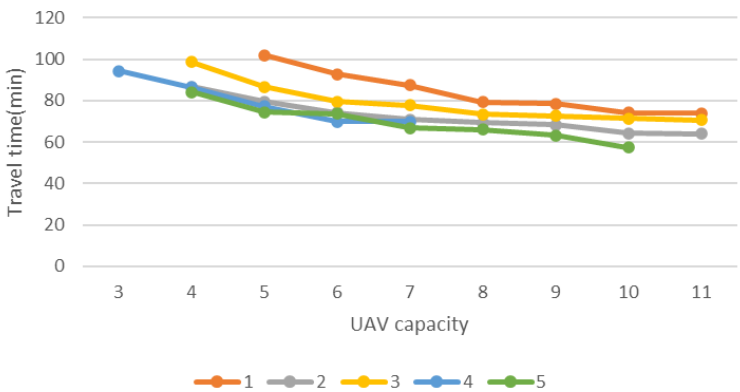

Fig. 4. Changes of time with UAV capacity

As the capacity of the UAV increases, there is a corresponding progressive decrease in travel time. This reduction in travel time can be attributed to the UAV's ability to accommodate a greater number of packages in a single trip, thereby enabling it to cover more delivery locations along the designated route before returning to the depot. Consequently, the overall time required for completing the deliveries is reduced.

4.1.2. Sensitivity to vehicle speed

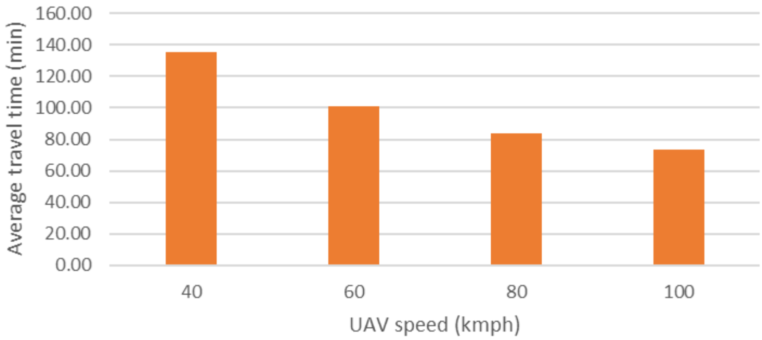

Fig. 5. Average travel time change with speed

The average travel time consistently decreases as the speed increases from 40 to 100. This suggests that higher speeds enable faster deliveries, reducing travel times.

Tab. 3. Percentage time reduction with speed variation

Speed variation (kmph)	Percentage time reduction
40→60	25%
60→80	17%
80→100	12%

As the speed of delivery vehicles increases, the percentage of time reduction in travel time decreases. This declining trend indicates that the effect of higher speeds on reducing travel time diminishes. This observation can be attributed to the presence of service time at each delivery node. It suggests that surpassing a certain threshold of speed may not lead to significant additional reductions in travel time.

4.2. Scenario comparison

This section provides a detailed analysis and comparison of three scenarios involving the utilization of VRP for route planning in the context of Motorbike and UAV deliveries. The three scenarios are evaluated and contrasted based on various crucial factors, namely travel distance, travel time, travel cost, and emissions.

The optimal set of routes recommended by the VRP model for both UAV and motorbike deliveries is illustrated through route maps, serving as visual representations for a singular dataset. These maps showcase the most efficient routes as determined by the VRP model, highlighting the effectiveness of the proposed approach in optimizing delivery operations for both types of vehicles.

Fig. 6. VRP route map for UAV

Fig. 7. VRP route map for motorbike

4.2.1. Distance comparison

The total travel distance to serve customers during 20 delivery instances (20 data sets) are analyzed to identify the nature of travel distance for each delivery method.

