Network-Aware Route Management Platform for Truck and Drone Operations

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***Abstract*—Route management platforms can provide innovative solutions to improve last-mile logistics, enhancing delivery operations, making them efficient and at the same time sustainable. In addition, these platforms can be integrated with systems that incorporate coordination and collaboration between vehicles, such as trucks and drones. Thus, providing optimized operations and the capability to handle complex or large operations. In this paper, we present our initial study to develop a cloud-based platform to address the gap between providing optimized route plans that leverage the use of fleets that involve both trucks and drones. In this first iteration, a modular mathematical model and a network-aware route management plan are integrated to facilitate operation decisions while considering efficient and safe routes. Our solution viz. *RoutePEARL* incorporates the challenge of collaborative truck-drone delivery problem in the presence of drone route disruptions for real-time management of traffic, and communication networks. Our approach is based on a Dynamic Travelling Salesman Problem (DTSP) with the nearest neighbor heuristic approach that improves fleet utilization, reducing the distance traveled, and maximizing the productivity of service providers. Experimental results aim to demonstrate our solution's effectiveness in optimizing routes and enhancing the efficiency of last-mile logistics.**

***Index Terms*—Last-mile logistics, Optimization algorithms, Dynamic routing, UAV, Machine Learning**

I. Introduction

Last-mile delivery systems equipped with new technologies, such as drones, have been on high-demand due to the growing number of businesses opting for these non-traditional delivery systems. These new technologies can be combined with traditional systems, leading to new last-mile delivery strategies, among which truck-drone delivery solution would be the most promising one []. These systems can also be equipped with route management systems, emerging as innovative solutions and offering significant potential to optimize delivery operations [?]. These systems also enable collaboration and coordination between different types of vehicles [?]. In recent years, the growth and use of Unmanned Aerial Vehicles (UAVs), commonly known as drones, have significantly increased in delivery operations [?]. These UAVs can provide benefits to make the last mile more efficient and fast. However, integrating UAVs into existing delivery systems can present unique challenges, including limited payload capability and the coordination or collaboration with other delivery vehicles such as trucks [?].

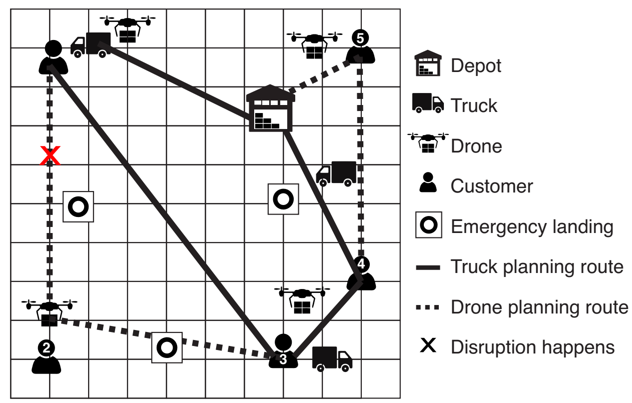

Fig. 1. An example image showing a route management system for last-mile delivery.

This collaborative integration between truck-drone can present challenges in route planning, task allocation, or fleet management [?]. Traditional route planning methods frequently fail to consider the distinct capabilities and constraints of both trucks and UAVs. For example, trucks might offer larger capacities for bulk deliveries, but they might face challenges with traffic and congestion. However, UAVs can navigate congested areas more efficiently, but face limitations in range and payload. Thus, collaborative truck-drone delivery systems require solutions that can effectively address these limitations. In addition, disruptions in the network communications, or environmental conditions can impact the operations. Robust and synergistic planning algorithms that can handle disruptions are crucial to guarantee the reliability and efficiency of the delivery services [?].

In this paper, we present our initial study on developing *RoutePEARL* – a cloud-based platform that addresses the gap in providing optimized route strategies for collaborative fleets involving trucks and UAVs. Our solution tackles the challenges of collaborative truck-UAVs delivery by integrating a modular mathematical model with a network-aware route management plan. Specifically, *RoutePEARL* aims to enable

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the decision making and to provide efficient and reliable routes, in addition to assess constrains accross traffic and communication networks. In addition, we consider additional challenges of route disruptions, to ensure robust operation in unpredictable circumstances. A fleet optimization strategy is considered to reduce the total travel distance, and to maximize the productivity of service providers. In this first iteration of the project, we present an experimental study to exemplify the main key features of our solution, an strategy to optimize routes using a Dynamic Travelling Salesman Problem (DTSP) with the nearest neighbor heuristic approach to enhance the efficiency of the last mile logistics.

