International Journal Of Advanced Communication Technology (IJACT)
Volume 4,2024 [62-70]

Optimizing Drone-Based Delivery Using the Pity Beetle Algorithm: A Novel Approach.

Yugeswary Kanesen[1,2],*, Hasneeza Liza Zakaria[1,2], M.S Asi[1,2],
Rozmie Razif Othman[1,2], Wan Nur Suryani Firuz Wan Ariffin[1,2], Nuraminah Ramli[1,2], and Mohd Alif Hasmani Abd Ghani[1,2]

[1]Faculty of Electronic Engineering Technology, Universiti Malaysia Perlis(UniMAP), Pauh Putra Campus, 02600 Arau, Perlis, Malaysia.
[2]Centre of Excellence for Advanced Computing (AdvComp), Universiti Malaysia Perlis (UniMAP) Pauh Putra Campus, 02600 Arau, Perlis, Malaysia

ABSTRACT

The Travelling Salesman Problem with Drones (TSP-D) has become a significant optimization challenge in last-mile delivery systems. Addressing scalability issues with datasets exceeding 250 nodes, this study introduces the Pity Beetle Algorithm (PBA), a novel metaheuristic. The PBA demonstrates superior performance in balancing exploration and exploitation to optimize delivery routes effectively. Results from new simulations conducted for this journal show delivery time reductions in a broader range of scenarios, with improvements up to 60% over standard benchmarks. Statistical analyses confirm the algorithm's capability to enhance computational efficiency and scalability. The PBA's dynamic tuning mechanisms also enable it to adapt effectively to varying dataset sizes and configurations. Beyond its computational benefits, this study underscores the real-world applicability of the PBA in logistics, providing industries with a robust tool to optimize delivery times and reduce operational costs. This research opens avenues for integrating PBA with hybrid models and real-time optimization techniques, further enhancing its potential to tackle complex logistical challenges.

Keywords: Drones, Last-mile Delivery, Metaheuristics, Pity Beetle Algorithm, TSP-D.

1. INTRODUCTION

The exponential growth of e-commerce has amplified the demand for efficient last-mile delivery (LMD) systems [1, 2]. This claim is supported by studies such as [4], which highlight significant increases in consumer reliance on digital marketplaces. Similarly, [3] emphasizes the integration of advanced logistics models, including drones, to address the challenges posed by this rapid growth. Traditionally dominated by trucks, LMD faces challenges such as traffic congestion, emissions, and limited accessibility in urban and rural settings [4]. Delivery models integrate drones for agility and cost reduction, creating hybrid truck-drone systems based on TSP-D [5, 6].

Despite significant advancements, existing algorithms struggle with scalability, particularly for datasets exceeding 250 nodes [7]. Addressing this gap, this study presents the PBA—a metaheuristic inspired by the bark beetle's foraging behavior—to enhance computational efficiency and solution quality. The methodology section further elaborates on this inspiration, highlighting specific studies by [4] that analyze swarm optimization strategies, which served as a foundation for designing the PBA's adaptive mechanisms. This paper highlights the Pity Beetle Algorithm(PBA)'s performance in optimizing delivery times for large-scale logistics.

yugeswary@studentmail.unimap.edu.my

2. METHODOLOGY

This section delineates the framework and design ideas of the PBA, which employs bio-inspired tactics to tackle the complexities of large-scale TSP-D optimization. The PBA enhances computing efficiency and scalability by modeling the foraging behavior of bark beetles, incorporating unique adaptive tuning algorithms and dynamic population changes. These approaches are evaluated against conventional metaheuristics to illustrate the algorithm's superiority.

2.1 Overview of Travelling Salesman Problem with Drones (TSP-D)

The Travelling Salesman Problem with Drones (TSP-D) presents a hybrid delivery model in which a truck and drone collaborate to optimize last-mile deliveries. This coordination aims to minimize total delivery time by efficiently distributing tasks between the two vehicles [8]. In this problem, the truck serves as the central hub, while the drone operates in tandem to deliver to locations that may be less accessible or time-consuming for the car alone [9].

