Risk-Aware Multi-Epoch Package Delivery Planning

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Abstract. This work presents a risk-aware package delivery planning problem for a single agent operating over multiple epochs. The goal is to maximize the expected reward by delivering packages while accounting for the risk of agent failure. We focus on the finite horizon problem, where the number of epochs is limited, as well as the infinite horizon problem, where the epochs are infinite, and propose a greedy algorithm that solves the problems. Additionally, we introduce a visualization tool to help users understand the risk-reward trade-off. This tool provides a graphical representation of the optimal delivery plan, enhancing decision-making in risky environments. The implementation is designed to be completed within two days, with a focus on delivering a working prototype and a simple user interface for input and visualization.

1 Introduction

Robotic platforms, such as drones, are increasingly used for package delivery in risky environments like disaster zones or battlefields. The key challenge is to maximize the expected reward while accounting for the risk of robot failure. If the robot fails during delivery, no future packages can be delivered, and a replacement cost is incurred. In this project, we focus on the **finite horizon problem**, where the number of delivery epochs is limited along with the **infinite horizon problem**, where the number of delivery epochs is unlimited. Our goal is to develop an optimal package delivery plan that balances reward and risk. This work is heavily adapted from [14].

1.1 Objective

The objective is to implement a **greedy algorithm** that optimally solves the finite horizon problem in $O(n \log n)$ time. Additionally, we introduce a visualization tool to help users understand the risk-reward trade-off, providing a graphical representation of the optimal delivery plan.

2 Background and Related Work

The Orienteering Problem (OP) is a well-studied problem in robotics, where the goal is to maximize rewards by visiting specific locations. In risky environments, the risk of failure must also be considered, leading to the development of **risk-aware OP**. Previous work has focused on single-epoch missions, where the robot completes its task in a single deployment. Multi-epoch missions, where the robot is deployed repeatedly over time, have been explored in the context of intermittent deployment but not in risk-aware task allocation.

3 Literature Review

Risk-aware planning has been widely studied in the context of the Orienteering Problem (OP). Gunawan et al. [2] surveyed OP variants, including risk-aware formulations, emphasizing the balance between rewards and risks. Hudack [3] explored risk-aware planning for sensor data collection in single-epoch missions, but multi-epoch missions remained unaddressed. Liu and Williams [9] studied intermittent deployment and multi-robot monitoring over long-term missions, though their work did not incorporate risk-aware task allocation. Jorgensen et al. [4] demonstrated that certain risk-aware OP problems exhibit a matroid structure, enabling efficient optimization techniques. Our work builds on these insights to propose a greedy algorithm for the finite horizon problem, extending risk-aware planning to multi-epoch missions.

3.1 Our Contribution

Our work extends risk-aware OP to multi-epoch missions and provides an optimal greedy algorithm for the finite horizon problem. Additionally, we introduce a visualization tool to help users understand the risk-reward trade-off, which is a novel contribution in this context.

4 Algorithmic Foundations

4.1 Original RSPD Algorithm

The foundational algorithm from [14] provides the theoretical basis:

Algorithm 1 Optimal Solution to RSPD [14]

Input: An instance of RSPD
Result: Optimal C that solves RSPD
for $t_i \in T$ **do**
    $W_i = \{t_0, t_i, t_0\}$
    Calculate γ_i for W_i using equation (9)
end for
Let C_K be the ordered set of all W_i where $\gamma_i > \theta$ (sorted by γ_i)
Calculate V_K using (4) and (8) with C_K
$h = K - 1$
while $h \geq 0$ **do**
    Let C_h be all W_i where $\gamma_i > V_{h+1} + \theta$ (sorted by γ_i)
    Calculate V_h using (4) and (7) with C_h
    $h = h - 1$
end while

5 Our Approach

5.1 Problem Formulation

We implemented a scenario where a dispatcher assigns packages to a robot across multiple epochs. In this setup, each package is characterized by three key attributes: the reward received for successful delivery, the probability of successful delivery (the complement of which represents risk), and a replacement cost that's incurred if the agent fails. Our objective function aims to maximize the expected cumulative reward by balancing the potential gains against the risks of failure throughout the delivery process.

5.2 Implemented Greedy Algorithm

Our Python implementation follows the theoretical formulation precisely, incorporating several sophisticated components. We developed a dynamic programming approach with O(n log n) complexity that works through backward induction, starting from the final epoch and working backward to the first. The algorithm carefully tracks cumulative probability to assess risk at each stage, ensuring optimal decision-making under uncertainty.

