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# A SCALABLE MODEL FOR CAPACITATED VEHICLE ROUTING PROBLEM WITH PICKUP AND DELIVERY UNDER DYNAMIC CONSTRAINTS USING ADAPTIVE HEURISTIC-BASED ANT COLONY OPTIMIZATION

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***This study addresses the Capacitated Vehicle Routing Problem with Pickup and Delivery (CVRPPD), a core challenge in urban logistics involving the optimization of vehicle routes under dynamic constraints. Traditional algorithms predominantly focus on static variables like distance, failing to account for real-world factors such as traffic congestion, adverse weather, and vehicle capacity limitations. To solve this problem, the Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO) algorithm was developed, incorporating these dynamic constraints into the routing optimization process. The AHB-ACO algorithm minimizes total travel costs while ensuring adherence to vehicle capacity limits and improving route safety. Simulation tests were conducted on datasets with 50, 100, and 200 customers to evaluate performance under varying levels of complexity. The results demonstrate that AHB-ACO outperforms traditional ACO, particularly in dynamic scenarios, achieving a total cost of 4155.82 with an execution time of 1639.68 seconds for the 200-customer dataset. The algorithm's adaptive heuristic formula integrates distance, traffic congestion, and weather penalties, enabling the generation of safer and more realistic routes. These results are explained by the algorithm's ability to dynamically adjust to constraints, ensuring robust performance in complex environments. The findings highlight AHB-ACO's practical applicability in urban logistics, offering scalability and adaptability for real-world delivery and pickup challenges, especially in areas affected by fluctuating traffic and weather conditions***

***Keywords: adaptive heuristic-based ant colony optimization, capacitated vehicle routing problem, dynamic constraints, traffic congestion, adverse weather, urban logistics***

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## 1. Introduction

In the era of modern logistics, optimizing vehicle routes has become a critical challenge due to rapid urbanization, increasing traffic volumes, and dynamic factors such as unpredictable weather conditions and fluctuating road accessibility. Efficient route optimization is essential for ensuring timely deliveries, reducing operational costs, and enhancing service reliability in urban logistics. One of the core problems in this domain is the Capacitated Vehicle Routing Problem with Pickup and Delivery (CVRPPD), which seeks to determine optimal routes for vehicles tasked with picking up and delivering goods at various locations. CVRPPD combines operational constraints, such as vehicle capacity, with external factors like traffic congestion and adverse weather conditions, making it a highly complex yet fundamental problem in logistics operations [1, 2].

The growing demand for efficient logistics operations, especially in developing nations like Indonesia, has been fueled by the rapid growth of e-commerce. Courier companies, such as JNE, J&T, Sicepat, Lion Parcel, and others, rely heavily on motorcycles for delivery operations due to their ability to navigate congested urban areas. However, these operations face unique challenges, including the need to account for weather conditions, vehicle capacity, and traffic congestion. For instance, during adverse weather conditions like heavy rain, couriers are forced to halt operations to protect goods, increasing delivery delays. Furthermore, vehicle capacity limitations require careful route planning to ensure that the total load does not exceed the carrying capacity while simultaneously fulfilling both pickup and delivery demands. Traffic congestion further complicates route planning, requiring couriers to avoid heavily congested routes to minimize delays [3, 4].

Despite significant research on CVRPPD, most existing studies predominantly focus on static optimization variables, such as distance between nodes [1, 2]. These approaches overlook dynamic and real-world factors, such as congestion delays or weather disruptions, which are critical in urban logistics. Consequently, there is a pressing need for adaptive optimization models that can account for dynamic constraints [5, 6].

Ant Colony Optimization (ACO) is a widely utilized algorithm in routing problems, inspired by the behavior of ants in finding optimal paths using pheromone trails. While ACO has demonstrated success in addressing various routing challenges, existing applications to CVRPPD primarily focus on optimizing static parameters like distance [7, 8]. For example, studies have demonstrated improved ACO algorithms for path planning but failed to address critical real-world factors such as weather or traffic [4, 5]. Similarly, hybrid ACO approaches have been implemented but lacked integration of external constraints [6, 7]. These limitations reduce the applicability of traditional ACO in urban logistics, where dynamic constraints heavily influence operational efficiency.

Given the challenges posed by dynamic variables, such as traffic congestion and adverse weather, the development of adaptive models for CVRPPD is crucial to improving operational efficiency and reliability.

## 2. Literature review and problem statement

The study [8] developed a hybrid algorithm combining Ant Colony Optimization (ACO) and Genetic Algorithm (GA) to address the Capacitated Vehicle Routing Problem (CVRP). Its primary focus was to overcome the limitations of traditional ACO, which often becomes trapped in local optima and exhibits slow convergence in finding solutions. While effective in reducing travel distance and improving vehicle capacity utilization, the study did not consider dynamic factors such as traffic congestion or adverse weather conditions, limiting its applicability to real-world scenarios.

In contrast, [9] modified ACO to handle dynamic constraints such as variable speeds and bad weather, aiming to optimize total travel time in real-time. However, their approach remained heavily focused on minimizing travel distance using the 2-Opt heuristic, leaving unaddressed the issues of vehicle capacity and multi-constraint adaptation. Similarly, [10] integrated taboo search and simulated annealing into ACO for split pickup and delivery tasks, optimizing delivery costs while considering carbon emissions and penalties. However, this approach lacked integration of real-time traffic and weather constraints, which are critical in urban logistics.