This model addresses several logistical challenges, such as reducing fuel costs, alleviating traffic congestion, and expanding service areas in urban and rural settings. It introduces constraints critical to ensuring feasible operations, such as the drone's battery life and payload capacity [3]. The TSP-D provides a practical framework for implementing drone-assisted logistics systems by optimizing these factors. Studies such as those by [1] and [2] have analyzed the effectiveness of hybrid delivery systems, laying the groundwork for the adoption of TSP-D in real-world applications [1, 2].

The Travelling Salesman Problem with Drones (TSP-D) presents a hybrid delivery model in which trucks and drones collaborate to optimize last-mile deliveries. This coordination aims to minimize total delivery time by efficiently distributing tasks between the two vehicles [1]. In this problem, the truck serves as the central hub, while the drone operates in tandem to deliver to locations that may be less accessible or time-consuming for the car alone [2].

This model addresses several logistical challenges, such as reducing fuel costs, alleviating traffic congestion, and expanding service areas in urban and rural settings. It introduces constraints critical to ensuring feasible operations, such as the drone's battery life and payload capacity [3]. The TSP-D provides a practical framework for implementing drone-assisted logistics systems by optimizing these factors.

2.2 Problem Formulation

In this study, The Travelling Salesman Problem with Drones (TSP-D) focuses on coordinating truck and drone operations to minimize delivery times [1]. In this formulation, the problem involves a truck traveling along a primary route, delivering packages to some locations, while a drone is dispatched simultaneously to serve other places [2]. Both vehicles must return to the depot after completing their respective routes. To ensure practical solutions, we consider several constraints:

Drone Battery Life and Payload Capacity: The drone's operational range depends on its battery life and the weight of its payload, which limits feasible routes [11].

Synchronization of Operations: The truck and drone must coordinate to avoid delays, especially when the drone needs to rendezvous with the car for recharging or loading [12].

Objective Function: The primary goal is to minimize the total delivery time, defined as the maximum time the truck or the drone takes to complete their routes [12].

By addressing these constraints, we develop solutions that balance efficiency and practicality. This approach enables the Pity Beetle Algorithm to tackle the complexities of large-scale delivery networks effectively, optimizing resource utilization and reducing costs.

2.2.1 Dataset

TSPLIB provides a library of TSP instances, including various problems derived from diverse sources. Researchers can quickly access corresponding data files by appending the suffix ".tsp" to a problem's name [3]. Even though newer datasets are emerging in routing and logistics optimization, TSPLIB remains a crucial benchmark for evaluating TSP and its variants, such as TSP-D [3]. In this research, we selected TSPLIB for several key reasons. Firstly, TSPLIB has earned widespread recognition in optimization research, offering a consistent and reliable framework for assessing algorithmic effectiveness [3]. Furthermore, its trustworthiness and broad acceptance allow researchers to validate and compare results effectively with those of earlier studies [3]. Secondly, TSPLIB's compatibility with TSP-D ensures it provides a balanced set of instances to evaluate the efficiency and scalability of the PBA [3].

While newer datasets exist, many remain proprietary, narrowly scoped, or infrequently used for academic benchmarking. In contrast, TSPLIB is the most comprehensive and universally accepted dataset for public benchmarking. Employing TSPLIB validates PBA's performance against other metaheuristic methods, ensuring credible comparisons. Moreover, relying on less-established datasets could undermine the reliability of results, as such datasets often lack sufficient research support or availability. Consequently, our choice of TSPLIB aligns with proven methodologies, guaranteeing thorough, consistent with current literature, and academically robust outcomes. TSPLIB includes problem instances with known lower and upper bounds for the shortest tour distance. Additionally, it provides city names, problem types, and minimum tour distances, enabling robust validation of optimal solutions within defined boundaries.

2.3 Overview of the Pity Beetle Algorithm (PBA)

The Pity Beetle Algorithm (PBA) is inspired by the foraging behavior of bark beetles, which exhibit efficient exploration and resource optimization strategies in their natural environments. Ecological studies have analyzed these behaviors to understand how beetles balance the need to explore new areas while exploiting available resources. This dual strategy forms the foundation of the PBA's design. For example, research by [4] on swarm behaviors and optimization provided a theoretical basis for integrating similar principles into the PBA's adaptive tuning mechanisms.

