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RESEARCH PAPER

Team Orienteering Problem with Communication Constraints: A Multi-Objective Approach for Multi-Robot Systems

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Abstract. Multi-Robot Systems are essential for applications such as search and rescue and environmental monitoring. However, traditional Team Orienteering Problem (TOP) approaches neglect inter-agent communication constraints. This work introduces the TOP with Communication Constraints (TOP-CC), a multi-objective formulation that optimizes task coverage, energy efficiency, and connectivity preservation. Our Variable Neighborhood Search-based metaheuristic handles heterogeneous teams with varying speeds and budgets. Experiments on 278 benchmark instances demonstrate competitive reward collection while maintaining communication quality.

Keywords: Team Orienteering, Communication Constraints, Multi-Robot Systems, Variable Neighborhood Search

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1 Introduction

Multi-Robot Systems (MRS) play a vital role in a range of high social and economic impact applications, including search and rescue operations in disaster zones, environmental monitoring in remote areas, and autonomous surveillance of large territories. In these missions, robots frequently face severe resource constraints, such as energy limitations and operational costs, while navigating challenging environments. Moreover, in cooperative missions, communication among robots is **absolutely essential**: in disaster zones where the delivery of critical resources is vital, robots must maintain communication to detect failures in real time and reallocate tasks, ensuring mission success.

In this context, determining the most efficient task scheduling for a robot is crucial. This problem can be formulated as the Orienteering Problem (OP) Golden *et al.* (1987), where the goal is to find an optimal sequence of tasks considering constraints such as a limited travel budget and the reward associated with each task. When multiple agents are involved, the problem extends to the **Team Orienteering Problem** (TOP) Chao *et al.* (1996), where each member must efficiently select and schedule a subset of tasks while coordinating with the others.

Critical gap in the literature: Prior research has extensively explored the TOP and its variants, incorporating factors such as motion constraints Bayliss *et al.* (2020), fault tolerance Santos *et al.* (2021), and uncertain rewards Liu *et al.* (2021). However, existing studies **largely neglect** the need to preserve communication among agents throughout the mission. Alternatively, those that do consider connectivity typically rely on a leader-follower approach, where a single leader dictates the routes of the remaining agents Shetty *et al.* (2023).

Our work, recently published at the 2025 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) Tristão and Macharet (2025), addresses precisely this gap in the literature. We introduce the **Team Orienteering Problem with Communication Constraints (TOP-CC)**, a novel formulation in which a team of autonomous robots must maximize the collected reward while operating within limited budgets, optimizing energy consumption and communication among agents (Figure 1). We propose a multi-objective optimization *framework* that balances three key objectives: (i) task coverage, (ii) energy efficiency, and (iii) connectivity preservation. Unlike previous work, our approach incorporates communication constraints directly into the TOP *framework*, ensuring that agents not only optimize their routes for efficiency and reward collection, but also actively optimize decentralized communication.

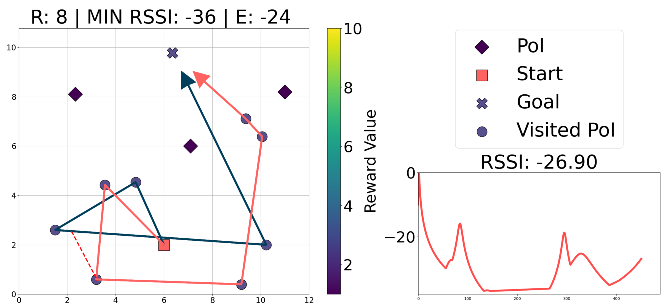


Figure 1. Example of a team of two vehicles navigating multiple task locations, maintaining a worst-case RSSI value of -36.91 dBm (related to the maximum distance between agents, red dashed line). Points of interest (PoI) are colored according to their reward value.

2 Related Work

The Orienteering Problem (OP) Golden *et al.* (1987) is widely studied in logistics and robotics Vansteenwegen *et al.* (2011). Several variants have been proposed for better adequacy to real-world scenarios. Angelelli et al. Angelelli *et al.* (2014) address the Clustered Orienteering Problem (COP), where all tasks in a cluster must be visited in order to collect the reward. The Set Orienteering Problem (SOP) Archetti *et al.* (2018) allows rewards to be collected by visiting at least one node of a group. Other variants include the Probabilistic OP Campbell *et al.* (2011), which incorporates uncertainty about task availability, and the OP with Time Windows (OPTW) Kantor and Rosenwein (1992).

