The Flying Sidekick Traveling Salesman Problem - State of the Art

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Abstract

The Flying Sidekick Traveling Salesman Problem (FSTSP) is a version of the well-known Traveling Salesman Problem (TSP), among the most prevalent and difficult optimization problems in computer science. The FSTSP introduces a truck and an Unmanned Aerial Vehicle (UAV) to transport items to various clients, adding a new degree of complexity. In this essay, we will look at the present state of the art in the FSTSP problem and the many solutions suggested.

1 Introduction

The FSTSP is a variant of the classic Traveling Salesman Problem (TSP) that involves finding the shortest possible route for a traveling salesman to visit a set of cities, each of which must be visited exactly once, and return to the starting point. However, in the FSTSP, the salesman travels by air, and each city has an airport. The distance between two cities is the Euclidean distance between their respective airport subnodes.

The FSTSP is a complex combinatorial optimization problem that belongs to the class of NP-hard problems. This means that finding an optimal solution for large instances of the problem is computationally intractable, and a polynomial-time algorithm for solving the problem has not been found.

As a result, much research has concentrated on building heuristic and metaheuristic algorithms capable of producing high-quality results in a reasonable period of time. Heuristic algorithms give a rough answer to a problem, but metaheuristic algorithms are more generic and powerful algorithms that may be applied to a wide range of optimization issues.

2 Approaches

One of the simplest and most basic approaches to the FSTSP is to break it into two subproblems: one for the truck and one for the UAV. The vehicle would visit a subset of clients, while the UAV would deliver items to the remaining customers. This method is known as the split delivery technique, and it has been proved to be beneficial in minimizing truck and UAV trip time. Nevertheless, this technique ignores the interaction between the truck and the UAV, which might result in inefficient solutions.

Despite the difficulty of the problem, several solution approaches have been proposed to obtain near-optimal or heuristic solutions. These approaches can be broadly classified into exact algorithms, heuristic algorithms, and metaheuristics.

Exact algorithms use mathematical formulations to find the exact optimal solution. One approach is to use branch-and-bound techniques that progressively explore the solution space, eliminating sub-optimal solutions. Another approach is to use cutting-plane algorithms that iteratively add constraints to a linear programming formulation until an optimal solution is found. However, these methods are computationally expensive and only feasible for small instances of the problem.

Heuristic algorithms use approximate methods to find good solutions quickly. One approach is to use construction heuristics, such as nearest-neighbor, farthest-insertion, and Christofides heuristics, to build a solution incrementally. Another approach is to use improvement heuristics, such as 2-opt, 3-opt, and Lin-Kernighan heuristics, to iteratively improve a given solution. These methods can find good solutions for larger instances of the problem in reasonable time.

Metaheuristics are high-level strategies that combine several heuristic methods to explore the solution space efficiently. Some popular metaheuristics for the FSTSP include genetic algorithms, ant colony optimization, simulated annealing, and tabu search. These methods can find high-quality solutions for large instances of the problem.

3 Recent research

More recent research has focused on developing more sophisticated algorithms that can take into account the interactions between the truck and the UAV. One approach is to use a multi-agent system, where the truck and the UAV are treated as separate agents that communicate with each other to coordinate their actions. The agents can exchange information about the current state of the problem, such as the location of customers, the remaining packages, and the current workload. This approach has been shown to be effective in improving the quality of solutions compared to the split delivery strategy.

Another approach is to use a hybrid algorithm that combines different optimization techniques. For example, some researchers have proposed combining a genetic algorithm with a tabu search algorithm to solve the FSTSP. The genetic algorithm is used to generate a set of candidate solutions, while the tabu search algorithm is used to refine the solutions and remove any infeasibilities. This hybrid approach has been shown to be effective in producing high-quality solutions for the FSTSP.