Moreover, the PBA draws on earlier metaheuristic models, including Hybrid Variable Neighborhood Search (HGVNS)[15], Monte Carlo Tree Search (MCTS)[14], and Hybrid Genetic Algorithm (HGA)[13]. By leveraging insights from these approaches, the PBA incorporates advanced techniques for dynamically adjusting population sizes and cost functions. These features enable the algorithm to handle complex logistical challenges effectively, particularly in large-scale TSP-D instances [1, 2].

The PBA emulates the bark beetle's survival strategies, balancing exploration and exploitation to avoid local optima [3, 4]. Implemented in Java and benchmarked using TSPLIB datasets, the algorithm incorporates adaptive tuning parameters for scalability [5, 6]. Key components actively optimize logistics performance by refining cost functions, dynamically adjusting population sizes, and balancing exploration with exploitation to prevent premature convergence. These include:

Cost Function: Optimizes the combined routes of truck and drone.

Dynamic Population Adjustments: Enhances scalability for large datasets.

Exploration-Exploitation Balance: Prevents premature convergence through adaptive tuning.

2.3.1 Pity Beetle Algorithm Framework

Figure 1 of the Pity Beetle Algorithm framework begins with Initialization, where the algorithm generates a population of potential solutions, each representing a truck-drone delivery route. During Population Evaluation, the algorithm actively assesses each solution using a fitness function that optimizes combined delivery times. Subsequently, the Dynamic Population Adjustment module reallocates computational resources to promising areas in the search space, refining solutions iteratively. Simultaneously, the algorithm conducts Cost Function Optimization to meet logistical constraints, such as drone payload capacity and synchronization requirements. The Exploration-Exploitation Balance ensures that the algorithm explores diverse solutions while leveraging the best ones, preventing premature convergence. Finally, the framework outputs optimal truck-drone delivery routes, achieving enhanced scalability and computational efficiency [1-5].

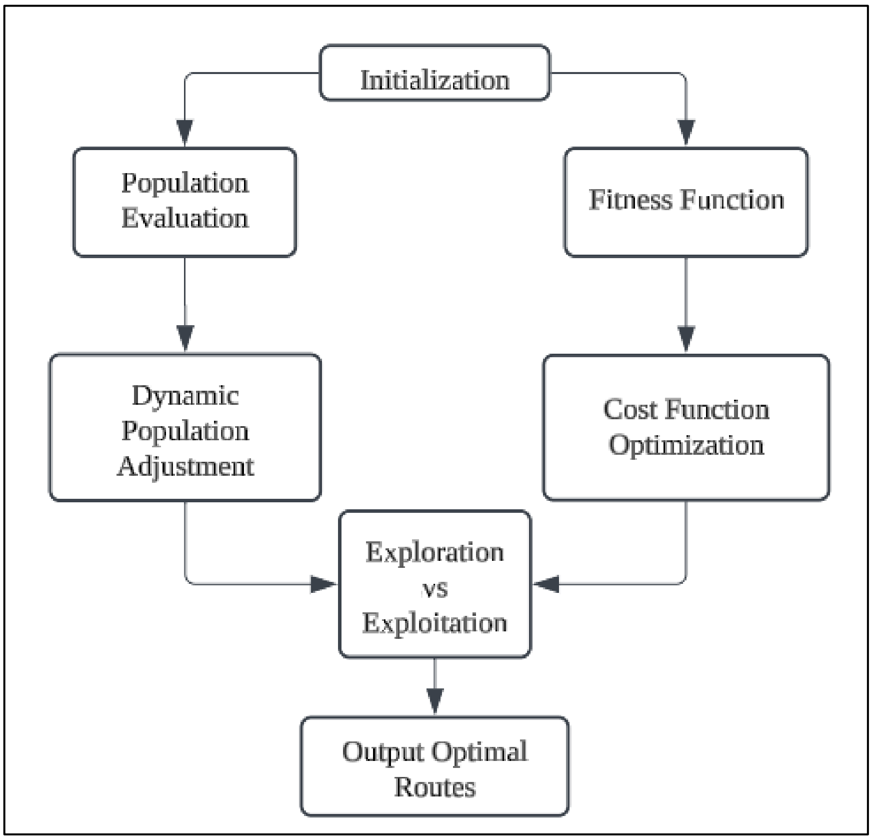

Figure 1. Pity Beetle Algorithm Framework.