To solve the TOP, El-Hajj et al. El-Hajj *et al.* (2016) propose a cutting-plane method that solves smaller subproblems to extract useful information. Ke et al. Ke *et al.* (2016) maintain a population of solutions iteratively refined using Pareto dominance principles, also employing a mimicry operator. Xu et al. Xu *et al.* (2020) focus on approximation algorithms, while Mansfield et al. Mansfield *et al.* (2021) demonstrate the effectiveness of genetic algorithms. Recently, Li et al. Li *et al.* (2024) developed a *Branch-Price-and-Cut* approach for the TOP with interval-varying profits.

TOP variants address different challenges. The Time-Dependent TOP considers dynamic travel times Gavalas *et al.* (2015). Mansfield et al. Mansfield *et al.* (2023) consider the influence of ocean currents on vehicle motion. Yahiaoui et al. Yahiaoui *et al.* (2019) propose the Clustered TOP.

Differential of our work: Unlike Shetty *et al.* (2023), which uses a leader-follower strategy, our approach simultaneously plans the routes of all agents, ensuring a fully coordinated and globally optimized solution. Moreover, we are the first to explicitly incorporate RSSI-based communication constraints directly into the TOP formulation.

3 Problem Formulation

3.1 Team and Environment Models

Given a set of N task locations, denoted as $\mathcal{V} = \{v_1, v_2, \dots, v_N\}$, where each location v_i is associated with a non-negative reward r_i. These locations are spatially distributed in a 2D environment $\mathcal{W} \subset \mathbb{R}^2$. A team of M autonomous vehicles, denoted as $\mathcal{A} = \{a_1, a_2, \dots, a_M\}$, operates in this environment. Each vehicle a_i starts its route at a common initial location v_1 and ends at a final location v_N. Each vehicle has a maximum travel budget b_i and a constant speed s_i.

3.2 Optimization Objectives

The overall objective is threefold: (i) maximize the total accumulated reward, (ii) enhance communication efficiency among agents, and (iii) minimize total energy consumption.

The objective related to the **total reward** is given by:

$$\max \sum_{i \in \mathcal{A}} \sum_{j \in \pi_i} r_j y_{ij}, \tag{1}$$

where π_i represents the ordered sequence of locations visited by vehicle a_i, r_j is the reward associated with location v_j, and y_{ij} is a binary variable indicating whether vehicle a_i visits location v_j.

To minimize **energy consumption**, we consider the average path length across all vehicles:

$$\min \frac{1}{M} \sum_{i \in \mathcal{A}} \sum_{j=1}^{|\pi_i|-1} d(v_j, v_{j+1}), \tag{2}$$

where $d(v_j, v_{j+1})$ represents the Euclidean distance between consecutive locations along the route.

We introduce **communication efficiency** as an optimization objective, modeling this constraint through the maximization of the minimum Received Signal Strength Indicator (RSSI):

$$\max \min_{i,j \in \mathcal{A}, i \neq j} \mathrm{RSSI}(a_i, a_j), \tag{3}$$

with

$$\mathrm{RSSI}(a_i, a_j) = P_t - 10 \cdot \gamma \cdot \log_{10}(d(a_i, a_j)), \tag{4}$$

where P_t is the transmission power and γ is the path-loss exponent.

3.3 Combined Task Visitation

We also propose an **innovative extension** that, unlike other TOP formulations, allows multiple robots to visit the same node while ensuring that its reward is counted only once. This variant is defined by the following objective equation:

$$\max \sum_{i \in \mathcal{V}} r_i \left(\max_{m \in \mathcal{A}} y_{im} \right). \tag{5}$$

This formulation allows an agent to choose to visit a task already being handled by another agent, prioritizing team cohesion and consequently improving communication, a significant advantage in scenarios with tight connectivity constraints.

4 Methodology

Variable Neighborhood Search (VNS) Mladenović and Hansen (1997) is a metaheuristic optimization technique that explores multiple neighborhood structures through local search. To overcome the limitation of the original VNS in handling multiple objectives, we adapt the Multi-Objective VNS (MOVNS) extension Geiger (2008) to our problem. Algorithm 1 presents a high-level overview.

