

Solving Stochastic Orienteering Problems with Chance Constraints Using Monte Carlo Tree Search

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Abstract—We present a new Monte Carlo Tree Search (MCTS) algorithm to solve the stochastic orienteering problem with chance constraints, i.e., a version of the problem where travel costs are random, and one is assigned a bound on the tolerable probability of exceeding the budget. The algorithm we present is online and anytime, i.e., it alternates planning and execution, and the quality of the solution it produces increases as the allowed computational time increases. Differently from most former MCTS algorithms, for each action available in a state the algorithm maintains estimates of both its value and the probability that its execution will eventually result in a violation of the chance constraint. Then, at action selection time, our proposed solution prunes away trajectories that are estimated to violate the failure probability. Extensive simulation results show that this approach can quickly produce high-quality solutions and is competitive with the optimal but time-consuming solution.

Note to Practitioners: In many practical scenarios one is faced with multiobjective sequential decision making problems that can be solved through constrained optimization. If some of the parameters are known with uncertainty, the event “violating one of the constraints” becomes a random variable whose probability should be bound. As an application of this general problem formulation, in this paper we consider stochastic orienteering, a problem that finds applications when a robot is tasked with performing multiple tasks of varying utility while being subject to a bound on the traveled distance. Many problems in logistics, precision agriculture, and environmental monitoring, just to name a few, can be cast as instances of this optimization problem.

Index Terms—Stochastic Orienteering; Chance Constraints; Monte Carlo Tree Search

I. INTRODUCTION

Orienteering is a combinatorial optimization problem that can be used to model numerous problems relevant to robotics and automation, such as logistics [1], environmental monitoring [2], surveillance [3], and precision agriculture [4], just to name a few (see Figure 1). In its basic formulation, one is given a graph G with rewards associated with vertices and costs assigned to edges, as well as a budget B . The goal is to find a path collecting the highest sum of rewards of the visited vertices while ensuring that the path cost does not exceed the budget B . In this paper, for the sake of simplicity, we assume that B is a temporal budget, but it could as well be energy or any other resource consumed by the

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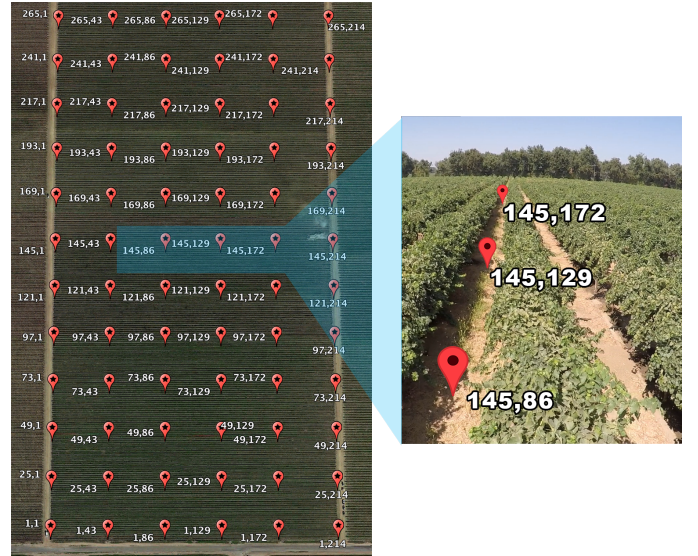


Fig. 1: An example of the application of orienteering in viticulture. The left panel shows an aerial view of a commercial vineyard located in California with more than 55,000 vines. Pins are displayed at locations where soil moisture samples must be collected. The left panel shows a zoomed version of the vineyard, illustrating how the pins are placed in the traversable regions between tree rows. Due to the extension of the vineyard, a robot tasked with automatically collecting samples cannot visit all locations, and has to select a suitable subset. Not all sampling locations have the same value, and therefore this is a natural instance of the orienteering problem. Note that in this specific problem setting the robot cannot move along straight lines when moving between different locations, but rather has to exit either end of the vineyard before moving to a different tree row because of the irrigation infrastructure.