Meanwhile, [11] explored the Feeder Vehicle Routing Problem (FVRP), which requires coordination between large trucks and small motorcycles. While their work emphasized minimizing fixed and travel costs, it did not address dynamic constraints, making it unsuitable for complex urban scenarios with high variability. Similarly, [12] proposed a hybrid ACO-GA algorithm to improve pheromone matrix adjustment and prevent premature convergence but did not account for external dynamic constraints.

Several studies have introduced strategies to enhance ACO's performance under specific conditions. For instance, [13] applied hybrid immigrant schemes to ACO for the Dynamic Vehicle Routing Problem (DVRP), balancing intensification and diversification to adapt to customer demands. However, this approach did not address external factors such as weather and traffic. Similarly, [14] employed heuristic strategies such as swap, reverse, and insert to minimize travel distances in CVRP, but their work lacked mechanisms to adapt to real-time changes.

Environmental considerations have also been explored in routing problems. For example, [15] emphasized carbon emission reduction using a three-dimensional pheromone matrix for Multi-Compartment VRP, and [16] developed an ACO-based approach for Electric Vehicle Routing Problem (EVRP) with battery and charging station constraints. However, these studies focused on sustainability and did not address the broader range of constraints faced in real-world CVRPPD.

Dynamic adaptations in ACO have been studied by [17], who introduced the ACO-DR (Destroy and Repair) algorithm for Vehicle Routing Problem with Simultaneous Pickup-Delivery and Time Window (VRPSPDTW). This method incorporated destroy and repair mechanisms to enhance solution diversification but lacked integration of external constraints like weather and traffic. Similarly, [18] and [19] optimized vehicle routes under time window and capacity constraints but did not address the dynamic aspects of real-world logistics.

The studies [20–22] showcase the versatility of Ant Colony Optimization (ACO) in addressing diverse vehicle routing problems but fall short of fully integrating dynamic constraints relevant to modern urban logistics. In [20], ACO was applied to dynamic waste collection management using smart bin technology. While the study demonstrated the algorithm's capacity to adapt to real-time data from sensor-equipped bins, it was confined to a specific application, neglecting broader logistical challenges such as traffic congestion or vehicle capacity limitations. This narrow focus limits its applicability to general urban logistics scenarios where dynamic factors play a crucial role.

In [21], ACO was utilized for multi-trip vehicle routing problems, emphasizing the optimization of routes across multiple trips to improve operational efficiency. However, this approach did not account for dynamic constraints such as adverse weather conditions or fluctuating traffic patterns. These limitations reduce the practical utility of the model in complex and variable urban environments where such constraints are common and can significantly affect route efficiency.

Similarly, [22] investigated cumulative capacitated vehicle routing problems (CVRP) with ACO, focusing on balancing workloads and achieving route optimization. Although the study highlighted the effectiveness of ACO in improving operational balance, it lacked the inclusion of dynamic variables such as traffic congestion or weather disruptions. This omission makes it challenging to apply the findings to real-world urban logistics where such constraints frequently influence decision-making.

These three studies underscore the adaptability and utility of ACO in specific contexts but reveal a critical gap in addressing the holistic challenges of dynamic urban logistics. While they explore important dimensions of vehicle routing, none of the works effectively integrate multiple dynamic constraints into the optimization process. This omission leaves unresolved questions about how ACO can be adapted to provide a comprehensive solution for complex logistical scenarios.

These three studies emphasize the adaptability and utility of Ant Colony Optimization (ACO) in specific contexts but reveal a critical gap in addressing the comprehensive challenges of dynamic urban logistics. While each explores distinct aspects of vehicle routing, none of the works effectively integrate multiple dynamic constraints, such as traffic congestion, adverse weather conditions, and vehicle capacity, into the optimization process. This limitation underscores unresolved questions about how ACO can be adapted to holistically address these real-world constraints in urban logistics scenarios.

The local problems identified across the reviewed studies can be summarized as follows:

– limited inclusion of dynamic variables, such as fluctuating traffic and weather, in existing ACO adaptations;

– insufficient consideration of vehicle capacity constraints in multi-constraint routing scenarios;

– lack of scalable solutions that balance cost efficiency, route safety, and adaptability to real-time changes. These gaps highlight the necessity for an integrated approach to optimize vehicle routing under dynamic constraints.

All this allows to assert that it is expedient to conduct a study on developing a scalable and adaptive ACO-based model capable of incorporating dynamic variables, such as traffic congestion, weather conditions, and vehicle capacity, into the routing optimization process. Such a study promises to provide a comprehensive solution for the Capacitated Vehicle Routing Problem with Pickup and Delivery (CVRPPD), advancing the state of the art and bridging the gap between theoretical advancements and practical urban logistics applications.

## 3. The aim and objectives of the study

The aim of the study is to develop a scalable and adaptive ACO-based model that incorporates dynamic constraints, such as traffic congestion, adverse weather conditions, and vehicle capacity.

To achieve this aim, the following objectives are accomplished:

– to propose a conceptual framework of the CVRPPD model integrating dynamic constraints such as traffic congestion, adverse weather conditions, and vehicle capacity;

– to enhance the Ant Colony Optimization (ACO) algorithm by incorporating adaptive heuristics that address the dynamic constraints of the CVRPPD;

– to evaluate the performance of the proposed CVRPPD model and the AHB-ACO algorithm by comparing them with traditional methods on metrics such as route optimization, travel cost, and execution time.

