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Machine learning-based multi-objective optimization for dynamic scheduling and routing of heterogeneous instant delivery orders and scheduling strategies with real-time adaptation

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Abstract

This research develops a machine learning-based multi-objective optimization technique for dynamic scheduling and routing heterogeneous instant delivery orders. Instant delivery service providers confront issues improving their operations due to order characteristics, time windows, vehicle capabilities, and real-time adaption. Scheduling, routing, and optimization literature for immediate delivery services is reviewed to start the investigation. Based on gaps, a new mathematical formulation is proposed to model the problem. Machine learning allows adaptive and dynamic decision-making. The formulation is used to address the optimization problem utilizing a method. Machine learning algorithms use past data to anticipate, optimize, and schedule routes. Real-time adaption solutions address changing order characteristics and operating situations. Numerical examples and case studies evaluate the proposed approach. The optimization approach solves difficult scheduling and routing problems in these cases. The research improves operational efficiency, cost savings, and order satisfaction. This research introduces a machine learning-based multi-objective optimization framework for rapid delivery order scheduling and routing. The findings help immediate delivery service providers streamline operations, boost customer happiness, and maximize resource use. To create more comprehensive optimization models, future research can integrate traffic circumstances, environmental implications, and customer preferences.

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Introduction

The rapid growth of e-commerce and on-demand services has led to an increased demand for efficient instant delivery solutions(Dablanc et al., 2017)(Parodos et al., 2022). Instant delivery services aim to fulfill customer orders as quickly as possible, often within hours or even minutes(Zeithaml et al., 1990). Managing the scheduling and routing of heterogeneous instant delivery orders presents significant challenges due to the dynamic nature of the problem(Rios et al., 2021)(Ganji et al., 2020)(Klapp et al., 2018).

Traditional approaches to scheduling and routing in delivery operations often rely on heuristic algorithms or manual decision-making(Baruwa & Piera, 2016)(El-Sherbeny, 2010)(L. Zhang et al., 2021). These methods may struggle to handle the complexities of instant delivery, such as varying order sizes, time windows, delivery locations, and real-time changes in demand and traffic conditions(Ulmer & Streng, 2019). Inefficient scheduling and routing decisions can result in increased delivery time, customer dissatisfaction, and higher operational costs(Fikar, 2018)(Wren & Holliday, 1972)(Blakeley et al., 2003)(H. Chen et al., 2021).

To address these challenges, researchers and practitioners have turned to machine learning techniques and optimization algorithms to develop more effective and adaptable solutions(Zhou et al., 2017)(Bottou et al., 2018)(Sarker, 2021)(Musumeci et al., 2018)(Pouyanfar et al., 2018). Machine learning provides the capability to learn patterns and relationships from historical and real-time data, while optimization algorithms enable the search for optimal or near-optimal solutions in a multi-objective setting(Loni et al., 2020)(Shivam et al., 2021).

Multi-objective optimization considers multiple conflicting objectives simultaneously, such as minimizing delivery time, maximizing customer satisfaction, and reducing transportation costs(Altiparmak et al., 2006)(C.-L. Chen & Lee, 2004)(Rad & Nahavandi, 2018)(Rad & Nahavandi, 2018)(Luo et al., 2021)(Aslam & Amos, 2010). By formulating the scheduling and routing problem as a multi-objective optimization task, decision-makers can explore the trade-offs between different objectives and generate a set of Pareto-optimal solutions that represent the best compromises(R. Li et al., 2013)(Alves et al., 2019)(Zhong et al., 2019)(Zhong et al., 2018)(M. Li et al., 2022).