The remainder of this paper is organized as follows. Section II reviews the related work on route management platforms, collaborative truck-drone delivery systems, and network-aware routing algorithms. We will then present our proposed approach, RoutePEARL, in Section IV. This section includes the modular route optimization approach for trucks and drones and the Drone Trajectory Prediction (DTP) to handle uncertainties. Section V provides the results and discussion, demonstrating how our solution methodology can effectively optimize routes and enhance a last-mile logistic use-case. Finally, Section VI summarizes the key contributions of this paper and outlines future research directions for RoutePEARL. We will discuss next steps in the project and broader implications for the future of truck-drone fleet logistics management.

II. Related Work

This section will explore the growing importance of last-mile logistics and the increasing adoption of EVs and UAVs. It will then explain the concept of hybrid truck-drone delivery systems, highlighting their foundation in classic routing problems like the Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP). The section will provide a comprehensive review of recent research on truck-drone route planning, mentioning relevant algorithms and applications (e.g., single truck with multiple drones, simultaneous pickup and delivery). Crucially, this section will emphasize the limitations of these approaches, particularly their lack of consideration for critical practical constraints like communication network limitations and real-world uncertainties. Additionally, existing research on direct drone deliveries and EV truck route optimization will be briefly discussed, with a focus on their limitations in not considering combined operations or real-time adaptation.

III. Problem Definition

In this section, we will introduce the problem and describe the narrative. Subsequently, we will model the problem as a sequential decision process.

A. Problem Narrative

In this paper, we address the challenge of collaborative truck multi-drone delivery problems in the presence of drone route disruptions (CTDDP-RD). We can change this part if we do the problem for only one drone. In particular, one truck carrying $d \in \mathcal{D}$ drones on its roof is utilized to deliver goods from a depot to a set of $i \in \mathcal{N}$ customers, with the delivery route starting and ending at the depot. Each customer $i \in \mathcal{N}$ must be visited exactly once either by the truck or one of the $d \in \mathcal{D}$ drones. The drones launched from a truck stop can be retrieved at the same stop or the next stop. Each drone sortie is limited to transporting one customer order. We assumed that the drones travel between nodes in the network at a constant speed ν and have an endurance (range) of η. Furthermore, the drones' batteries are replaced after every flight, ensuring that they start each delivery with a full charge. The truck is considered to have sufficient capacity to carry $i \in \mathcal{N}$ customer orders and $d \in \mathcal{D}$. Additionally, the truck and drone have a service time of τ_i^T and τ_i^D at location $i \in \mathcal{N}$, respectively.

When executing the delivery plan, the drone route may lose network connectivity due to various reasons, such as adverse weather conditions, drone malfunctions, or congested/dense environments.There are $l \in \mathcal{L}$ locations identified in the delivery region for landing drones in case of emergencies/travel disruptions. The network failure/disruptions are not known apriori and occur dynamically. Whenever a drone route is impacted, the route planner must decide on how to update the delivery plan to ensure safe and efficient delivery operations. The dispatcher must decide whether to abort the drone route for which network connectivity is impacted. If drone delivery is aborted, then the dispatcher must decide on how to re-route the drone to one of the emergency landing locations $l \in \mathcal{L}$. In addition, the dispatcher must also update the master route plan (truck and drones) to complete the package delivery and drone retrieval from the emergency landing spot. The objective function is to minimize the overall completion time of the delivery operation while ensuring all drones are returned to the depot at the end of the delivery operations.

B. Scaling

I think it would be better to include this section in the solution procedure part, based on the size of the problem we solved. Agreed Alicia

C. Model

In most cases, VRPs are modelled with mathematical programs like Integer Programming (IP) or Mixed-Integer Programming (MIP) due to their effectiveness in network problems. However, these methods struggle to handle stochastic and dynamically changing environments. Therefore, for problems with uncertainty, alternative approaches like Markov Decision Processes (MDPs) are better suited for capturing the dynamics of decision-making. In this paper, we use MDP to model the VRP problem, considering the inherent uncertainty of potential loss of network connectivity in drone routes.

1) Decision Point: We define a decision point as a moment at which a decision is made. In this model, a decision point occurs when a network disruption occurs. The k^{th} disruption is denoted by C_k, and the time of the k^{th} decision point is $t_k = t(C_k)$.

2) State: The state vector represents the status and positions of our delivery system, including both the truck and the drone. The state components can be defined as follows:

C_k: New disruption

$t_k = t(C_k)$: The time when the decision point occurs

$c_k = (c^{\theta}_{V,k}, c^{\theta}_{D,k})$: The set of nodes (including customers and emergency spots) that still need to be visited, divided between the vehicle and the drones.