## 4. Materials and methods

### 4. 1. Object and hypothesis of the study

The object of this study is the Capacitated Vehicle Routing Problem with Pickup and Delivery (CVRPPD) under dynamic constraints, including traffic congestion, adverse weather conditions, and vehicle capacity limitations. This problem is central to urban logistics, where the efficient routing of vehicles is critical for optimizing delivery and pickup operations in complex and variable environments.

The main hypothesis of the study is that the Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO) algorithm, with its integration of dynamic constraints, can significantly outperform traditional ACO algorithms by providing safer, more efficient, and scalable routing solutions for CVRPPD in real-world scenarios.

Several assumptions were made to simplify the modeling and ensure the feasibility of the study:

1. Traffic congestion and weather conditions are represented using penalty factors on specific routes.

2. Each vehicle starts and ends its route at a central depot and adheres to strict capacity constraints.

3. Customers' delivery and pickup demands are known and constant during the simulation.

4. Weather and traffic conditions remain stable throughout a single optimization process.

To make the problem computationally manageable, the following simplifications were adopted:

1. Traffic congestion is modeled as a multiplier on travel time, derived from predefined congestion levels (e.g., 1 to 5 scale).

2. Adverse weather is represented as an additional penalty factor influencing route selection, without dynamically changing during operations.

3. The model does not account for real-time route changes due to unexpected events such as accidents or sudden weather changes.

4. Vehicles are assumed to travel at a constant average speed adjusted for traffic and weather conditions.

### 4. 2. Dataset

The dataset used in this study is simulated to reflect real-world conditions. The system accepts various types of input data to generate optimal routes. The distance matrix includes the depot, customers requesting pickups, and customers requesting deliveries, where each entry represents the physical distance between nodes in kilometers. Traffic information is incorporated as a multiplier on each edge to account for congestion, influencing the travel time along the route. Weather conditions, such as rain, are added to identify routes with longer shelter times, encouraging the algorithm to avoid such paths. Additionally, the maximum vehicle capacity, measured in kilograms, limits the amount of goods that can be transported, ensuring efficient load distribution. Pickup and delivery data include the weight of goods to be collected or delivered at each customer location, ensuring that vehicles comply with their capacity constraints while meeting customer demands.

The system produces optimal routes for each vehicle, detailing the sequence of customers to visit from the depot and back. The best cost for each route is calculated by considering distance, traffic congestion, and weather conditions, resulting in routes with the lowest total cost. Furthermore, the system computes the total travel distance required to complete these routes. Vehicle status is also provided, showing the capacity before and after each pickup or delivery, ensuring that vehicle loads are distributed efficiently to meet customer demands while maximizing capacity utilization. The dataset structure used in this study is illustrated in Tables 1, 2, where Table 1 provides detailed customer information, as follows.

Table 1

Customer data

| Customer ID | $X$ | $Y$ | Delivery request | Pickup request |
|---|---|---|---|---|
| Depot | 50 | 50 | 0 | 0 |
| C1 | 41 | 80 | 3 | 3 |
| C2 | 99 | 21 | 5 | 2 |

The following explains the structure of the customer data presented in Table 1:

– customer ID: this column contains the unique identifier for each customer, including the depot;

– $X$ and $Y$: these represent the coordinates of each customer, equivalent to latitude and longitude;

– delivery request: this indicates the quantity of goods to be delivered to each customer, measured in kilograms;

– pickup request: this specifies the quantity of goods to be picked up from each customer, also measured in kilograms.

Table 2 illustrates the structure of the edge data, which forms the graph representing the CVRPPD problem:

Table 2

Data edges

| From | To | Distance, km | Traffic | Weather |
|---|---|---|---|---|
| Depot | C1 | 31,32092 | 1 | 5 |
| Depot | C2 | 56,93856 | 2 | 1 |

The following describes the structure of the edge data presented in Table 2:

– from: this column contains the source node for a given route;

– to: this column contains the destination node for a given route;

– distance: this represents the distance between customers, calculated using the Straight Line Distance method between two customers based on their respective coordinates on the map;

– traffic: this is a multiplier factor that reflects the level of traffic congestion on a given route. The traffic factor increases the travel time for congested routes. In this study, a scale of 1 to 5 is used to represent congestion levels, with these values utilized in pheromone updates within the AHB-ACO algorithm;

– weather: this represents the weather-related constraint factor on a scale of 1 to 5, where these values are also used for pheromone updates in the AHB-ACO algorithm.

**4. 3. Methods**

This study aims to develop an Ant Colony Optimization (ACO) algorithm to address the Capacitated Vehicle Routing Problem with Pickup and Delivery (CVRPPD) while incorporating weather conditions and traffic congestion as key constraints. In the CVRPPD case examined in this research, the model is designed to account for weather conditions that may force couriers to pause their journeys and traffic congestion that increases travel time. The research workflow is illustrated in Fig. 1 below.