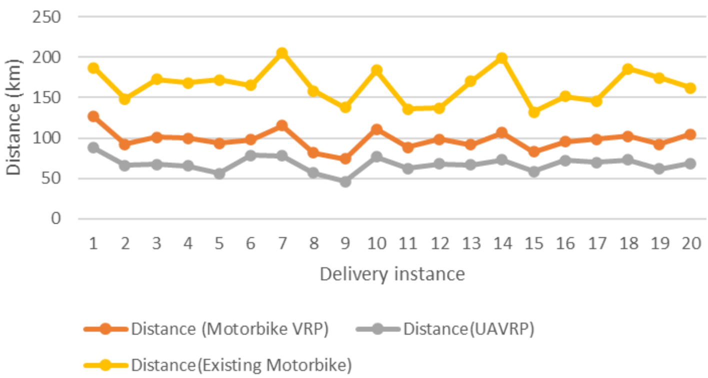

Fig. 8. Travel distance comparison for 20 delivery instances

A descriptive analysis is conducted to summarize and describe the main characteristics, patterns and trends present in the analysis.

Tab. 4. Statistics analysis for distance comparison

Parameter	Distance (MBVRP-DS)	Distance (UAVRP-DS)	Distance (MB-DS)
Mean	97.75	67.67	164.72
Min	74.33	45.94	132.06
Max	126.39	87.72	205.62
Std deviation	11.64	9.14	20.83

The average distance covered by the MB-DS is greater than that of the UAVRP-DS and MBVRP-DS. The calculations demonstrate that the MBVRP-DS method achieves a noteworthy reduction of 40.66% in distance compared to the MB-DS. In contrast, the UAVRP-DS achieves a higher percentage re-duction of 58.92% in distance compared to the MB-DS. Additionally, the UAVRP-DS achieves a 30.77% reduction in distance compared to the MBVRP-DS. This analysis reveals that both the MBVRP-DS and UAVRP-DS significantly decrease the distance compared to the MB-DS. However, the UAVRP-DS method exhibits a more substantial percentage reduction in distance, indicating a more significant improvement in reducing the total distance traveled for deliveries.

4.2.2. Time comparison

The total travel time to serve customers during 20 delivery instances (20 data sets) are analyzed to identify the nature of travel time for each delivery method.

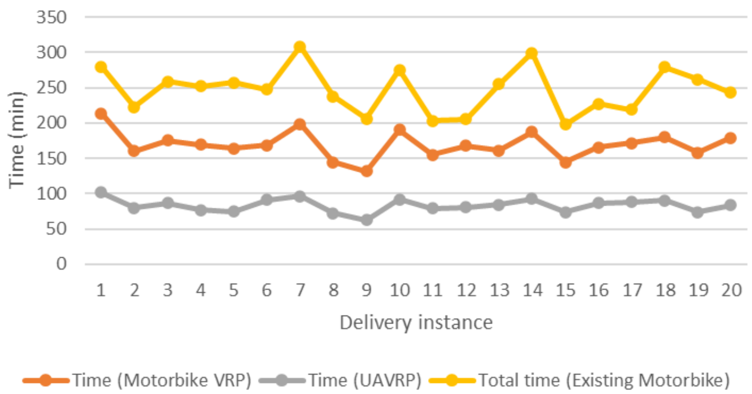

Fig. 9. Travel time comparison for 20 delivery instances

A descriptive analysis is conducted to summarize and describe the main characteristics, patterns and trends present in the analysis.

Tab. 5. Statistics analysis for time comparison

Parameter	Time (MBVRP-DS)	Time (UAVRP-DS)	Time (MB-DS)
Mean	169.44	83.40	247.10
Min	131.51	62.49	198.12
Max	213.61	101.86	308.46
Std deviation	18.83	9.25	31.24

The mean values of the time parameters indicate that MB-DS has the highest average time, followed by Total time for MBVRP-DS, while UAVRP-DS has the lowest average time. The calculations demonstrate that the MBVRP-DS method achieves a time reduction of 31.43% compared to MB-DS. In contrast, UAVRP-DS achieves a higher percentage time reduction of 66.25% compared to MB-DS. Additionally, UAVRP-DS achieves a time reduction of 50.78% compared to MBVRP-DS. These findings suggest that integrating UAVs with the VRP model represents the most efficient approach for delivery.