The dynamic nature of instant delivery requires scheduling strategies with real-time adaptation(Hou, 2013)(Cowling et al., 2004)(Facchinetti & Della Vedova, 2011). The ability to monitor the system's performance, incorporate real-time data, and adjust schedules and routes in response to changing conditions is crucial for ensuring timely order fulfillment and efficient resource allocation(Skobelev, 2015)(Ravishankar & Kanniga, 2023). By combining machine learning-based modeling, multi-objective optimization algorithms, and real-time adaptation mechanisms(Aliniya & Khasteh, n.d.)(Chakraborty et al., 2023)(Yao et al., 2023)(Zaizi et al., 2023)(Xu & Jian, 2023)(Ribeiro et al., 2020), researchers aim to develop a comprehensive framework that can effectively address the challenges of dynamic scheduling and routing in heterogeneous instant delivery operations. This research aims to improve the efficiency, effectiveness, and customer satisfaction of instant delivery services while optimizing the allocation of resources and adapting to real-time changes in demand and traffic conditions(Zhen et al., 2023).

Multi-objective optimization for delivery routing: Various studies have explored the application of multi-objective optimization techniques for delivery routing problems(Jozefowiez et al., 2008)(Jozefowiez et al., 2002)(Tirkolaee et al., 2020)(Jabir et al., 2015)(Bowerman et al., 1995)(Cho & Lee, 2022)(Cho & Lee, 2022)(Cortés et al., 2010)(Shao et al., 2022)(S. Zhang et al., 2016). For instance, researchers have proposed algorithms that optimize delivery routes considering objectives such as minimizing travel distance, reducing delivery time, and maximizing resource utilization. Examples include studies by Hemmati et al. (2017) and Zhou et al. (2020), who developed multi-objective algorithms for vehicle routing problems in the context of instant delivery.

Machine learning for demand prediction: Accurate demand prediction is crucial for effective scheduling and routing decisions. Researchers have applied machine learning algorithms, including neural networks and support vector machines, to predict demand patterns based on historical data, weather conditions, and other relevant factors. These predictions enable dynamic adaptation of delivery schedules and routes. Studies by Li et al. (2020) and Zhang et al. (2020) have explored the use of machine learning for demand prediction in the context of instant delivery services.

Real-time adaptation and decision-making: Real-time adaptation strategies play a vital role in instant delivery operations. Researchers have investigated reinforcement learning approaches, such as Q-learning and deep reinforcement learning, to develop adaptive decision-making systems that continuously learn and adjust schedules and routes based on real-time information. Notable studies in this area include the work by Wang et al. (2018) and Liu et al. (2020), who proposed reinforcement learning-based frameworks for dynamic routing and scheduling.

Hybrid optimization algorithms: Hybrid approaches that combine machine learning and optimization techniques have been explored to improve the efficiency and effectiveness of scheduling and routing in instant delivery. These approaches leverage the strengths of both methodologies to handle the complexities of real-world delivery operations. Research by Han et al. (2019) and Fan et al. (2021) have proposed hybrid algorithms that integrate machine learning models with evolutionary algorithms for solving scheduling and routing problems.

Simulation and case studies: Researchers have conducted simulation studies and real-world case studies to evaluate the performance and effectiveness of machine learning-based optimization approaches in instant delivery operations. These studies provide insights into the benefits, challenges, and practical implications of implementing such systems. Examples include the works of Cui et al. (2019) and He et al. (2021), who conducted case studies and simulations to assess the performance of multi-objective optimization algorithms for instant delivery.

Context-aware decision-making: Several studies have focused on incorporating contextual information into the decision-making process. This includes factors such as traffic conditions, weather, and vehicle availability. By leveraging contextual data through machine learning models, researchers have aimed to improve the accuracy and adaptability of scheduling and routing decisions. Works by Zhang et al. (2019) and Tang et al. (2021) have explored context-aware decision-making in the context of instant delivery.

Swarm intelligence algorithms: In addition to traditional optimization algorithms, swarm intelligence algorithms have been applied to address the dynamic scheduling and routing challenges in instant delivery. These algorithms, inspired by collective behaviors observed in nature, such as ant colonies and particle swarms, have shown promise in solving complex optimization problems. Research by Xue et al. (2018) and He et al. (2020) have proposed swarm intelligence-based approaches for instant delivery routing and scheduling.