robot as it moves from location to location. Numerous variants have been proposed and, as discussed in section II, most are computationally intractable. In robotics applications this model is usually adopted in scenarios where vertices are associated with places that a robot must visit (e.g., to pick a package, or to deploy a sensor, collect a sample, etc.), and edges are associated with paths connecting the different locations, with the edge cost modeling the time or energy spent by the robot to traverse it. Most former research in this area has considered scenarios where costs and rewards are deterministic, and only a few works have explicitly considered cases where these are affected by uncertainty. In most practical applications, however, the time or energy spent to traverse an edge (i.e., to move from one location to another) is not known upfront, but is rather a continuous random variable whose realization will only be known at run time. When this is the case, it

follows that for a given traversed path the incurred cost is also a random variable. For example, the robot may have to wait to traverse an aisle in a warehouse to give way to another robot coming in the opposite direction, or it may have to take a detour because a passage is blocked, and so on. The variant of the problem where edge costs are stochastic is known as the *stochastic orienteering problem*, and while studied in the past [5], it has received far less attention than its deterministic version. Obviously, the stochastic version is not simpler than the deterministic one. Assuming that the probability density function (pdf) characterizing the traversal time of edges is known, some former solutions reduced the stochastic problem to the deterministic one by using the expected traversal time. Such solutions are in many situations unsatisfactory, because optimizing for expectation may lead to realizations where the robot exceeds the budget B while executing the task. This may be a major inconvenience because if the robot runs out of energy and stops, it has to be recovered and recharged.

In our recent works [6–8] we presented a new approach to solve the stochastic orienteering problem whereby we introduce *chance constraints*, i.e., while solving the problem we consider a constraint on the probability that the stochastic cost of the path exceeds the assigned budget. It shall be mentioned that besides our works, there is very little former literature attacking this specific problem, as discussed in Section II. Differently from all previous works, our recently developed algorithms produce a *path policy*, i.e., a time-parametrized schedule that, depending on how much budget is left, determines where to move next while ensuring that the probability of exceeding the budget remains bounded below an assigned constant. This approach is therefore adaptive, i.e., rather than producing one path, it gives a policy that will result in different paths depending on the actual realizations of the edge traversal times. This is achieved by reducing the planning problem to a constrained Markov Decision Process (CMDP) with a suitable structure. This approach, while effective, has some limitations. First, the path policy is determined using an initial solution to the deterministic version of the orienteering problem. This initial solution is computed using a heuristic, and if the heuristic selects a poor path, the algorithm has no way to move away from it. Second, in constructing the finite CMDP, the continuous temporal dimension capturing the time left is discretized into time intervals. This generates a tradeoff, where a finer grain discretization generates a larger state space for the associated CMDP, and this translates to increased computation time. Moreover, the discretization naturally leads to an approximation of the underlying transition probabilities in the state space.

In an effort to overcome these limitations of former solutions, in this paper we present a completely different approach to solve the stochastic orienteering problem with chance constraints. The main idea is to repeatedly search the space of possible paths using a Monte Carlo Tree Search (MCTS) approach in an online fashion. Following a typical rolling horizon approach, after an initial path has been identified, only the first segment is executed. Then, based on the *actual* time spent to execute the first motion, the remaining budget is updated, and the method run again. Additionally, to account for

the chance constraint, we introduce a novel *backup* procedure based on Monte-Carlo sampling that eliminates from the search tree the paths that would violate the budget constraint. Accordingly, the search in the tree is informed by a novel criterion we dub UCTF (Upper-bound Confidence for Trees with Failures) that extends the widely used UCT formulation. The original contributions of this paper are the following:

- we formulate the stochastic orienteering problem with chance constraints as an MCTS planning problem;
- we introduce novel tree policies and backup policies to incorporate and manage the probability of violating the given constraint;
- we demonstrate that this approach is competitive with optimal, time-consuming solutions based on mixed integer linear programming.

The rest of the paper is organized as follows. Section II discusses selected related work, while detailed background on stochastic orienteering and MCTS algorithms is provided in section III. Our new algorithm is introduced in section IV and theoretically analyzed in section V. Experimental evaluations are then given in section VI and we then draw conclusions and discuss future work in section VII.

II. RELATED WORK

The deterministic orienteering problem was first formalized in [9] where it was also shown to be *NP*-hard. Consequently, most solutions to the problem rely on heuristic approaches [10,11]. Exact solutions for limited size instances can be found using integer programming formulations [12], while approximate solutions have been proposed but have seen limited use [13]. Stochastic variants of the problem can encompass stochastic costs for the edges or stochastic rewards for the vertices. As the deterministic orienteering problem is a special case of stochastic orienteering, it follows that stochastic orienteering is *NP*-hard, too. In [5] the authors propose an exact solution for a special class of graphs, and various heuristics for general graphs, but do not consider chance constraints, i.e., bounds on the probability of exceeding the budget. The works presented in [14] and [15] tackle a problem similar to ours, inasmuch as they consider a risk-sensitive formulation for the stochastic orienteering problem. In [14] the authors propose an algorithm to solve it based on local search, while in [15] the authors propose a mixed integer program based on sample average approximation. These solutions are fundamentally different from the one we propose because they are formulated offline a priori, and not updated as the mission unfolds based on the travel costs experienced during the mission. This may lead to excessively conservative solutions that collect less reward on average (think for example to the case when one follows a predetermined path where traversal times are much lower than expected.) Our previous works [6–8] are the first ones to propose the concept of a *path policy* while solving the stochastic orienteering problem with chance constraints. While the computation is still offline, rather than computing a single path, these methods produce a set of rules that can be queried at runtime to determine which vertex to visit next based on the remaining budget. Therefore these solutions will return

different paths depending on the specific realization of the stochastic processes governing travel times along the edges.