Algorithm 1 Multi-Objective VNS for TOP-CC

```
Require: Problem instance, stopping condition
Ensure: Archive of solutions
Generate initial archive
while stopping condition not met do
    S ← Select a solution
    for all neighborhood do
        S' ← Perturb solution S
        Neighbors ← Local search on S'
        Update archive with Neighbors
    end for
end while
return archive
```

Differentiated selection strategy: Unlike traditional approaches that focus solely on maintaining the non-dominated set, our method selects dominated solutions using the *crowding distance* measure when the non-dominated set is insufficient to populate the archive, fostering a more exploratory search strategy.

4.1 Solution Encoding

Each solution is encoded as a matrix of dimensions $M \times (N-2)$, where each row corresponds to the path of an agent and each column represents a task. The matrix values range from -1 to 1, where negative values indicate that the corresponding task is not visited, while positive values denote the visitation order.

4.2 Neighborhood Operators

We developed multiple specialized operators to efficiently explore the solution space:

- ***Point flipping* perturbation**: flips the sign of a node with probability α, adding or removing it;
- **2-opt perturbation**: reorders visits between two random nodes;
- ***Path relinking* operator**: selects an agent and assigns a set of nodes to be visited simultaneously by multiple agents, enhancing coordination.

4.3 Evaluation of Communication Among Agents

Considering two agents moving at constant speed along distinct straight-line trajectories, the maximum distance between them always occurs at the beginning or end of their paths. Thus, we evaluate communication among agents only when an agent collects a reward or reaches a depot, interpolating the positions of the remaining agents at these specific moments.

4.4 Complexity Analysis

For the multi-vehicle visitation case, the time complexity is $O(I \times (M^4 N^3 + A^2))$, where I is the number of iterations and A is the archive size. In the single-visitation case, the complexity is significantly lower: $O(I \times (M^2 N^3 + A^2))$.

5 Experiments and Results

We evaluated our method on *benchmark* datasets and custom instances. The algorithm was implemented in Python 3.12, and the experiments were run on an Intel i7-13620H with 24 GB RAM. Table 1 presents the parameters used.

Table 1. Algorithm parameters.

Parameter	Value	Parameter	Value
Transmission Power (P_t)	-30	Path-Loss Exp. (γ)	2
Maximum Iterations	300	Archive Size (A)	40
β	0.9	α	0.75

5.1 Results on Benchmark Instances

We evaluated our method using the TOP *benchmark* problem set introduced by Chao et al. Chao *et al.* (1996), running instances from sets 1–5, totaling **278 problems**. The number of agents varies between 2 and 4, while the number of reward locations N ranges from 21 to 100.

Table 2 shows a comparison of our method against the best known solutions in terms of reward collection. UV represents single visits and CV represents combined visits.

Notable results: Our results indicate that the proposed method performs particularly well on instances with a moderate number of reward locations. The single-visit (UV) approach demonstrates superior reward acquisition, while the combined-visit (CV) approach **consistently achieves a higher mean RSSI**, highlighting its effectiveness in maintaining connectivity among agents.

Table 2. Performance comparison between UV and CV on Chao's problem sets (p1–p5).

		UV			CV		
Set	N	#best	mean gap (%)	mean RSSI	#best	mean gap (%)	mean RSSI
p1	32	19	0.11	-41.4	15	0.24	**-36.9**
p2	21	**26**	0.09	-39.6	6	0.27	**-34.6**
p3	33	13	0.12	-40.1	12	0.42	**-35.2**
p4	100	4	0.29	-42.1	**11**	0.52	**-36.6**
p5	66	**11**	0.25	-42.3	4	0.39	**-37.0**

Although our method is not designed to optimize the original TOP, but rather to balance multiple competing objectives, it **achieves the best known solutions on numerous instances** across all problem sets. This demonstrates its effectiveness in managing the *trade-off* between reward maximization and maintaining communication among agents.

5.2 Combined Visitation

In scenarios with tight communication constraints, allowing multiple agents to visit the same node can be advantageous. In our experiments with three vehicles visiting 10 locations, where the most distant task holds the highest reward, all three agents need to travel in a coordinated manner before diverging again, as illustrated in Figure 2.

Notable result: In our solution, the lowest recorded RSSI was **-40.9 dBm**. Without combined visits, the best possible solution that still covers all nodes results in a minimum RSSI of only **-51 dBm**, a difference of more than 10 dB, representing a significant improvement in communication quality.