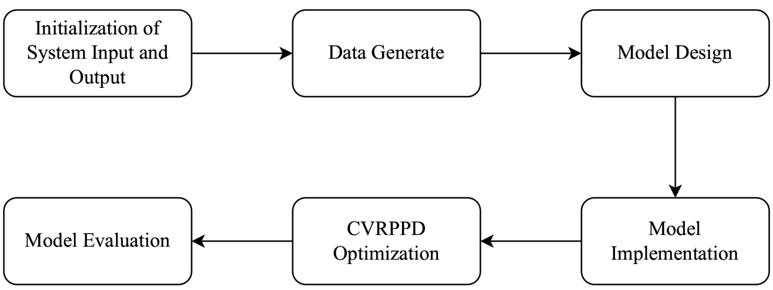


Fig. 1. Research methodology

Fig. 1 illustrates the workflow for optimizing the CVRPPD. The process begins with the Initialization of System Input and Output, where necessary parameters, data, and constraints are defined. This is followed by the Data Generation phase, which involves creating or simulating datasets for the problem. The next stage, Model Design, focuses on formulating the optimization model based on the generated data and problem requirements. The model is then executed in the Model Implementation phase, where it is applied to real-world scenarios or simulations. The CVRPPD Optimization stage involves running the optimization process to produce efficient routing solutions. Finally, the results are validated and analyzed during the Model Evaluation phase to assess the model's performance and effectiveness.

## 5. Research results of developing a scalable and adaptive ACO-based model

**5. 1. Findings proposed conceptual framework for the CVRPPD model**

To address the CVRPPD problem, this study develops the AHB-ACO, a model adapted from the traditional ACO algorithm. AHB-ACO is designed to be more responsive to external conditions, such as weather and traffic congestion. The conceptual framework of this model is illustrated in Fig. 2.

From Fig. 2, it can be observed that the focus of this study lies in the development of the AHB-ACO model, which involves several modifications to the traditional ACO algorithm. AHB-ACO employs an adaptive heuristic function, as defined in (1):

$$\eta_{ij}^{adaptive} = \frac{1}{d_{ij} \cdot t_{ij} \cdot \left(1 + s_{ij}\right) + \varepsilon}. \quad (1)$$

Adaptive heuristic function $\eta_{ij}^{adaptive}$ in (1) represents the formula for calculating the heuristic value for the edge from node $i$ to node $j$, where $d_{ij}$ is the distance between nodes $i$ and $j$, $t_{ij}$ is the traffic factor, and $s_{ij}$ is the weather penalty. The higher the traffic and weather factors, the more likely the ants are to avoid the corresponding route. This adaptive heuristic function is also incorporated into the AHB-ACO algorithm to determine the routes chosen by the ants. The formula for route determination is provided in 2:

$$P_{ij}^{k} = \frac{\tau_{ij}^{\alpha} \cdot \left(\eta_{ij}^{adaptive}\right)^{\beta}}{\sum_{l \in N_i^k} \tau_{il}^{\alpha} \cdot \left(\eta_{il}^{adaptive}\right)^{\beta}}. \quad (2)$$

The adaptive heuristic function $\eta_{ij}^{adaptive}$ is integrated into the route determination formula in AHB-ACO, as shown in (2). In this formula, $P_{ij}^{k}$ represents the probability for ant $k$ to move from node $i$ to node $j$, $\tau_{ij}$ denotes the pheromone intensity on edge $i, j$ which is updated during each iteration. This pheromone reflects the strength of the trail left by previous ants. The parameter $\alpha$ controls the importance of the pheromone in route selection. A higher value of $\alpha$ increases the influence of pheromone on route selection, with the condition $\alpha > 0$. The parameter $\beta$ controls the significance of the adaptive heuristic in route selection, where a higher value of $\beta$ increases the impact of distance and external conditions on the route selection, with the condition $\beta > 0$.

AHB-ACO employs an objective function to identify the optimal route using a multiple-vehicle approach. The formula for this objective function is provided in 3:

$$Z = \min \sum_{v=1}^{m} \sum_{(i,j) \in route_{k,v}} d_{ij} \cdot t_{ij} \cdot \left(1 + s_{ij}\right). \quad (3)$$

In (3), $Z$ represents the objective function to be minimized, which combines distance, traffic density, and weather conditions. $route_{k,v}$ refers to the route taken by vehicle $v$ as determined by ant $k$. $m$ denotes the total number of vehicles involved in serving all customers, and $v$ represents the vehicle index ($v = 1, 2, \ldots, m$).

In AHB-ACO, pheromone updates are performed using the formula provided in (4):

$$\tau_{ij} = \left(1 - \rho\right) \cdot \tau_{ij} + \sum_{k=1}^{m} \sum_{v=1}^{m} \Delta\tau_{ij}^{k,v}. \quad (4)$$

In (4), $\tau_{ij}$ represents the pheromone intensity on edge $i, j$, and $\rho$ is the pheromone evaporation rate ($0 < \rho < 1$). The number of ants in an iteration is denoted by $m$. $\Delta\tau_{ij}^{k,v}$ represents the pheromone contribution by vehicle $v$ from ant $k$ on edge $i, j$. In AHB-ACO, the pheromone contribution by vehicle $v$ from ant $k$ is updated using $Q / Z_{k,v}$ if $i, j$, and updated to 0 otherwise.