$\Theta_k = (\Theta_{V,k}, \Theta_{D,k})$: The planned routes for the vehicle ($\Theta_{V,k}$) and the drones ($\Theta_{D,k}$) at the time of the disruption C_k.

λ: The probability that the drone maintains network connectivity.

To summarize, we represent the state S_k as the tuple $(t_k, C_k, c_k, \Theta_k, \lambda)$.

3) Action and reward: At each decision point t_k, the drone's response is captured by an action x_k. This action includes whether the drone should continue to the customers' location or go to emergency spots. The chosen action is represented as the tuple $\mathbf{x}_k = (\alpha_k, \Theta^x_{V,k}, \Theta^x_{D,k})$. Here, α_k denotes the specific decision made in response to the disruption, and $\Theta^x_{V,k}$ and $\Theta^x_{D,k}$ refer to the updated planned routes for the vehicle and the drone, respectively.

$$\alpha_k = \begin{cases} 0 & \text{Continue to customer location} \\ 1 & \text{Go to the nearest emergency spot} \end{cases}$$

In addition, $c^x_k = (c^{\theta,x}_{V,k}, c^{\theta,x}_{D,k})$ represents the updated set of vertices planned to be visited by vehicle $c^{\theta,x}_{V,k}$ and drones $c^{\theta,x}_{D,k}$.

The feasibility of an updated $\Theta^x_{V,k}$ depends on satisfying the following four conditions:

1) The route plan in $\Theta^x_{V,k}$ contains all spots in $c^{\theta}_{V,k}$. It also contains the emergency spot in the case $\alpha_k = 1$ and drone carrying package. The updated route plan for the truck $\Theta^x_{V,k}$ must include stops at emergency landing spots if any drones have been diverted due to disruptions. This ensures that the truck collects all drones and supports continuous delivery operations.
2) If a drone is proceeding to a customer location $\alpha_k = 0$, the route plan in $\Theta^x_{V,k}$ should include the customer location to pick up the drone. I am not sure if I am correct
3) The number of nodes is equal to the sum of travel time and service/emergency time.

Likewise, an updated $c^{\theta}_{D,k}$ for a drone is considered feasible if it fulfills the following four conditions:

1) The route plan in $\Theta^x_{D,k}$ includes all spots in $c^{\theta}_{D,k}$. It also contains the emergency spot in the case $\alpha_k = 1$.
2) If a drone is diverted to an emergency landing spot due to a disruption ($\alpha_k = 1$), it must be considered out of operation. This ensures that the drone is not used in any updated plan.
3) In case of a disruption requiring an emergency landing, a drone must have a predefined protocol for selecting the closest or most suitable emergency landing spot, considering the current location and remaining battery life.
4) The feasibility of a drone's updated route $\Theta^x_{D,k}$ must account for battery life, including the energy consumption for carrying loads. The plan must ensure that the drone has enough battery power to complete its delivery and return to the truck or an emergency spot, with a margin for safety.

The action $\mathbf{x}_k = (\alpha_k, \Theta^x_{V,k}, \Theta^x_{D,k})$ is always feasible. The reward of an action $\mathbf{x}_k$ is:

$$R(S_k, \mathbf{x}_k) = T_{\text{Completion}} + T_{\text{Emergency}} + T_{\text{Crash}}$$

$T_{\text{Completion}}$ is the reward for completing deliveries.

When $\alpha_k = 1$, indicating that an action involves an emergency landing due to potential risk factors like connectivity loss or adverse weather conditions, the system might incur reduced reward due to the detour or delay. However, this is balanced against the potential avoidance of more severe penalties associated with drone failures. Thus, $T_{\text{Emergency}}$ can be understood as a moderated reward or lesser penalty acknowledging the proactive mitigation of risk.

A substantial penalty is imposed for decisions that result in drone crashes T_{Crash}, particularly when no emergency landing is attempted ($\alpha_k = 0$ and a crash occurs). This should clearly be a penalty, indicating added time or delay due to the crash, which could be expressed as a positive value that increases the total time, reflecting the severity of the crash consequences.