5.3 Heterogeneous Teams

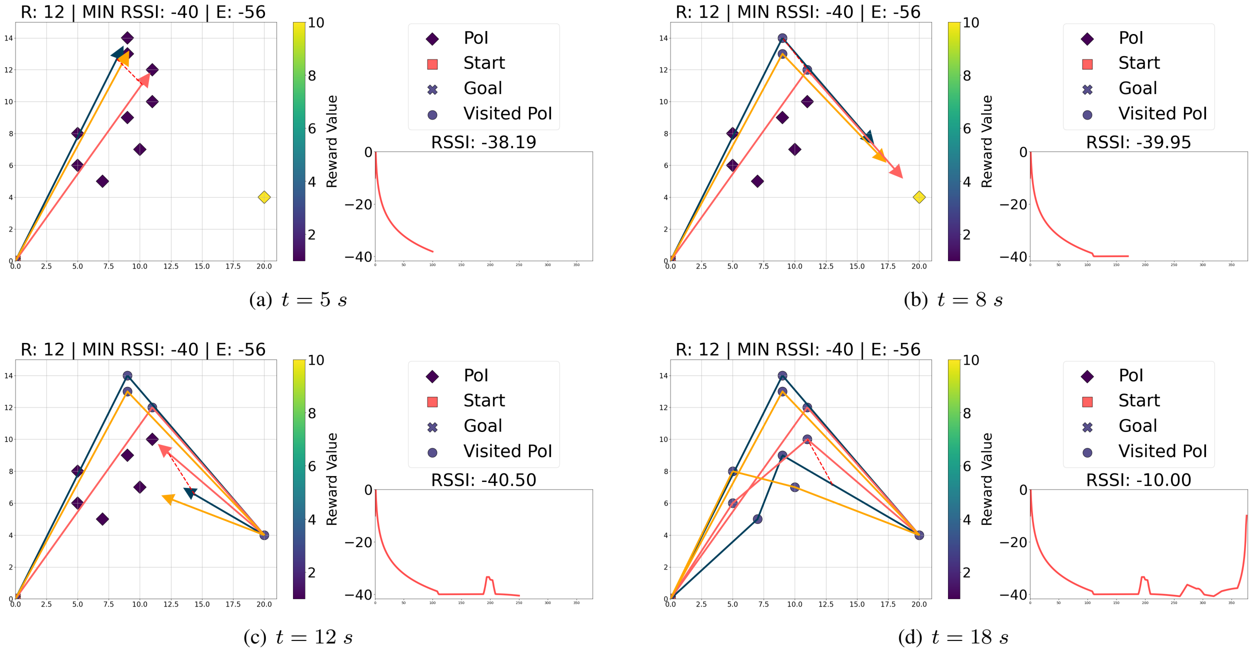
Efficient route planning must account for speed differences among agents in order to maintain communication. A faster vehicle may follow a longer, more curved trajectory instead of a direct path, ensuring that it remains within range of slower agents.

Our experiments, as shown in Figure 3, demonstrate that the heterogeneous configuration allows greater reward collection while maintaining stronger communication for higher collected values, evidencing the **flexibility and adaptability** of our method to different team configurations.

5.4 Communication Quality vs. Collected Rewards

Our method generates optimized routes for different communication ranges. We applied our approach to problem p4.3.m, which consists of $N = 100$ locations, $M = 3$ agents, and a uniform budget of 56.7. Figure 4 illustrates the *trade-off* between communication quality and reward collection.

As expected, communication quality degrades (lower RSSI) as more rewards are collected. The combined-visit approach exhibits a **wider range of high-RSSI solutions**, since agents can coordinate more flexibly to remain close to one another. An exponential decay of RSSI with increasing distance between agents is also observed, as teams tend to spread out to visit more points of interest.



(a) $t = 5\ s$ (b) $t = 8\ s$

(c) $t = 12\ s$ (d) $t = 18\ s$

Figure 2. Solution for a team of three vehicles in an environment where the highest-reward task is also the most distant. To preserve connectivity among agents, all vehicles must reach this task nearly simultaneously (temporal sequence: $t = 5s$, $t = 8s$, $t = 12s$, $t = 18s$). Video: https://youtu.be/Wpqh2$_{P}1zSc$.