Finally, some researchers have proposed using machine learning techniques to solve the FSTSP. For example, some researchers have proposed using deep reinforcement learning, which is a machine learning technique that can learn optimal policies by trial and error. The idea is to train a deep neural network to learn how to coordinate the actions of the truck and the UAV in order to minimize the travel time. This approach has shown promising results, but it requires a large amount of training data, which can be difficult to obtain.

3.1 A CSP approach

In the "Optimization Approaches for the Traveling Salesman Problem with Drone"[ABS18] article, the authors extended the TSP problem to include drones, which can travel faster and have different travel characteristics compared to ground-based vehicles.

The authors proposed a CSP approach with two heuristics: a dynamic programming and a greedy one. The authors also conducted sensitivity analyses to evaluate the impact of different factors such as the speed of the drone and the weight capacity of the drone. Overall, the article provides insights into the use of drones in solving optimization problems and highlights the potential benefits of incorporating drones into delivery systems.

In the "A Study on the Traveling Salesman Problem with a Drone"[stu19] article, the authors proposed a CP model that considers the drone's travel characteristics, such as its speed, range, and carrying capacity, and optimizes the delivery routes of both the drone and the ground-based vehicle. The CP model is designed to find a solution that minimizes the total distance traveled while meeting the constraints, such as the drone's range limit and the capacity limit of the ground-based vehicle. The authors evaluated the performance of their CP model using a set of benchmark instances with varying numbers of locations and drone capabilities. The results showed that the CP model provided high-quality solutions for small and medium-sized problem instances. For larger problem instances, the CP model had longer runtimes and was less effective in finding optimal solutions. The paper provides insights into the use of CP-based approaches to solve the TSP with a drone and highlights the potential benefits of incorporating drones into delivery systems. The study also sheds light on the challenges of scaling up the CP model to larger problem instances and the need for further research in this area.

3.2 A reinforcement learning approach

The article "A deep reinforcement learning approach for solving the Traveling Salesman Problem with Drone"[BYK+23] describes a novel approach to solving the Traveling Salesman Problem (TSP) with Drone (TSP-D) using deep reinforcement learning. TSP-D involves routing a fleet of vehicles, including a truck and a drone, in coordination to optimize delivery routes. The authors propose a hybrid model that combines an attention encoder and a Long Short-Term Memory (LSTM) network decoder, allowing the decoder's hidden state to represent the sequence of actions taken during routing. This approach addresses the coordination challenges between the two vehicles that traditional state-less attention-based models struggle with.

The authors conducted experiments on the min-max Capacitated Vehicle Routing Problem (mm-CVRP) to evaluate the effectiveness of their proposed model. Results show that the hybrid model outperforms the purely attention-based model in terms of solution quality and computational efficiency. Additionally, the hybrid model is found to be more suitable for coordinated routing of multiple vehicles than the attention-based model. The results also demonstrate that the proposed approach achieves comparable results to operations research baseline methods.

The article suggests that the proposed approach has potential applications in transportation and logistics, particularly in the optimization of delivery routes involving multiple vehicles. The study contributes to the growing body of research on the use of deep reinforcement learning in solving combinatorial optimization problems, and highlights the effectiveness of hybrid models in addressing coordination challenges in multi-vehicle routing problems.

4 Benchmark instances

Multiple benchmark instances can be found at Unimore Group.

5 Applications

The FSTSP has practical applications in fields such as logistics, transportation, and distribution. For example, in air cargo transportation, the FSTSP can be used to determine the most efficient route for a cargo aircraft to visit several airports and deliver goods. In addition, the FSTSP can be used in military logistics to plan supply routes for air transport of troops and equipment.

6 Conclusions

In conclusion, the FSTSP is a challenging optimization problem that requires sophisticated algorithms to solve. The current state of the art in the FSTSP includes a range of heuristic and metaheuristic algorithms that can provide good quality solutions. Future research will likely focus on developing more advanced algorithms that can take into account the dynamic nature of the problem, such as changes in customer demand and weather conditions. Additionally, the use of machine learning techniques will likely become more prevalent in solving the FSTSP as the availability of training data increases.

References

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