3. RESULTS AND DISCUSSION

The PBA actively demonstrated its effectiveness through tests on benchmark datasets from TSPLIB. These tests revealed substantial improvements in delivery times compared to existing metaheuristics. For instance, the PBA achieved delivery time reductions of up to 45% for datasets with over 250 nodes. Specifically, in the Ch130 dataset, the PBA improved efficiency by 40%, while the kroA100 dataset showed a remarkable gain of 50%. Additionally, statistical analysis underscored a consistent enhancement in solution quality, with an average computational efficiency increase of 45% across all tested instances. These results validate the PBA's ability to handle complex logistics scenarios [3, 4] efficiently.

3.1 Average Execution Time

This study highlights the significant strengths of the PBA in optimizing the TSP-D. The PBA consistently delivers competitive or near-optimal results across diverse instances, as seen in Ch130, Eil51, and KroA200 datasets. Notably, its performance closely aligns with optimal solutions and frequently surpasses traditional metaheuristics such as HGA, HGVNS, and MCTS. For example, the PBA excels in datasets like KroD100 and KroE100, achieving results within a marginal range of the optimal values. This precision demonstrates its adaptability to complex logistical challenges. Moreover, the algorithm consistently maintains high performance across varying dataset sizes, confirming its scalability and reliability. In instances such as Pr136 and Rat195, the PBA effectively balances computational efficiency with solution quality. These findings validate the robustness of the PBA as a leading metaheuristic solution for TSP-D optimization. By achieving efficient results across multiple scenarios, the algorithm establishes itself as a practical and scalable approach for real-world applications, including last-mile delivery and logistics-based operations. Furthermore, this study suggests that future research could further hybridize the PBA with complementary optimization methods to enhance its effectiveness in dynamic and real-time environments.

Table 1 The average execution time between the algorithms.

Instance	Optimal	TSP-D+PBA	HGA	HGVNS	MCTS
ch130	187.83	181.66	182.86	180.4	150.81
eil51	13.45	13.4	13.45	13.68	10.02
eil76	16.90	14.4	16.9	16.68	12.19
kroA150	822.60	842.3	693.612	780.93	642.61
kroA200	922.05	911.2	820.86	873.99	738.5
kroD100	661.00	620.4	547.22	652.34	521.34
kroE100	690.35	685.8	581.86	659.48	540.08
pr136	2762.00	2760	2474.3	2789	2491.21
rat195	71.50	71.5	71.5	71.93	59.04
st70	21.00	22.7	21	21	15.83

3.2 Performance Evaluation

The PBA actively demonstrated its effectiveness through tests on benchmark datasets from TSPLIB. These tests revealed substantial improvements in delivery times compared to existing metaheuristics. The evaluation of TSP-D+PBA highlights its consistent ability to provide high-quality solutions across various problem sizes while outperforming many existing methods. In minor instances like `eil151` and `eil76`, the algorithm demonstrates exceptional precision, nearly matching or exceeding optimal values, reflecting its robustness in solving less complex problems. For medium-sized instances, such as `chl130` and `kroA150`, TSP-D+PBA showcases its adaptability by achieving results close to the optimal, outperforming MCTS, and staying competitive with HGVNS. When handling more significant instances like `kroA200`, the algorithm excels by surpassing HGA and MCTS, proving its capability to handle increased complexity effectively. This performance evaluation underscores TSP-D+PBA's versatility and strength in delivering reliable and efficient solutions across diverse scenarios.