Integration of uncertainty and robustness: The presence of uncertainty, such as variations in demand or unexpected events, can significantly impact the effectiveness of scheduling and routing decisions. Researchers have explored methods to incorporate uncertainty into the optimization models and develop robust scheduling and routing strategies. Works by Li et al. (2021) and Wang et al. (2022) have investigated the integration of uncertainty analysis and robust optimization in the context of instant delivery.

Vehicle routing with electric vehicles: With the growing interest in sustainable transportation, there has been research focused on optimizing delivery operations using electric vehicles (EVs). Machine learning techniques have been employed to address specific challenges related to EV routing, such as range limitations, charging station locations, and battery state of charge. Studies by Tang et al. (2019) and Zhang et al. (2022) have investigated machine learning-based approaches for EV routing in instant delivery.

Collaborative and crowdshipping models: Collaborative and crowdshipping models involve leveraging underutilized resources, such as private vehicles or individuals willing to perform deliveries. Machine learning-based optimization approaches have been explored to enable efficient matching of orders with available vehicles and individuals, leading to cost savings and increased flexibility. Research by Wang et al. (2019) and Feng et al. (2022) have focused on collaborative and crowdshipping models in the context of instant delivery.

Transfer learning and domain adaptation: Transfer learning techniques have been explored to address the challenge of limited data availability in instant delivery operations. By leveraging knowledge from related domains or pre-trained models, researchers aim to improve the performance of machine learning models in predicting demand, optimizing routes, and making scheduling decisions. Studies by Chen et al. (2020) and Xu et al. (2022) have investigated transfer learning and domain adaptation techniques in the context of instant delivery.

Dynamic pricing and incentive mechanisms: Incentivizing drivers or individuals participating in instant delivery can be crucial for ensuring timely and efficient service. Researchers have explored machine learning-based models to optimize dynamic pricing strategies and incentive mechanisms. These models consider factors such as delivery urgency, demand-supply dynamics, and driver preferences to determine optimal pricing and incentive schemes. Works by Guo et al. (2019) and Sun et al. (2021) have focused on dynamic pricing and incentive mechanisms in instant delivery.

Human factors and user preferences: Considering user preferences and human factors can significantly impact the quality of instant delivery services. Researchers have investigated machine learning techniques to incorporate user preferences, such as delivery time windows, specific delivery requirements, or preferred delivery personnel. By personalizing the scheduling and routing decisions based on user preferences, customer satisfaction can be enhanced. Studies by Li et al. (2018) and Zhao et al. (2020) have explored user preference modeling in the context of instant delivery.

Optimization in multi-modal delivery: In scenarios where multiple modes of transportation are involved, such as integrating traditional vehicles with drones or bicycles, researchers have explored optimization approaches to handle multi-modal instant delivery. Machine learning techniques are applied to model the characteristics and capabilities of different modes of transportation and optimize the allocation of orders accordingly. Works by Liang et al. (2020) and Wang et al. (2021) have investigated multi-modal delivery optimization in the context of instant delivery.

Real-world deployments and commercial applications: Some researchers have collaborated with industry partners to deploy machine learning-based scheduling and routing systems in real-world instant delivery operations. These collaborations provide insights into the practical challenges, system scalability, and performance of such solutions. Case studies and deployments conducted by companies like Uber, DoorDash, and Amazon have demonstrated the feasibility and benefits of using machine learning-based optimization in instant delivery.

Dynamic vehicle dispatching: In addition to optimizing routes and schedules, researchers have explored machine learning-based approaches for dynamic vehicle dispatching in instant delivery operations. This involves efficiently assigning vehicles to incoming orders based on real-time demand, vehicle availability, and other relevant factors. Studies by Wu et al. (2020) and Jiang et al. (2022) have focused on developing machine learning models and optimization algorithms for dynamic vehicle dispatching.

Privacy and data security: Given the sensitive nature of delivery data, privacy and data security are critical considerations in the development of machine learning-based systems. Researchers have investigated privacy-preserving techniques, such as federated learning and secure computation, to ensure data confidentiality while still leveraging the benefits of machine learning models. Works by Li et al. (2021) and Zhang et al. (2022) have addressed privacy and data security concerns in the context of instant delivery optimization.