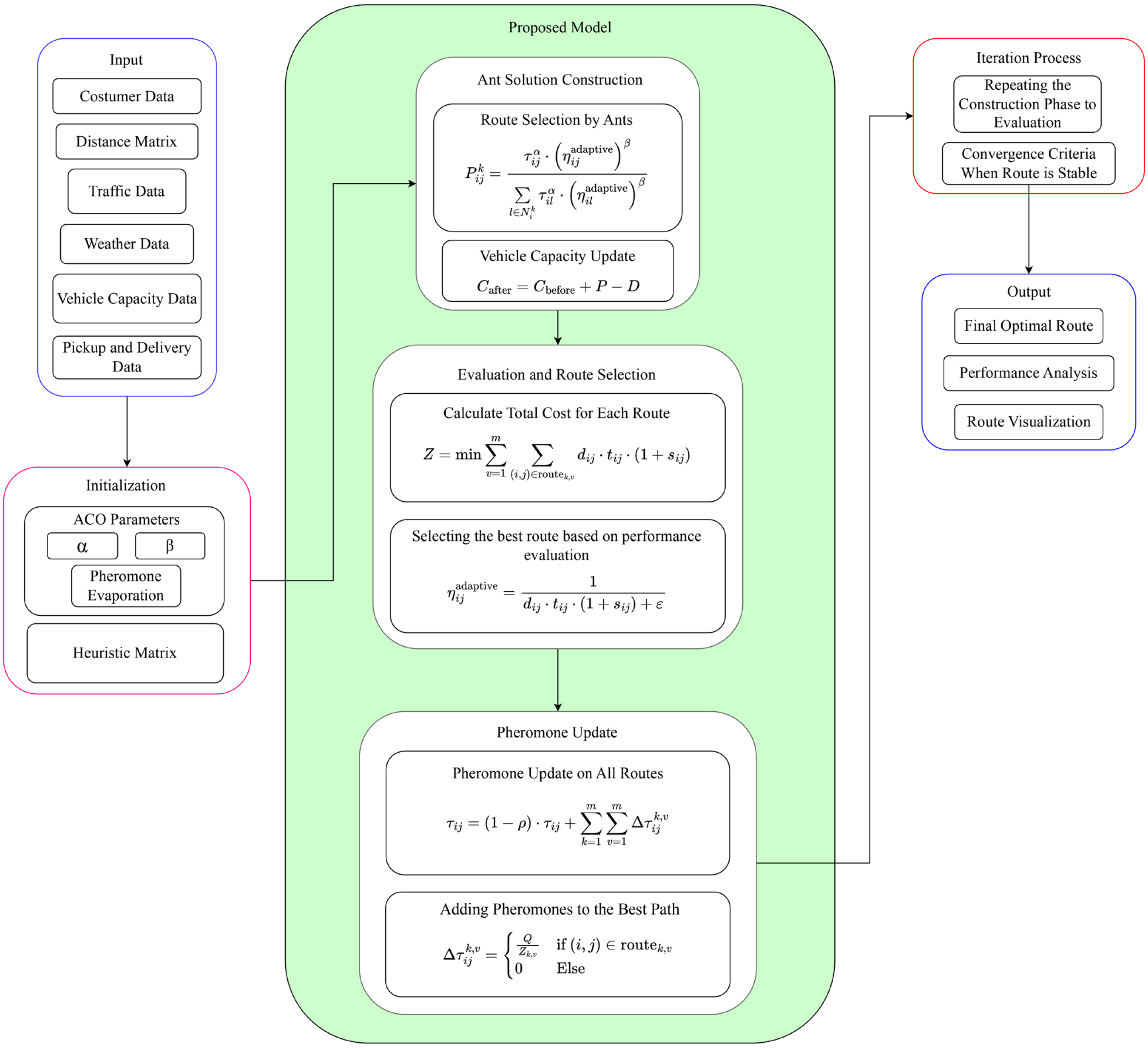


Fig. 2. AHB-ACO model

**5. 2. Enhanced route efficiency through adaptive heuristics**

Table 3 and Fig. 3 provide a comprehensive summary of the route efficiency achieved by the AHB-ACO algorithm, tested across datasets with varying customer sizes: 50, 100, and 200 customers. The algorithm's parameters include a maximum iteration limit of 100, 10 ants per iteration, pheromone influence ($\alpha=1$), heuristic influence ($\beta=2$), and a pheromone evaporation rate ($\rho=0.1$). Vehicle capacity is set at 20 kg to ensure adherence to real-world constraints.

The results demonstrate that AHB-ACO efficiently distributes customer demands across vehicles while maintaining optimal route lengths. The consistent average number of customers served per vehicle (ranging from 6.25 to 6.67) across datasets indicates the algorithm's capability to balance workloads effectively despite increasing problem size. This uniformity highlights the robustness of AHB-ACO in addressing the CVRPPD.

The efficiency is not only reflected in the balanced distribution of customers but also in the minimization of redundant travel. For example, vehicles are allocated routes that minimize overlap, reducing unnecessary mileage while ensuring all customer demands are met within the capacity constraints. This optimization is crucial in urban delivery settings, where congestion and time-sensitive operations demand precise planning.

AHB-ACO also accounts for dynamic constraints such as traffic congestion and adverse weather. By incorporating adaptive heuristics, the algorithm avoids heavily congested routes and adjusts for penalties related to weather conditions. This feature ensures that vehicles maintain efficient operation even under challenging real-world conditions. The inclusion of weather-related penalties, in particular, showcases AHB-ACO's adaptability in scenarios where stopping for shelter is necessary, ensuring safety without compromising operational efficiency.