In terms of average time per route, the three delivery methods exhibit different patterns. MB-DS has an average time per route of approximately 21.69 minutes, MBVRP-DS has an average time per route of approximately 34.94 minutes, and UAVRP-DS has an average time per route of approximately 17.16 minutes. UAVRP-DS emerges as the most time-efficient method with the lowest average time per route. MB-DS shows longer average times per route, while MBVRP-DS exhibits the longest average times per route. These findings emphasize the potential time-saving benefits of integrating UAVs into the delivery process.

4.2.3. Travel cost comparison

The travel cost to serve customers during 20 delivery instances (20 data sets) are analyzed to identify the nature of travel cost for each delivery method.

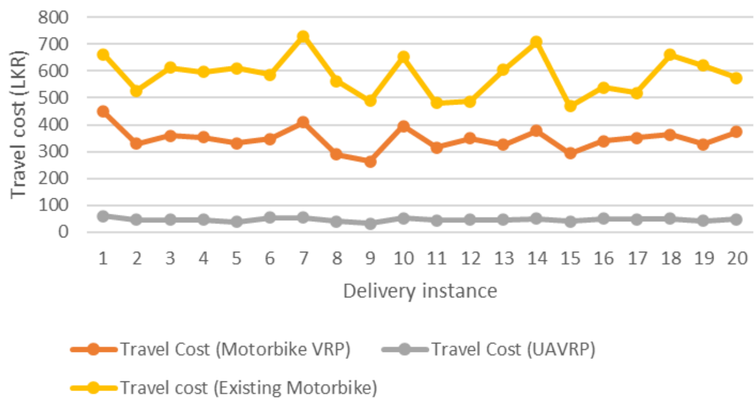

Fig. 10. Travel cost comparison for 20 delivery instances

A descriptive analysis is conducted to summarize and describe the main characteristics, patterns and trends present in the analysis.

Tab. 6. statistics analysis for travel cost comparison

Parameter	Cost (MBVRP-DS)	Cost (UAVRP-DS)	Cost (MB-DS)
Mean	347.00	46.60	584.76
Min	263.87	31.64	468.81
Max	448.69	60.40	729.95
Std deviation	41.33	6.29	73.95

The results indicate that the average travel cost is highest for the MB-DS method, followed by the MBVRP-DS method, while the UAVRP-DS method exhibits the lowest average travel cost. This suggests that the UAVRP-DS method is the most cost-effective option, followed by the MBVRP-DS method, whereas the MB-DS method incurs higher average travel costs. The calculations reveal that the MBVRP-DS method achieves a 40.66% reduction in cost compared to the MB-DS method. In contrast, the UAVRP-DS method achieves a significantly higher percentage cost reduction of 92% compared to the MB-DS method. Furthermore, the UAVRP-DS method demonstrates a substantial reduction in time, with an 86.57% decrease compared to the MBVRP-DS method.

4.2.4. CO_2 emission comparison

The CO_2 emission to serve customers during 20 delivery instances (20 data sets) are analyzed to identify the nature of emission for each delivery method.