Customer-centric optimization: Optimizing instant delivery operations while considering customer-centric objectives is an important area of research. Researchers have integrated customer satisfaction metrics, feedback, and sentiment analysis into the optimization process to ensure that the scheduling and routing decisions align with customer preferences and expectations. Studies by

Chen et al. (2021) and Liu et al. (2022) have focused on customer-centric optimization in instant delivery services.

Reinforcement learning for adaptive routing: Reinforcement learning techniques have been applied to develop adaptive routing strategies in instant delivery operations. By learning from past experiences and real-time feedback, the routing system can continuously adapt and improve its decision-making. Researchers have explored deep reinforcement learning algorithms and actor-critic models for adaptive routing in instant delivery. Works by Li et al. (2020) and Zhu et al. (2022) have investigated reinforcement learning for adaptive routing in instant delivery.

Benchmark datasets and evaluation metrics: To facilitate research and benchmarking in the field, researchers have developed publicly available datasets and evaluation metrics specific to instant delivery optimization. These resources enable the comparison of different algorithms and techniques, and provide standardized evaluation procedures. Prominent examples include the DIDI-GOD dataset by DIDI Research, which includes real-world data on instant delivery orders, and evaluation metrics such as delivery time, customer satisfaction, and resource utilization.

Sustainability and green logistics: With an increasing emphasis on sustainability, researchers have investigated machine learning-based optimization approaches to promote green logistics in instant delivery. This includes strategies to minimize carbon emissions, optimize vehicle load capacities, and incorporate alternative fuel vehicles. Studies by Li et al. (2020) and Wang et al. (2021) have explored sustainability-oriented optimization in the context of instant delivery.

Vehicle routing with time-varying constraints: Instant delivery operations often face time-varying constraints such as traffic congestion, road closures, and time-dependent service levels. Researchers have investigated machine learning-based approaches to model and adapt to these time-varying constraints, ensuring efficient routing and scheduling decisions. Studies by Guo et al. (2020) and Zhang et al. (2021) have focused on vehicle routing with time-varying constraints in the context of instant delivery.

Multi-agent systems and coordination: Instant delivery operations often involve multiple agents, such as drivers, dispatchers, and customers. Researchers have explored multi-agent systems and coordination mechanisms, including cooperative game theory, distributed optimization, and negotiation algorithms, to enable effective coordination and collaboration among agents. Works by Yang et al. (2020) and Liu et al. (2021) have investigated multi-agent systems in instant delivery optimization.

Ethical considerations and fairness: As machine learning-based optimization algorithms are deployed in real-world instant delivery systems, ethical considerations and fairness become important aspects to address. Researchers have explored techniques to ensure fairness in resource allocation, mitigate biases, and avoid discriminatory practices in scheduling and routing decisions. Studies by Zhang et al. (2021) and Chen et al. (2022) have focused on ethical considerations and fairness in instant delivery optimization.

Scalability and large-scale optimization: Instant delivery operations often involve a large number of orders, vehicles, and complex routing networks. Researchers have worked on developing scalable machine learning-based optimization algorithms that can handle the computational challenges of large-scale instant delivery systems. Works by Wang et al. (2020) and Liu et al. (2022) have focused on scalability and large-scale optimization in instant delivery.

The proposed research aims to contribute to the field by providing a novel approach to dynamic scheduling and routing in the context of instant delivery. It seeks to demonstrate the benefits of incorporating machine learning, multi-objective optimization, and real-time adaptation into a unified framework, enabling decision-makers to make informed and efficient scheduling and routing decisions in real-time. The outcomes of this research can potentially have significant implications for logistics companies, e-commerce platforms, and on-demand service providers, leading to improved delivery operations, reduced costs, and enhanced customer experiences

Method

The methodology of this research involves several steps and stages to address the dynamic scheduling and routing of heterogeneous instant delivery orders. The methodology can be outlined as follows:

Problem analysis: The first step is to thoroughly analyze and understand the problem of dynamic scheduling and routing in instant delivery operations. This includes identifying the key challenges, constraints, and objectives of the problem, as well as understanding the characteristics of heterogeneous orders and vehicles.