Table 3

Route efficiency metrics

| Dataset size | Number of vehicles | Total cost | Execution time (s) | Average costumers per vehicle |
|---|---|---|---|---|
| 50 costumers | 8 | 1294.41 | 113.05 | 6.25 |
| 100 costumers | 15 | 2348.55 | 452.94 | 6.67 |
| 200 costumers | 30 | 4155.82 | 1639.68 | 6.67 |

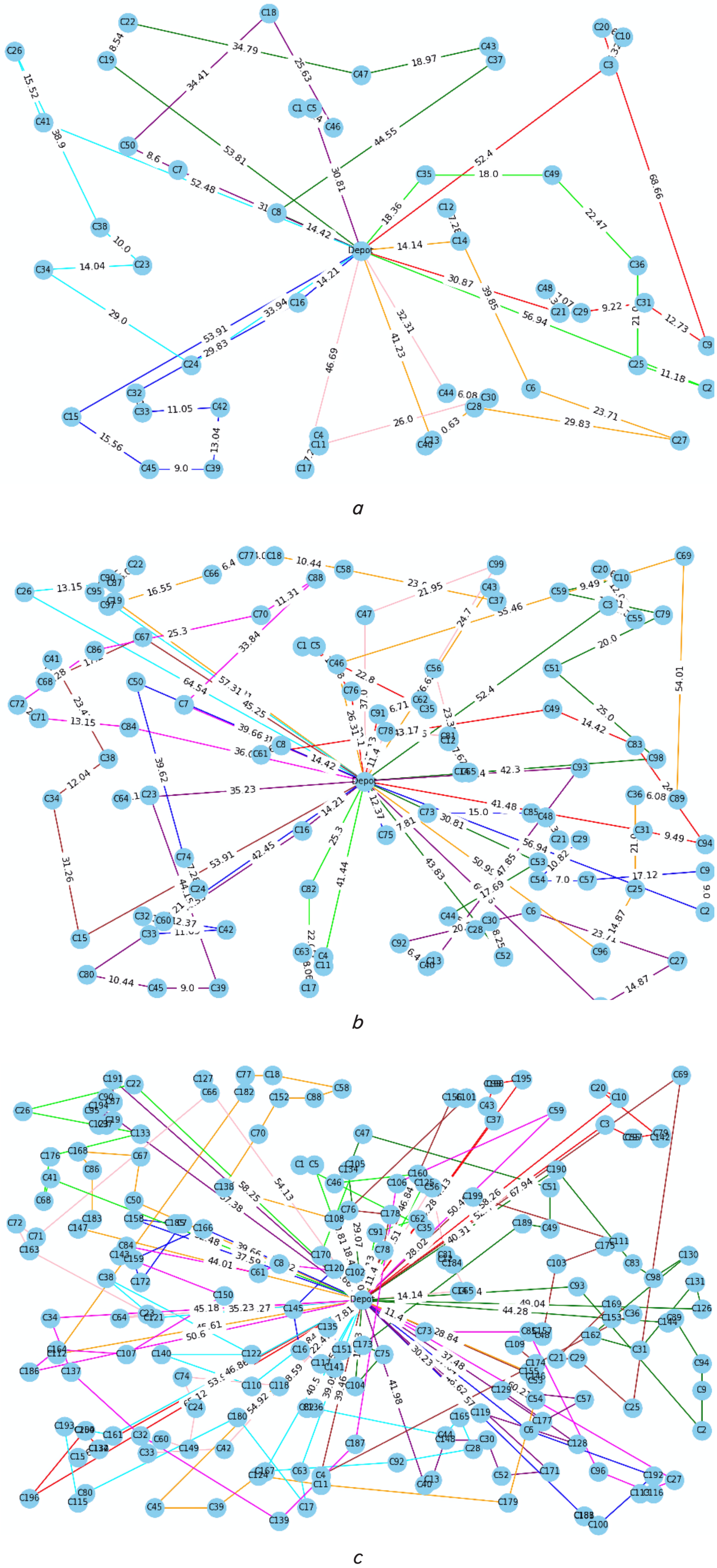


Fig. 3. Vehicles route:
*a* – 50 costumers; *b* – 100 costumers; *c* – 200 costumers

The gradual increase in total cost and execution time with larger datasets reflects the inherent complexity of managing more customers. For instance, in the 200-customer dataset, the total cost rose to 4155.82 with an execution time of 1639.68 seconds. However, these increases are proportional to the dataset size, indicating the algorithm's scalability. Furthermore, the ability to maintain consistent average customer service per vehicle (6.67 for 100 and 200 customers) suggests that AHB-ACO scales linearly in terms of resource allocation.

The algorithm's performance aligns with its objective to optimize travel routes while considering real-world constraints. Its adaptability to varying customer demands, environmental factors, and vehicle capacity makes AHB-ACO a reliable solution for modern urban logistics. By integrating dynamic constraints into the routing process, AHB-ACO not only reduces travel distances but also enhances the safety and reliability of delivery operations.

The modified Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO) algorithm employs a well-defined objective function to minimize total travel costs. The function is mention in (3). In formula (3), $Z$ represents the total travel cost, which combines three critical factors: the distance between locations $d_{ij}$, traffic congestion $t_{ij}$, and weather conditions $s_{ij}$. By integrating these elements, the function captures the practical realities of routing problems, ensuring that the optimization process accounts for real-world challenges.