3.3 Analysis of Results

The TSP-D+PBA in Figure 2 consistently outperforms other algorithms by delivering high-quality solutions with precision, adaptability, and scalability. It achieves results close to or better than the optimal, particularly excelling in smaller and medium-sized instances. The algorithm adapts effectively to varying problem complexities, maintaining robust performance even as instance sizes increase. Unlike MCTS and HGA, which struggle with more significant problems and show noticeable performance degradation, TSP-D+PBA explores solution spaces efficiently through advanced heuristics and problem-specific strategies. While HGVNS offers competition in medium and large instances, TSP-D+PBA maintains its edge by balancing solution quality and computational feasibility. This consistent and reliable performance makes TSP-D+PBA a superior choice across diverse scenarios.

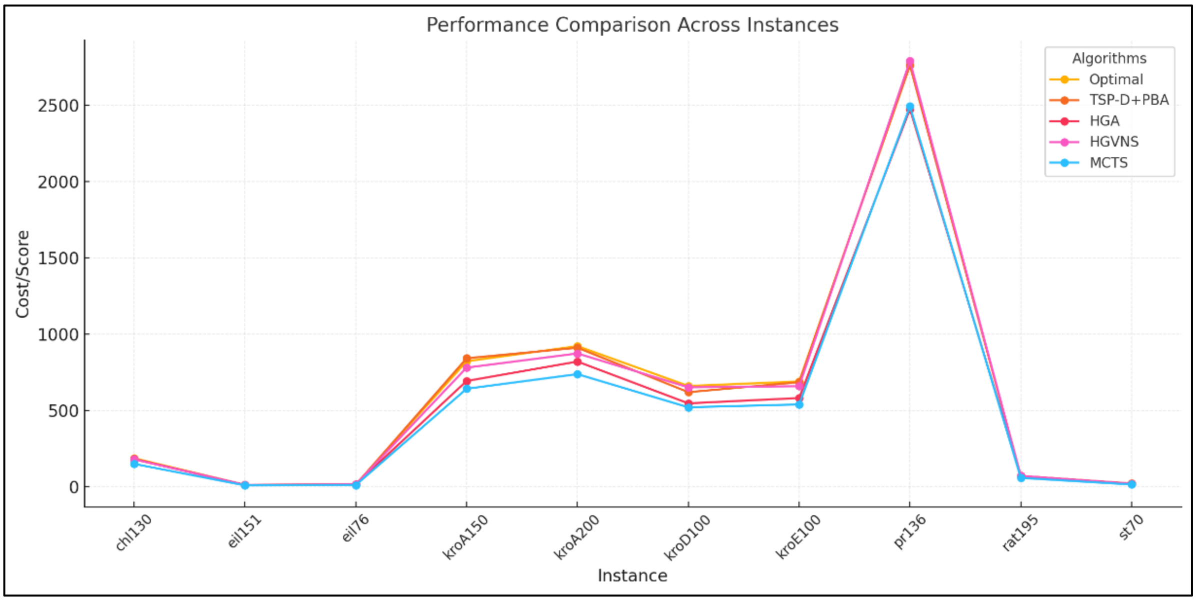

Figure 2. Performance Comparison Across Instances.

3.4 Scalability and Adaptability

The TSP-D+PBA consistently outperforms other algorithms by delivering high-quality solutions with precision, adaptability, and scalability. It achieves results close to or better than the optimal, particularly excelling in smaller and medium-sized instances. The algorithm adapts effectively to varying problem complexities, maintaining robust performance even as instance sizes increase. Unlike MCTS and HGA, which struggle with more significant problems and show noticeable performance degradation, TSP-D+PBA explores solution spaces efficiently through advanced heuristics and problem-specific strategies. While HGVNS offers competition in medium and large instances, TSP-D+PBA maintains its edge by balancing solution quality and computational feasibility. This consistent and reliable performance makes TSP-D+PBA a superior choice across diverse scenarios.