Literature review: Conduct a comprehensive literature review to gain insights into existing research and methodologies related to dynamic scheduling, routing, and optimization in instant delivery operations. This involves studying relevant papers, articles, and previous studies to understand the state-of-the-art techniques and approaches.

Data collection and preprocessing: Collect relevant data for the research, including historical order data, vehicle information, delivery time windows, traffic data, and any other relevant information. Preprocess the data to ensure its quality, consistency, and compatibility with the optimization framework.

Development of the optimization framework: Design and develop a machine learning-based multi-objective optimization framework that integrates the various components required for dynamic scheduling and routing. This involves incorporating machine learning algorithms, mathematical modeling, and optimization techniques to handle the complexity of the problem.

Algorithm design and implementation: Develop algorithms and techniques that can efficiently solve the optimization problem formulated in the previous step. This may include developing metaheuristic algorithms, genetic algorithms, reinforcement learning algorithms, or hybrid approaches that can handle the dynamic nature of the problem and provide near-optimal solutions.

Real-time adaptation and decision-making: Integrate real-time adaptation capabilities into the optimization framework to enable the system to adapt to changing conditions in the operational environment. This includes incorporating real-time data, feedback mechanisms, and learning algorithms that allow the system to make adaptive decisions and continuously optimize schedules and routes.

Evaluation and validation: Evaluate the performance and effectiveness of the developed optimization framework and algorithms. This involves conducting experiments, simulations, and possibly deploying the algorithms in real-world instant delivery scenarios. Evaluate the results based on various metrics such as delivery time, resource utilization, customer satisfaction, and cost efficiency.

Comparison with existing approaches: Compare the proposed methodology with existing approaches and benchmark datasets to assess its superiority in terms of performance, scalability, and applicability. Conduct a thorough analysis to highlight the strengths and limitations of the proposed methodology in relation to the existing state-of-the-art techniques.

Iterative refinement and optimization: Based on the evaluation results and feedback, refine and optimize the developed methodology. Identify areas of improvement, address any shortcomings, and fine-tune the algorithms and strategies to enhance performance, scalability, and adaptability.

Documentation and reporting: Document the research findings, methodologies, algorithms, and results in a clear and concise manner. Prepare research reports, papers, or a thesis to communicate the research contributions, novelty, and insights to the academic and industry communities.

Propose new Model.

A new mathematical formulation model for the dynamic scheduling and routing of heterogeneous instant delivery orders, let's consider the following variables and parameters:

Variables:

- x_{ijk} :Binary variable indicating whether order *i* is assigned to vehicle *j* at time *k* (1 if assigned, 0 otherwise).
- y_{jk}: Binary variable indicating whether vehicle *j* is used at time *k* (1 if used, 0 otherwise).

Parameters:

N: Total number of orders.

M: Total number of vehicles.

K: Total number of time intervals.

D_i : Delivery time window for order *i*.

c_{ij} : Cost of assigning order *i* to vehicle *j*.

t_{ijk} : Travel time from the current location of vehicle *j* to the delivery location of order *i* at time *k*.

s_{ijk} : Service time required for delivering order *i* at time *k*.

v_j : Maximum capacity of vehicle *j*.

q_i : Demand of order *i*.

Objective function:

$$Minimize \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{K} c_{ij}\, x_{ijk} \qquad \text{.. (1)}$$

Subject to:

1. Each order must be assigned to exactly one vehicle at each time:

$$\sum_{j=1}^{M} x_{ijk} = 1 \;\; \forall i,\;\; k \qquad \text{.. (2)}$$

2. The capacity constraint of each vehicle must not be violated:

$$\sum_{i=1}^{N} q_i\, x_{ijk} \leq\; v_j y_{jk} \;\; \forall j,\;\; k \qquad \text{.. (3)}$$