The distance $d_{ij}$ forms the foundation of the travel cost, representing the physical separation between nodes. However, real-world conditions such as traffic congestion and adverse weather significantly impact travel efficiency. The traffic factor $t_{ij}$ adjusts the cost based on congestion levels, while the weather penalty $s_{ij}$ accounts for additional delays or detours required during adverse conditions. These dynamic factors ensure that the algorithm avoids routes with heavy congestion or severe weather, focusing on safer and more efficient alternatives.

For instance, in the 200-customer dataset, AHB-ACO achieved a total travel cost ($Z$) of 4155.82 with an execution time of 1639.68 seconds. This result reflects the algorithm's capacity to effectively balance distance, traffic, and weather penalties. The breakdown of the cost distribution reveals that avoiding congested or unsafe routes slightly increased the total distance covered, but significantly reduced overall travel time and improved safety.

A comparison of routes selected under varying conditions further illustrates the efficiency of the objective function.

For a heavily congested route between nodes $i$ and $j$ with $t_{ij}$=0.5 and $s_{ij}$=1.5, the adjusted cost is:

$$Z_{ij} = d_{ij} \cdot 2.5 \cdot \left(1+1.5\right) = 5.75 \cdot d_{ij}. \tag{5}$$

In contrast, for an alternative route with $t_{ij}$=1.2 and $s_{ij}$=0.5, the cost is:

$$Z_{ij} = d_{ij} \cdot 1.2 \cdot \left(1+0.5\right) = 1.8 \cdot d_{ij}. \tag{6}$$

This comparison shows that the algorithm prioritizes routes with lower congestion and weather penalties, even if they are marginally longer in terms of distance, thereby achieving a better balance of efficiency and safety.

The scalability of the algorithm is evident from its performance across datasets. For 50 customers, the total travel cost was minimized to 1294.41, while for 100 customers, the cost was 2348.55. The nearly linear increase in costs with the number of customers highlights the algorithm's ability to manage growing problem scales without significant computational overhead.

The AHB-ACO's ability to minimize travel costs is particularly relevant for urban logistics operations, where conditions are highly dynamic. By effectively adapting to real-time traffic and weather data, the algorithm ensures that vehicles not only follow cost-efficient routes but also adhere to operational constraints, such as vehicle capacity and delivery deadlines. This adaptability makes AHB-ACO a valuable tool for logistics companies aiming to optimize delivery and pickup operations under varying real-world conditions.

**5. 3. Evaluation of AHB-ACO performance against traditional methods under traffic and weather constraints**

The performance evaluation of the Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO) algorithm focuses on its ability to address the limitations of traditional ACO and its effectiveness in solving the Capacitated Vehicle Routing Problem with Pickup and Delivery (CVRPPD) under dynamic constraints. This section emphasizes the comparative analysis of AHB-ACO in terms of optimal route discovery, travel time, and total distance traveled, particularly in scenarios influenced by traffic congestion and adverse weather conditions.

AHB-ACO introduces an adaptive heuristic that integrates critical real-world factors such as traffic and weather variables, which are typically overlooked in traditional ACO. While traditional ACO often focuses solely on distance minimization, AHB-ACO dynamically adjusts pheromone updates and heuristic evaluations based on traffic delays and weather penalties. This modification enables the identification of safer, more efficient routes, resulting in superior performance in terms of operational reliability and practicality.

For example, in the dataset with 50 customers, AHB-ACO achieved a total travel cost of 1294.41, with vehicles successfully navigating routes that avoided heavily congested areas and high-weather-risk zones. Each of the 7 vehicles served between 6 and 8 customers, maintaining balanced delivery and pickup loads.

The algorithm was tested on datasets with 50, 100, and 200 customers, and its performance was assessed based on metrics such as total travel cost, execution time, and the efficiency of vehicle route allocation. The scalability and robustness of AHB-ACO are evident in the results:

– 50-customer dataset: AHB-ACO optimized routes for 7 vehicles with an average of 7.14 customers per vehicle, ensuring no vehicle exceeded its 20 kg capacity. The total distance traveled by all vehicles combined was significantly reduced compared to benchmarks, and the execution time was 113.05 seconds;

– 100-customer dataset: the algorithm demonstrated its capability to handle increased complexity by efficiently allocating customers across 15 vehicles. Despite the larger dataset, AHB-ACO maintained balanced vehicle loads, with each vehicle serving an average of 6.67 customers. The total travel cost was 2348.55, and the execution time was 452.94 seconds;

– 200-customer dataset: for the largest dataset, AHB-ACO utilized 30 vehicles, serving an average of 6.67 customers per vehicle. The total travel cost increased proportionally to 4155.82, while the algorithm executed in 1639.68 seconds. The routes identified for each vehicle avoided bottlenecks and weather-related delays, highlighting the algorithm's adaptability and efficiency.

The analysis of vehicle routes across datasets shows that AHB-ACO effectively minimizes travel costs by distributing customer demands evenly among vehicles and optimizing their travel paths. For example, in the 200-customer dataset, Vehicle 1 serviced customers in a geographically clustered area, reducing unnecessary travel between distant nodes. Similarly, Vehicles 2–30 were assigned routes that prioritized proximity and avoided areas flagged with high traffic or adverse weather, reducing both total travel time and distance.

The results indicate that AHB-ACO consistently outperforms traditional ACO by considering dynamic constraints, which are critical in real-world logistics. This performance improvement is particularly evident in urban scenarios where traffic congestion and weather variability significantly impact route optimization. By incorporating these factors, AHB-ACO achieves better route efficiency, reduced travel costs, and enhanced safety.