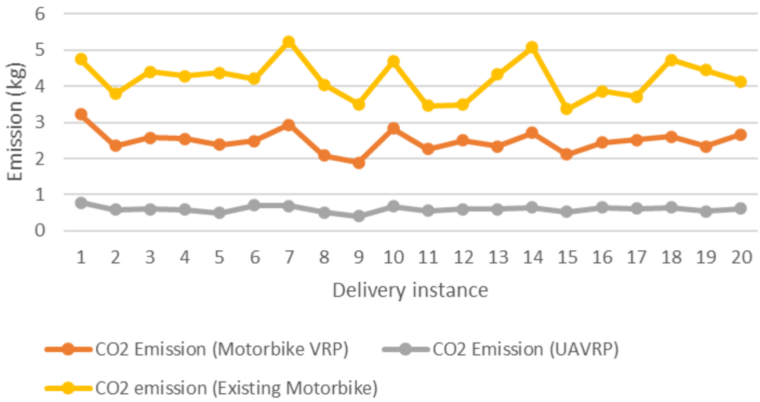

Fig. 11. Emission comparison for 20 delivery instances

Tab. 7. Statistics analysis for emission comparison

Parameter	CO_2 emission (MBVRP-DS)	CO_2 emission (UAVRP-DS)	CO_2 emission (MB-DS)
Mean	2.49	0.60	4.19
Min	1.89	0.41	3.36
Max	3.22	0.78	5.23
Std deviation	0.30	0.08	0.53

The UAVRP-DS method demonstrates the lowest average CO_2 emissions, with the MBVRP-DS method following closely behind. Conversely, the MB-DS method exhibits the highest average CO_2 emissions. The calculations reveal that the MBVRP-DS method achieves a significant 40.57% reduction in emissions compared to the MB-DS method. In contrast, the UAVRP-DS method achieves an even higher percentage reduction of 85.68% compared to the MB-DS method. Furthermore, the UAVRP-DS method achieves a substantial 75.90% reduction in emissions compared to the MBVRP-DS method. These findings indicate that the UAVRP-DS method is the most environmentally friendly option, emitting considerably less CO_2 than the other methods. It is worth noting that the MBVRP-DS method also exhibits relatively lower emissions compared to the MB-DS method. The potential to decrease CO_2 emissions showcased in this study reflects its alignment with

United Nations Sustainable Development Goal 13 (Climate Action) and the Paris Agreement's objective to curb global warming by achieving a 45% reduction in CO_2 emissions by 2030 compared to 2010 levels (Figueres, 2015).

Tab. 8. Travel distance, time, cost, and emission reduction summary

Parameter	MB-DS vs MBVRP-DS	MB-DS vs UAVRP-DS	MBVRP-DS vs UAVRP-DS
Distance	40.66%	58.92%	30.77%
Time	31.43%	66.25%	50.78%
Cost	40.66%	92%	86.57%
Emission	40.57%	85.68%	75.90%

The summary findings indicate that both the VRP-based motorbike and UAV delivery systems offer substantial advantages over the existing delivery system in terms of travel distance, time, cost, and emissions. However, it is noteworthy that the UAV with VRP system demonstrates superior performance compared to the motorbike with VRP system. Specifically, the utilization of UAVs enables significantly greater reductions in travel distance (59% vs. 41%), travel time (66% vs. 31%), travel cost (92% vs. 41%), and emissions (86% vs. 41%). These results highlight the potential of UAVs in achieving more efficient and environmentally friendly food delivery operations, thereby emphasizing their significance in the logistics and transportation industry.

4.2.5. Total cost comparison

The cost per package is a crucial factor in determining a delivery system's feasibility and long-term cost-effectiveness.

Tab. 9. Cost per package comparison

Parameter	MB-DS	MBVRP-DS	UAVRP-DS
Number of vehicles	12	12	12
Cost per package	LKR 140.50	LKR 116.70	LKR 83.60

Significantly, all three systems maintain an equal number of vehicles, with 12 vehicles assigned to each system. This ensures uniformity in terms of vehicle capacity and fleet size, enabling a fair and unbiased comparison of cost-effectiveness.

The cost per package is determined over a five-year period, considering the anticipated lifespan of the employed vehicles. By considering this long-term perspective, it becomes evident that the UAVRP-DS system demonstrates the lowest cost per package, indicating its potential to facilitate more economical package deliveries.

5. CONCLUSION

The optimization of routing strategies for fast food delivery is particularly crucial due to the limited geographical areas and strict delivery time windows within which these services operate. Despite the limited adoption of UAVs for food delivery by a small number of companies globally, research on the implementation of UAVs in this context remains largely unexplored locally and globally providing an opportunity to investigate this area.