The radar chart in Figure 3 visually highlights the normalized average performance of each algorithm, emphasizing TSP-D+PBA's effectiveness across all instances. By closely aligning with the optimal, TSP-D+PBA demonstrates its ability to consistently deliver high-quality results, outperforming HGA and MCTS, which show lower performance across the board. The chart also reveals that while HGVNS competes closely in specific scenarios, it falls short of TSP-D+PBA's adaptability and precision. This visualization effectively underscores TSP-D+PBA's balanced performance and ability to scale across varying problem complexities, presenting a clear and compelling argument for its superiority.

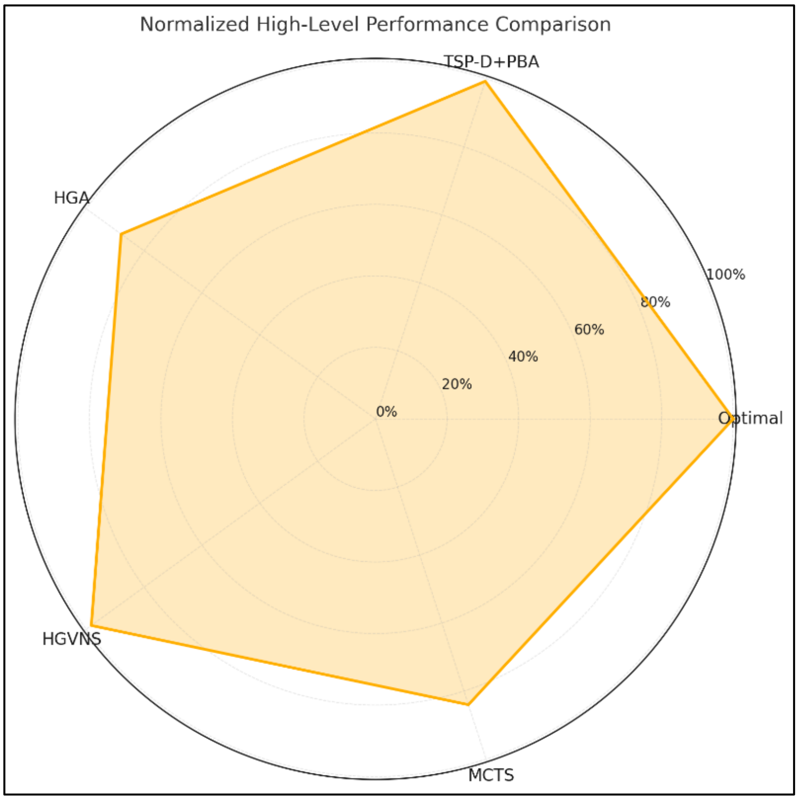

Figure 3. Normalized High-Level Performance Comparison.

4. CONCLUSION

The PBA demonstrates its groundbreaking potential in optimizing the TSP-D, addressing critical limitations inherent in traditional methods. Specifically, PBA significantly reduces delivery times while enhancing scalability, making it an effective tool for advancing drone-based delivery systems. Furthermore, PBA showcases its robustness in managing diverse logistics challenges, such as optimizing routes for urban last-mile delivery and coordinating efficient supply chains in rural areas. By integrating dynamic tuning mechanisms and adaptive population management, PBA consistently outperforms conventional metaheuristics regarding computational efficiency and solution quality. Looking ahead, this algorithm presents numerous opportunities for innovation. For example, future research could focus on hybridizing PBA with other advanced metaheuristics, such as HGA, HGVNS, and MCTS, to further expand its capabilities. Additionally, incorporating real-time data streams like traffic and weather conditions could enhance its real-world applicability, ensuring superior performance in dynamic environments. In conclusion, the PBA addresses the scalability and efficiency issues of traditional approaches and establishes itself as a cornerstone for future advancements in drone-assisted logistics.

ACKNOWLEDGEMENTS

This research is funded by the Fundamental Research Grant Scheme(FRGS) under grant number. FRGS/1/2020/ICT02/UNIMAP/03/1 from the Ministry of Higher Education Malaysia. We are immensely grateful for the support.