4) Transition Probability: Given a state S_k and action $\mathbf{x}_k$, the transition to a new state S_{k+1} involves:

- The time of the decision point t_{k+1} which is a function of the action taken and the state of the network connectivity.
- The update of the truck and drone locations based on their actions. If a drone experiences a connectivity issue, it may transition to an emergency landing point.
- Removal of delivered customer orders from the list of pending deliveries. If the drone successfully delivers its package, the state reflects this by updating w and d accordingly.
- The update of the network connectivity status λ based on the stochastic model of network disruptions.
- The transition probability $P = (S_{k+1}|S_k, \mathbf{x}_k)$ would be conditioned on the current state, the action taken, and the stochastic elements of network connectivity. This probability would be higher for transitions that follow the expected outcome of actions under normal conditions and lower for transitions that represent unexpected events like network disruptions.

Given the current state s and action a, the transition probability to a new state s' can be defined as:

$$P(s'|s, x) = \prod_{i \in s'} P_i(s'_i|s, x)$$

Here $P_i(s'_i|s, x)$ represents the transition probability of individual elements in the state vector, assuming independence.

$$P(s'|s,x) = \begin{cases} 1 & \text{if } \lambda < \lambda_{\text{threshold}} \\ 0 & \text{Otherwise} \end{cases}$$

IV. Proposed Approach: RoutePEARL

A. Objective R1: Modular Route Optimization Approach for EV Trucks and Drones

This section will introduce the concept of the last-mile logistics problem and its objective (e.g., minimizing operational cost). It will then define the key decision types involved in route planning for a hybrid truck-drone system: **Assignment Decisions:** This includes selecting the appropriate vehicle type (EV or UAV) for each delivery and determining deployment locations for the drones.

Routing Decisions: This involves planning efficient paths for both trucks and drones, considering their respective capabilities and constraints.

Sequencing/Timing Decisions: This section will discuss how RoutePEARL determines the arrival and departure times for vehicles at various locations, ensuring efficient coordination between trucks and drones.

Communication Decisions: This involves determining the communication range for UAVs and potentially using relay nodes to ensure reliable data transmission within the network.

The section will also highlight the various considerations for route planning, including vehicle constraints (range, capacity), temporal constraints (time windows for deliveries), spatial constraints (geofenced areas, obstacles), logistical constraints (customer needs, package types), and network communication constraints (obstacles, wind interference).

This section will conclude by explaining how RoutePEARL's modular approach can be adapted for different delivery scenarios: **EV-truck only routing:** This mode would ignore network communication decisions, focusing solely on optimizing routes for the electric vehicle. **Direct drone delivery with multiple UAVs:** This scenario would consider all decision types (assignment, routing, sequencing/timing, communication) to optimize delivery using multiple drones.

Algorithm 1 presents a modular generalized route planning algorithm designed to optimize routes for a set of vehicles, including trucks and UAVs (drones), based on spatial parameters, temporal factors, and cost data. The process begins by obtaining an initial feasible solution using a constructive heuristic, which serves as the starting point. This solution is iteratively improved through a series of steps: first, the locations are assigned to trucks, then remaining locations are assigned to UAVs, and finally, the routes for these vehicles are sequenced. This process is repeated until a set number of feasible neighborhood solutions are generated. Each of these solutions is evaluated based on an objective function, and the best solution is determined. If this best solution meets certain acceptance criteria, it becomes the current solution. The algorithm keeps track of the best solution found so far and updates it if a better solution is found during the iterations. This loop continues until a predefined termination criterion, such as a maximum number of iterations or a time limit, is met. The algorithm ultimately returns the best solution and its corresponding objective value.

Algorithm 1 Modular Route Planning

Require: R, V, L (spatial parameters, temporal factors, and cost data)

Obtain a feasible initial solution using a constructive heuristic (s_0)
Initialize current solution ($s = s_0$) and current objective value ($f(s) = f(s_0)$)
Set best solution ($s_B = s$) and best objective value ($f(s_B) = f(s)$)
while termination criterion is not met **do**
  repeat
    Subproblem 1: Assign a subset of locations to trucks and determine the route plan
    Subproblem 2: Assign and route the UAVs and SADRs to the remaining locations
    Subproblem 3: Sequence the vehicles given their routes and stops
  until N feasible neighborhood solutions to s are obtained
  for $n \in \{1, \ldots, N\}$ **do**
    Compute $f(s_n)$
  end for
  Determine best neighborhood solution $s^* = \arg\min\{f(s_n) \mid n = 1, \ldots, N\}$
  if $f(s^*)$ is accepted based on acceptance criterion **then**
    $s \leftarrow s^*$, $f(s) \leftarrow f(s^*)$
  end if
  if $f(s) < f(s_B)$ **then**
    $s_B \leftarrow s$, $f(s_B) \leftarrow f(s)$
  end if
end while
return s_B and $f(s_B)$

B. Task R2.1: Drone Trajectory Prediction (DTP) to Handle Uncertainties

This section will introduce the concept of Drone Trajectory Prediction (DTP) and its role in handling uncertainties during route execution. It will then briefly explain the Partially Observable Markov Decision Process (POMDP) framework as the foundation for the DTP algorithm.