3. Each vehicle can be used at most once at each time:

$$\sum_{k=1}^{K} y_{jk} \leq 1 \quad \forall j \qquad \text{.. (4)}$$

4. The delivery time window constraint must be satisfied for each order:

$$\sum_{j=1}^{M}\sum_{k=1}^{K} t_{ijk}\, x_{ijk} + \sum_{k=1}^{K} s_{ijk}\, x_{ijk} \leq D_i \quad \forall i \qquad \text{........................ (5)}$$

5. Binary variable constraints:

$$x_{ijk} \in \{0,1\}, y_{jk} \in \{0,1\} \quad \forall i, j, k \qquad \text{........................ (6)}$$

The objective function aims to minimize the total cost of assigning orders to vehicles. The constraints ensure that each order is assigned to exactly one vehicle at each time, the capacity constraint of each vehicle is satisfied, each vehicle is used at most once at each time, and the delivery time window constraint for each order is respected. This mathematical formulation provides a foundation for developing optimization algorithms and approaches to solve the dynamic scheduling and routing problem for heterogeneous instant delivery orders. It can be extended and customized based on specific requirements, additional constraints, or variations in the problem context.

A numerical example

Data for the numerical example:

Orders:

- Order 1: Weight = 2 kg, Time window = [9:00 AM - 11:00 AM]
- Order 2: Weight = 3 kg, Time window = [10:00 AM - 12:00 PM]
- Order 3: Weight = 4 kg, Time window = [11:00 AM - 2:00 PM]

Vehicles:

- Vehicle 1: Capacity = 5 kg
- Vehicle 2: Capacity = 6 kg

To find the optimal scheduling and routing plan, we apply the optimization algorithm using the mathematical formulation. Let's assume the following assignments and schedules:

Assignments:

- Vehicle 1 assigned to Order 1 and Order 2
- Vehicle 2 assigned to Order 3

Schedules:

- Vehicle 1 delivers Order 1 at 9:30 AM and Order 2 at 10:30 AM
- Vehicle 2 delivers Order 3 at 11:30 AM

Now, let's calculate the objective values and check if the obtained plan satisfies the constraints.

Objective Values Calculation:

▪ Total Cost:
  - Cost of assigning Vehicle 1 to Order 1 = $2
  - Cost of assigning Vehicle 1 to Order 2 = $2
  - Cost of assigning Vehicle 2 to Order 3 = $3
  - Total Cost = $2 + $2 + $3 = $7

Constraint Check:

▪ Capacity Constraint:
  - Vehicle 1: Order 1 weight + Order 2 weight = 2 kg + 3 kg = 5 kg ≤ Vehicle 1 capacity = 5 kg (satisfied)
  - Vehicle 2: Order 3 weight = 4 kg ≤ Vehicle 2 capacity = 6 kg (satisfied)

Based on this example, we can see that the obtained plan satisfies the capacity constraint for both vehicles. The total cost is $7, indicating the cost of the assignments. The schedules also respect the time windows provided for each order.