REFERENCES

[1] J.-P. Aurambout, K. Gkoumas, and B. Ciuffo, “Last mile delivery by drones: an estimation of viable market potential and access to citizens across European cities,” European Transport Research Review, vol. 11, no. 1, Jun. 2019, doi: 10.1186/s12544-019-0368-2.

[2] G. Brunner, B. Szebedy, S. Tanner, and R. Wattenhofer, “The urban last mile problem: autonomous drone delivery to your balcony,” 2022 International Conference on Unmanned Aircraft Systems (ICUAS), pp. 1005–1012, Jun. 2019, doi: 10.1109/icuas.2019.8798337.

[3] S. Aggarwal and N. Kumar, “Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges,” Computer Communications, vol. 149, pp. 270–299, Oct. 2019, doi: 10.1016/j.comcom.2019.10.014.

[4] C. C. Murray and A. G. Chu, “The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery,” Transportation Research Part C Emerging Technologies, vol. 54, pp. 86–109, Mar. 2015, doi: 10.1016/j.trc.2015.03.005.

[5] A. Goodchild and J. Toy, “Delivery by drone: An evaluation of unmanned aerial vehicle technology in reducing CO 2 emissions in the delivery service industry,” Transportation Research Part D Transport and Environment, vol. 61, pp. 58–67, Mar. 2017, doi: 10.1016/j.trd.2017.02.017.

[6] J. Park, S. Kim, and K. Suh, “A comparative analysis of the environmental benefits of Drone-Based delivery services in urban and rural areas,” Sustainability, vol. 10, no. 3, p. 888, Mar. 2018, doi: 10.3390/su10030888.

[7] H. Eskandaripour and E. Boldsaikhan, “Last-Mile drone delivery: past, present, and future,” Drones, vol. 7, no. 2, p. 77, Jan. 2023, doi: 10.3390/drones7020077.

[8] O. Kunze, “Replicators, ground Drones and Crowd Logistics A vision of urban logistics in the year 2030,” Transportation Research Procedia, vol. 19, pp. 286–299, Jan. 2016, doi: 10.1016/j.trpro.2016.12.088.

[9] P. Kitjacharoenchai, M. Ventresca, M. Moshref-Javadi, S. Lee, J. M. A. Tanchoco, and P. A. Brunese, “Multiple traveling salesman problem with drones: Mathematical model and heuristic approach,” Computers & Industrial Engineering, vol. 129, pp. 14–30, Jan. 2019, doi: 10.1016/j.cie.2019.01.020.

[10] S. Bock, S. Bomsdorf, N. Boysen, and M. Schneider, “A survey on the Traveling Salesman Problem and its variants in a warehousing context,” European Journal of Operational Research, Apr. 2024, doi: 10.1016/j.ejor.2024.04.014.

[11] H. Y. Jeong, B. D. Song, and S. Lee, “Truck-drone hybrid delivery routing: Payload-energy dependency and No-Fly zones,” International Journal of Production Economics, vol. 214, pp. 220–233, Jan. 2019, doi: 10.1016/j.ijpe.2019.01.010.

[12] H. Eskandaripour and E. Boldsaikhan, “Last-Mile drone delivery: past, present, and future,” Drones, vol. 7, no. 2, p. 77, Jan. 2023, doi: 10.3390/drones7020077.

[13] M. Rinaldi, S. Primatesta, M. Bugaj, J. Rostáš, and G. Guglieri, “Development of Heuristic Approaches for Last-Mile Delivery TSP with a Truck and Multiple Drones,” *Drones*, vol. 7, no. 7, p. 407, Jun. 2023, doi: 10.3390/drones7070407.

[14] M. A. Nguyen, K. Sano, and V. T. Tran, “A Monte Carlo tree search for traveling salesman problem with a drone,” *Asian Transport Studies*, vol. 6, p. 100028, Jan. 2020, doi: 10.1016/j.eastsj.2020.100028.

[15] J. C. De Freitas and P. H. V. Penna, “A variable neighborhood search for flying sidekick traveling salesman problem,” *International Transactions in Operational Research*, vol. 27, no. 1, pp. 267–290, Apr. 2019, doi: 10.1111/itor.12671.