Here, define the key components of the POMDP model used in RoutePEARL:

State space (S): Represents the drone's position, truck's location, headings, capacities, remaining range, and delivery locations. **Action set (A):** Defines possible actions for the drone (changing coordinates, speed, altitude). **Transition probabilities (P):** Model the probability of transitioning between states based on actions taken. **Reward function (R):** Defines rewards for actions that move the drone towards the delivery location and penalties for deviations or failures. **Observations (O) and probability distribution function for**

observed states (Z): Capture the information available to the system about the environment (e.g., traffic updates, weather changes).

The section will then explain how the POMDP model is used for DTP:

Detect deviations from the planned path based on observations. Predict the drone's trajectory for the next T seconds based on the current state, possible actions, and transition probabilities.

This allows RoutePEARL to dynamically adjust routes in real-time to handle unforeseen circumstances and maintain efficiency.

C. Innovation and Contribution (Section 4)

This section will highlight the key innovations of RoutePEARL and how it advances the state-of-the-art in last-mile logistics:

Joint Optimization of EV and UAV Routes: Unlike existing solutions that often focus on a single mode of transport (trucks or drones), RoutePEARL offers a novel approach that considers the capabilities of both EVs and UAVs for comprehensive route planning. This allows for a more efficient allocation of resources and potentially shorter delivery times by utilizing the strengths of each vehicle type.

Modular Models for Adaptable Route Planning: RoutePEARL incorporates a modular design that enables it to adapt to various delivery scenarios. The system can be configured for EV-only routing, direct drone deliveries with multiple UAVs, or a combination of both. This flexibility allows service providers to tailor RoutePEARL to their specific needs and fleet composition.

Dynamic Models for Real-Time Route Adaptation: Traditional route planning approaches often struggle to handle uncertainties in real-world situations. RoutePEARL addresses this challenge by incorporating a Drone Trajectory Prediction (DTP) module based on the Partially Observable Markov Decision Process (POMDP) framework. This allows RoutePEARL to dynamically adjust routes in real-time based on factors like traffic congestion, weather changes, or unexpected delays. This ensures that deliveries are completed efficiently even when disruptions occur.

Cloud-Based Implementation for Scalability and Reliability: RoutePEARL's cloud-based platform offers several advantages. It enables scalability to handle large fleets of vehicles and ensures reliable access to RoutePEARL's functionalities for service providers. Additionally, the cloud environment facilitates ongoing updates and improvements to the system, ensuring RoutePEARL remains at the forefront of last-mile logistics technology.

D. Methodology (Section 5)

This section will describe the methodology for evaluating the performance of RoutePEARL. It could include:

Simulation environment setup: Specify the software, hardware, and data used to simulate real-world delivery scenarios. **Definition of performance metrics:** Define metrics like total distance traveled, delivery time, communication overhead to evaluate RoutePEARL's effectiveness. **Baseline routing algorithms for comparison:** Include existing truck-only or drone-only routing algorithms for comparison with RoutePEARL. **Different scenarios for testing RoutePEARL's capabilities:** Design scenarios with varying numbers of vehicles, delivery locations, and network complexities to test RoutePEARL's adaptability. **Evaluation process and expected outcomes:** Describe the evaluation process and the expected outcomes in terms of performance metric improvements achieved by RoutePEARL.

V. Results and Discussion

This section will present the results of the performance evaluation, including relevant data and visualizations. Discuss the findings based on the chosen metrics:

How effectively does RoutePEARL optimize routes compared to baseline approaches? Provide data to quantify the improvement in routing efficiency. **Does RoutePEARL's DTP module improve efficiency and handle uncertainties?** Analyze results to demonstrate how DTP helps RoutePEARL adapt to unexpected situations. **Are there any limitations or trade-offs observed in RoutePEARL's performance?** Discuss any limitations observed during evaluation, and potential areas for future improvement.

VI. Conclusion and Future Work

This section will summarize the key findings of the research and the contributions of RoutePEARL to last-mile logistics optimization. Briefly reiterate the innovations and potential impact of RoutePEARL. The section can conclude by outlining potential future directions for research and development related to RoutePEARL. This could include exploring integration with advanced traffic management systems, further refinement of the DTP module, or investigating the use of alternative vehicle types (e.g., autonomous ground vehicles) within the RoutePEARL framework.

References