This study facilitates a comparison of the effectiveness and efficiency of three distinct food delivery systems. The first system follows the traditional approach of delivering meals using motorbikes, with each customer being served individually by a single motorbike. The second system implements VRP optimization specifically designed for motorbikes, aiming to optimize the delivery process by combining multiple parcels into a single motorbike trip. The third system concentrates on UAV-based food delivery, utilizing VRP-driven optimization techniques to enhance the overall delivery procedure.

Comparing the traditional motorbike delivery system to the modified version incorporating VRP showed substantial reductions in four key factors: total travel distance, cost, and CO_2 emissions, accompanied by a decrease in travel time. However, the VRP-implemented motorbike system had a longer average route time, potentially affecting timely deliveries. Despite this, it demonstrated overall efficiency gains. Additionally, when comparing the VRP-implemented motorbike system to the VRP-implemented UAV system, the UAV system showed significant reductions in distance, travel time, cost, and CO_2 emissions, affirming the hypothesis from the first research objective.

Comparatively, the VRP-implemented motorbike delivery system reduced the cost per package by 17%, while the VRP-implemented UAV delivery system achieved an additional 28% reduction. This represents an overall cost reduction of approximately 40% compared to the existing method, establishing the VRP-implemented UAV delivery system as the most cost-effective option for long-term considerations.

The sensitivity analysis conducted on the developed VRP model for motorbike and UAV delivery systems revealed that an increase in capacity leads to reductions in travel distance, time, cost, and CO_2 emissions. However, this reduction reaches a point of diminishing returns, necessitating the optimization of capacity selection considering the constraints imposed by UAVs due to their current technological limitations in payload capacity. Additionally, higher vehicle speeds were found to decrease travel time, but the impact was gradually diminished by fixed service times at nodes. Therefore, when determining the optimal speed for vehicles, all factors, including energy consumption, reduced travel range, and vehicle safety, must be carefully considered, particularly for UAVs.

In conclusion, among the three delivery systems, the VRP-implemented UAV delivery system emerged as the most suitable choice for food delivery, demonstrating substantial reductions in travel distance, time, cost, and CO_2 emissions. Furthermore, its feasibility was confirmed by having the lowest cost per package compared to the other systems analyzed in the feasibility study.

In this study the model development is based on specific assumptions, such as using identical and fully charged UAVs, disregarding weather effects, assuming a fully occupied payload, and maintaining constant service times. These assumptions are chosen to simplify computational processes of model development. In future research, researchers have the opportunity to improve the practicality of studies by investigating various UAV types with different battery capacities and charges, considering diverse weather conditions, adjusting payloads, and incorporating variable service times.

Implementing UAVs in the delivery industry faces challenges including obstacles in urban areas (trees, power lines, structures), restricted zones limiting service area, weather impacts, and concerns about misuse in monitoring. Addressing these issues, alongside comprehensive regulations, is crucial for overcoming obstacles and marking a significant milestone in the delivery industry.

As a contribution to the logistics industry, this research study presents a novel VRP model tailored to the dynamics of on-demand food delivery, incorporating practical constraints to enhance real-world applicability. The study underscores the consequential implications of employing the VRP in optimizing food delivery operations. Furthermore, the investigation assesses the viability of integrating UAVs for food delivery, elucidating its feasibility as a long-term solution.

Author Contributions

Conceptualization, R.E. and A.T.; methodology, R.E., A.T., and M.F.; software, R.E., and M.F.; validation, A.T., and M.F.; formal analysis, R.E., P.N.; investigation, R.E., P.N.; resources, A.T., and M.F.; data curation, R.E.; writing—original draft preparation, R.E.; writing—review and editing, A.T., N.P and M.F.; visualization, R.E.; supervision, A.T. and N.P.; project administration, A.T. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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