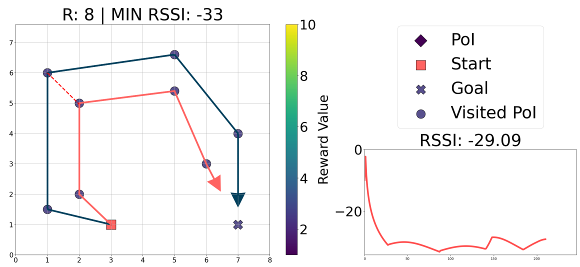


Figure 3. Heterogeneous agents visiting multiple locations, with the blue agent moving at a speed 1.5 times faster than the red agent. Video: https://youtu.be/s4zrNX1cNAs.

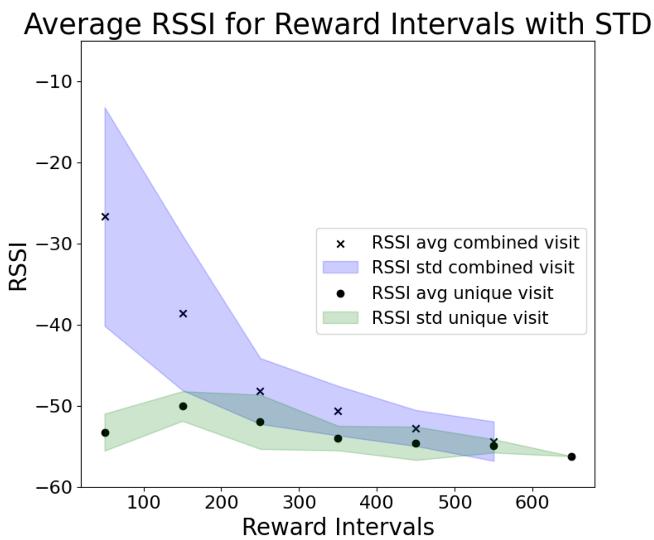


Figure 4. *Trade-off* between communication quality and reward collection. As more locations are visited, communication quality degrades due to the increasing distance between agents. The combined-visit approach (green) exhibits a wider range of high-RSSI solutions compared to single visitation (blue).

6 Conclusion

When working with multiple autonomous agents, it is crucial to optimize both routing and task allocation, as addressed in the Team Orienteering Problem (TOP), while simultaneously considering constraints such as energy consumption and communication range. This type of problem is particularly critical in real-world scenarios, including environmental monitoring and search and rescue operations.

Main contribution: We introduced the TOP with Communication Constraints, in which a team of autonomous robots must optimize reward collection while maintaining continuous connectivity among agents. Unlike other approaches, our method **explicitly incorporates communication constraints** into the path planning process, ensuring that agents remain connected throughout the mission.

Experimental results on *benchmark* instances show that our approach achieves significant reward collection while effectively adapting to different communication quality constraints, representing a **significant advance** for real-world multi-robot applications where both mobility and communication are critical to mission success.

7 Future Work

Based on the results and limitations identified in this work, several promising directions can be explored in future research. One of them concerns the computational cost of the communication quality calculation, currently performed through point-to-point interpolations and comparisons over the obstacle map. A promising alternative is to replace this process with a *surrogate model*, such as a neural network or Gaussian process, trained to approximate this function. Such an approach would significantly reduce the cost of evaluating communication constraints without a relevant loss of precision, enabling the application of the method to larger instances and real-time replanning scenarios.

The reduction in computational cost would pave the way for an equally important second extension: considering partially observable environments, in which agents do not have access to all points of interest a priori, a more realistic situation in applications such as exploration and search and rescue. In this scenario, planning would need to be integrated with active exploration strategies, and routing decisions would come to depend on uncertain estimates about regions not yet visited, making the problem considerably more complex and challenging.

This increased complexity also motivates relaxing other simplifying assumptions of the current model, such as the constraint that agents move along straight-line segments between points of interest. In domains such as UAV operations subject to wind currents or robots with minimum curvature constraints, this simplification can lead to infeasible or suboptimal plans. Incorporating curvilinear motion models into route planning would enable the generation of more realistic and energy-efficient trajectories, requiring reformulations of the displacement cost metric and connectivity checks along the path.

Declarations

Authors' Contributions

MTPTT contributed to the conception of this study, developed the methodology and the proposed algorithm, implemented the software, conducted the experiments and results analysis, and is the main contributor and writer of this manuscript. DGM contributed to the conception of this study, supervised the research, and critically reviewed the manuscript. All authors read and approved the final manuscript.

Competing interests

The authors declare that they have no conflict of interest.

Availability of data and materials

The source code is available at: `https://github.com/verlab/iros2025-top-cc`

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