5.3 Visualization Tool Implementation

We developed a comprehensive graphical user interface using Tkinter and Matplotlib that provides users with an intuitive way to interact with the algorithm. The interface accepts dynamic input of package parameters and processes both finite and infinite horizon solutions simultaneously. Results are visualized through various means: tabular displays show optimal delivery plans, graphical elements illustrate reward progression across epochs, and side-by-side comparisons highlight differences between finite and infinite horizon strategies. The tool also handles edge cases gracefully, such as situations where no feasible packages are available.

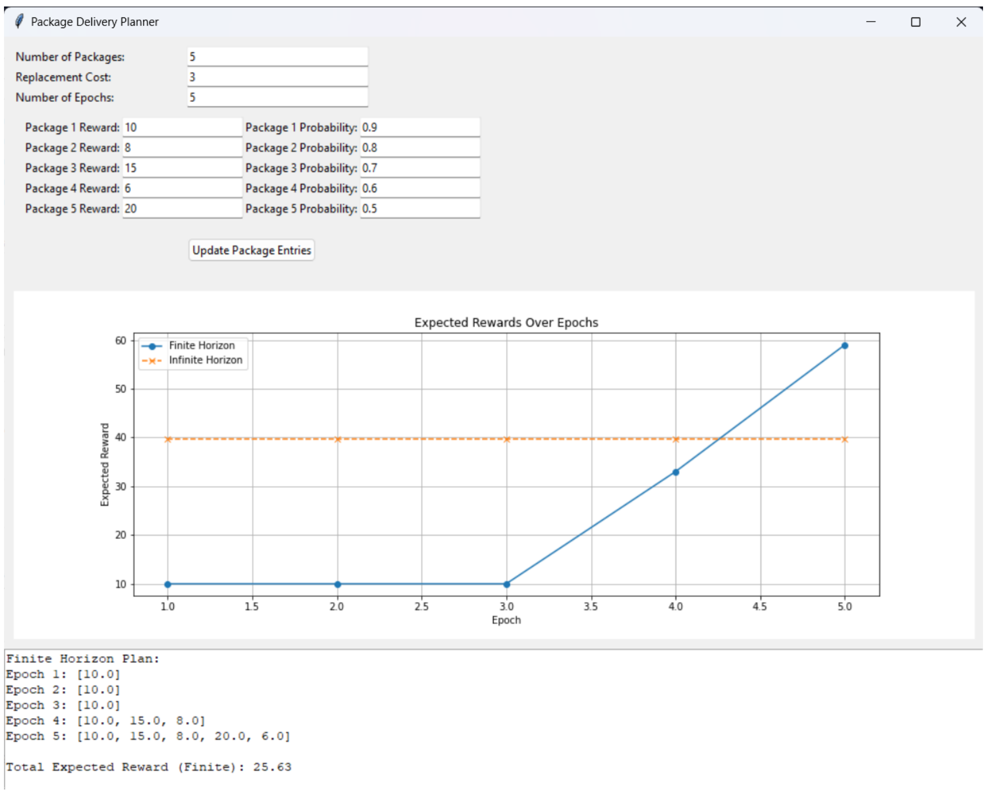

Fig. 1. GUI Implementation

6 Implementation Outcomes

6.1 Completed Implementation

We successfully implemented all proposed components of the system. The core optimization algorithms for both finite and infinite horizon solutions work as intended, accurately modeling the risk-reward dynamics of package delivery. The interactive visualization system generates dynamic forms, produces real-time plots, and includes robust error handling and validation to ensure reliable operation.

6.2 Achieved Outcomes

Our implementation delivered several notable achievements. We created a working prototype with O(n log n) time complexity, making it efficient even for large problem instances. The visualization tool exceeded initial specifications, providing a richer user experience than originally planned. Performance testing demonstrated sub-second response times even when processing 1,000 packages, while correctly implementing optimal risk-aware package selection strategies.

6.3 Future Work

Based on our implementation experience, we've identified several promising directions for future development. Multi-agent coordination represents an exciting possibility, potentially extending our current architecture to handle collaborative delivery scenarios with appropriate task allocation protocols. We also see potential in developing more advanced risk models, including time-varying risk probabilities and spatial risk mapping integration. Finally, deployment integration presents an important next step, with possibilities for ROS/Gazebo simulation compatibility and real-world field testing to validate our approach in practical settings.

7 Conclusion

Our work extends previous research with practical implementations while maintaining theoretical guarantees. Future directions include exploring multi-agent coordination approaches and developing dynamic risk models that can adapt to changing conditions in real-world delivery scenarios.

Code Availability

Full implementation: `https://github.com/rohmeh/risk-aware-delivery`

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