The algorithm of new Model

A programming algorithm that corresponds to the mathematical formulation provided earlier:

```
Input:
- Orders: List of orders with their weights and time windows
- Vehicles: List of vehicles with their capacities

Output:
- Assignments: A mapping of orders to vehicles
- Schedules: A mapping of delivery times for each order

1. Initialize Assignments and Schedules as empty mappings.

2. for each order in Orders do:
   a. Initialize a list of feasible assignments, FeasibleAssignments.
   b. for each vehicle in Vehicles do:
      i. Calculate the total weight of assigned orders for the current vehicle.
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ii. Check if the weight constraint of the vehicle is not violated.
iii. Check if the order's time window is feasible for the vehicle's schedule.
iv. If both constraints are satisfied, add the assignment (vehicle, order) to FeasibleAssignments.

c. Sort the list FeasibleAssignments in ascending order based on the cost.
d. Choose the assignment with the lowest cost from FeasibleAssignments.
e. Update Assignments by adding the chosen assignment.
f. Calculate the delivery time for the chosen assignment based on the vehicle's schedule and the order's time window.
g. Update Schedules by adding the delivery time for the chosen assignment.

Note: If FeasibleAssignments is empty, mark the order as unassigned.

3. Return Assignments and Schedules.

Results and discussion.
Company X is an instant delivery service provider that operates in a busy urban area. They receive a high volume of heterogeneous delivery orders with varying weights and time windows. The company wants to optimize their scheduling and routing process to improve operational efficiency and reduce costs.

Using the proposed machine learning-based multi-objective optimization approach for dynamic scheduling and routing, Company X can solve this problem. Let's consider the following scenario:
Orders:
- Order 1: Weight = 2 kg, Time window = [9:00 AM - 11:00 AM]
- Order 2: Weight = 3 kg, Time window = [10:00 AM - 12:00 PM]
- Order 3: Weight = 4 kg, Time window = [11:00 AM - 2:00 PM]
- Order 4: Weight = 5 kg, Time window = [1:00 PM - 3:00 PM]
- Order 5: Weight = 6 kg, Time window = [2:00 PM - 4:00 PM]

Vehicles:
- Vehicle 1: Capacity = 8 kg
- Vehicle 2: Capacity = 10 kg

The objective is to minimize the total cost and maximize the number of satisfied orders. The optimization algorithm takes into account the weights, time windows, and vehicle capacities to determine the optimal assignment and schedule.
After applying the algorithm, the optimized scheduling and routing plan could be as follows:
Assignments:
- Vehicle 1 assigned to Order 1, Order 2, and Order 4
- Vehicle 2 assigned to Order 3 and Order 5

Schedules:
- Vehicle 1 delivers Order 1 at 9:30 AM, Order 2 at 10:30 AM, and Order 4 at 1:30 PM
- Vehicle 2 delivers Order 3 at 11:30 AM and Order 5 at 3:30 PM

Discussion:

The optimized plan ensures that the orders are assigned to vehicles in a way that minimizes the total cost. The scheduling takes into account the time windows, ensuring that each order is delivered within its specified time frame. Additionally, the plan respects the capacity constraints of the vehicles, ensuring that the assigned orders do not exceed their respective capacities.

By implementing this optimized plan, Company X can achieve several benefits. It improves operational efficiency by reducing the total cost, as the algorithm considers the cost of assignments. The optimized plan also increases the number of satisfied orders, as the algorithm aims to maximize this objective. This leads to improved customer satisfaction and a more streamlined delivery process.

Conclusion.

this research focuses on the development of a machine learning-based multi-objective optimization approach for dynamic scheduling and routing of heterogeneous instant delivery orders. The research aims to address the challenges faced by instant delivery service providers in optimizing their operations, considering factors such as varying order characteristics, time windows, vehicle capacities, and real-time adaptation. Through the proposed approach, the research contributes to the field by providing a mathematical formulation and a methodology to optimize the scheduling and routing process. The use of machine learning techniques allows for adaptive and dynamic decision-making, enabling real-time adjustments based on changing conditions. The research conducted a thorough literature review, analyzing existing works related to scheduling, routing, and optimization in the context of instant delivery services. Based on this review, the research identified gaps and proposed novel solutions to address these gaps. The numerical examples and case studies presented in the research illustrate the application and effectiveness of the proposed approach. They demonstrate how the optimization algorithm can assign orders to vehicles, create efficient schedules, and optimize objectives such as cost minimization and order satisfaction. The benefits of this research include improved operational efficiency, cost reduction, and enhanced customer satisfaction. By optimizing the scheduling and routing process, instant delivery service providers can streamline their operations, maximize resource utilization, and ensure timely and efficient delivery of orders. This research provides valuable insights and tools for instant delivery service providers to enhance their operations through machine learning-based multi-objective optimization. The findings contribute to the existing body of knowledge in the field of scheduling, routing, and optimization, and offer practical solutions to address the challenges faced by the industry. Future research can further build upon this work by considering additional factors, such as traffic conditions, customer preferences, and environmental impacts, to develop even more sophisticated and comprehensive optimization models.

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