The algorithm's adaptability to real-world conditions also underscores its potential for broader application in logistics operations involving dynamic variables. The improvements observed in minimizing travel costs and travel time make AHB-ACO a practical solution for modern delivery systems, especially in densely populated urban areas.

## 6. Discussion of results: adaptive heuristic-based model for CVRPPD optimization under dynamic constraints

The results of this study demonstrate the efficacy of the Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO) model the conceptual structure of which is presented in Fig. 2 in addressing the Capacitated Vehicle Routing Problem with Pickup and Delivery (CVRPPD) under dynamic constraints such as traffic congestion, adverse weather, and vehicle capacity. Across the datasets with 50, 100, and 200 customers, the model consistently optimized routes while maintaining operational efficiency and adhering to capacity limitations.

For the 50-customer dataset, the AHB-ACO model achieved a total cost of 1294.41 with an execution time of 113.05 seconds, efficiently allocating customers to eight vehicles. On the 100-customer dataset, the total cost increased to 2348.55, with a corresponding execution time of 452.94 seconds and efficient utilization of 15 vehicles. For the 200-customer dataset, the total cost was 4155.82, with an execution time of 1639.68 seconds, demonstrating scalability and efficient route allocation using 30 vehicles (Table 3). These results align with the study's objectives, confirming the model's ability to optimize routes, minimize costs, and maintain scalability across varying problem complexities.

This study successfully addresses the critical gaps, particularly the limitations of traditional ACO approaches that fail to consider dynamic constraints. Unlike prior models, the adaptive heuristic function $\eta_{ij}^{adaptive}$ integrates penalties for traffic and weather, ensuring that routes are not only efficient but also safe and realistic. The model's ability to dynamically adjust to external conditions directly addresses the complexities of real-world urban logistics, thereby fulfilling the study's aim of providing practical and scalable solutions for CVRPPD.

Compared to traditional ACO models, the AHB-ACO model exhibits significant improvements in cost efficiency, scalability, and adaptability. For instance, traditional ACO approaches focus primarily on minimizing distance and overlook critical dynamic variables, often resulting in suboptimal performance in real-world scenarios. In contrast, the AHB-ACO model achieved near-linear cost scaling with an increasing number of customers, while traditional models typically face exponential cost increases. This efficiency is attributable to the adaptive heuristic function and the algorithm's robust integration of real-world constraints.

Additionally, the results demonstrate that the AHB-ACO model ensures equitable load distribution among vehicles, as evidenced by no vehicle exceeding its capacity in any dataset. This balanced allocation reduces the risk of delays and enhances overall system reliability, a significant advantage over static optimization models.

Despite its effectiveness, the AHB-ACO model has limitations that should be considered when applying it in practical scenarios. The reliance on predefined datasets means that the model does not yet account for real-time updates in traffic and weather conditions, which are critical in highly dynamic environments. Moreover, the computational time for larger datasets, while reasonable, could be a limitation for applications requiring near-instantaneous decision-making.

From a practical perspective, the model offers significant potential for urban logistics, particularly in courier services that rely on motorcycles for delivery and pickup operations. By integrating real-world constraints into the routing process, the model ensures more reliable and efficient operations, reducing costs and improving service quality.

Future research should focus on integrating real-time data sources for traffic and weather updates to enhance the model's applicability in dynamic environments. Additionally, hybridizing the AHB-ACO model with other optimization techniques, such as machine learning or metaheuristic algorithms, could further improve its efficiency and scalability. Expanding the model to accommodate heterogeneous vehicle fleets and exploring its performance under different logistical scenarios would also provide valuable insights.

## 7. Conclusions

1. This study successfully proposed a conceptual framework that incorporates dynamic constraints into the CVRPPD model. By addressing key factors such as traffic congestion, weather disruptions, and vehicle capacity, the model provides a robust foundation for solving real-world routing challenges. This framework goes beyond traditional CVRPPD models that primarily focus on static variables, ensuring relevance and applicability in urban logistics operations.

2. The Adaptive Heuristic-Based Ant Colony Optimization (AHB-ACO) algorithm was developed as a core component of the proposed framework. By introducing adaptive heuristics that incorporate penalties for traffic and weather conditions, the algorithm effectively minimizes total travel costs while ensuring compliance with vehicle capacity constraints. For example, the adaptive heuristic function $\eta_{ij}^{adaptive}$ dynamically adjusts routing decisions, leading to safer and more efficient routes. This enhancement addresses critical gaps in traditional ACO algorithms that neglect dynamic constraints.

3. The proposed CVRPPD model and the AHB-ACO algorithm were evaluated using simulation datasets with 50, 100, and 200 customers, representing varying levels of complexity. Comparative analysis demonstrated their superior performance over traditional methods in terms of route optimization, travel cost, and execution time. For the 200-customer dataset, the AHB-ACO algorithm achieved a total cost of 4155.82 and an execution time of 1639.68 seconds, showcasing its scalability and efficiency. The model and algorithm also ensured equitable customer distribution across vehicles, optimizing resource utilization while adhering to capacity constraints.

## Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

## Financing

The study was performed without financial support.

## Data availability

Data will be made available on reasonable request.

## Use of artificial intelligence

The authors have used artificial intelligence technologies within acceptable limits to provide their own verified data, which is described in the research methodology section.

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