Monte Carlo Tree Search (MCTS) encompasses a family of any-time methods to solve planning problems using generative models. Albeit a mature technique [16–18], MCTS gained significant popularity while being recently used in combination with reinforcement learning, most notably in [19]. The use of MCTS algorithms for problems with chance constraints has been so far limited. In [20] the authors propose an algorithm for chance constrained Markov Decision Processes that is guaranteed to return a policy satisfying the chance constraint. However, the algorithm described in [20] assumes a discrete state space, because all explored state histories must be explicitly stored in a search tree to avoid repeated evaluations of already considered histories. This is evident in the case studies presented in [20] to illustrate its performance. The algorithm and application we present in this paper, instead, can handle continuous components in the state space. In particular, in the stochastic orienteering problem the state includes the residual budget, which is a continuous variable.

III. BACKGROUND

In this section, we first summarize the general definition of chance constrained optimization, and then show how to cast the stochastic orienteering problem with chance constraints (SOPCC in the following) as an instance of this class of problems. We also present some ideas and results related to the Sample Average Approximation approach (SAA) that are used in our solution, as well as in the alternative method we compare our solution with. In the first part we mostly follow the notation and formulation introduced in [21].

A. Chance Constrained Problems

A chance constrained problem is an optimization problem formulated as

$$\begin{aligned} \min_{x \in X} f(x) \\ \text{s.t. } \Pr[L(x, \xi) \leq 0] \geq 1 - \alpha \end{aligned} \quad (1)$$

where: X is the space of possible solutions; $f : X \rightarrow \mathbb{R}$ is a real valued objective function; ξ is a random vector with known probability density function and support $\Xi \subset \mathbb{R}^m$; $\alpha \in (0, 1)$ is an assigned confidence level; $L : X \times \Xi \rightarrow \mathbb{R}$. In general L could be a vector function, but we here consider the case where it is scalar as it is more directly connected to the problem we present later. The constraint involving L is the so-called *chance constraint* because it imposes an upper bound on the probability of violating the inequality $L(x, \xi) \leq 0$. Chance constrained problems are extensively used in portfolio optimization [22], but have also been used to model and solve robotics problems [20, 23, 24]. It is well known that these problems are in general difficult to solve [21, 25] and therefore approximate solutions have been proposed. One such method is the SAA approach where one uses N independently identically distributed samples of ξ to approximate the chance constraint. More precisely, problem (1) can be equivalently rewritten as

$$\min_{x \in X} f(x) \quad \text{s.t. } p(x) \leq \alpha$$

where we define the function $p(x)$ as $p(x) = \Pr[L(x, \xi) > 0]$, and we now evidence that α bounds the probability of violating the constraint $L(x, \xi) \leq 0$ introduced in (1). Then, after having drawn N independent samples $\xi_1 \dots \xi_N$ for the random vector ξ , one can approximate $p(x)$ with the function

$$\hat{p}_N(x) = \frac{1}{N} \sum_{i=1}^N \mathbb{I}(L(x, \xi_i)) \quad (2)$$

where $\mathbb{I}(\cdot)$ is the indicator function that is equal to 1 if its argument is positive and 0 otherwise. As shown in [21],

$$\lim_{N \rightarrow \infty} \hat{p}_N(x) = p(x).$$

B. Stochastic Orienteering with Chance Constraints

The deterministic orienteering problem is defined as follows. Let $G = (V, E)$ be a directed graph with n vertices, $r : V \rightarrow \mathbb{R}^+$ be a positive reward function defined over the set of vertices and $c : E \rightarrow \mathbb{R}^+$ be a positive cost function defined over the edges. Let $v_s \in V$ and $v_g \in V$ be assigned start and goal vertices, respectively. In the following, without loss of generality, we assume G is a complete graph. When this is not the case one can simply add all missing edges and set their costs equal to the sum of the costs along the shortest path. For a path $\mathcal{P}$ over G connecting v_s to v_g , the reward of the path $R(\mathcal{P})$ is defined as the sum of rewards of the vertices along the path, with the stipulation that if a vertex is visited more than once, then its reward is collected just once. The cost of the path $C(\mathcal{P})$ is instead the sum of the costs of the edges along $\mathcal{P}$, but in this case, if an edge appears multiple times, its corresponding cost is charged every time. However, since we assumed that V is a complete graph, it is therefore evident that an optimal solution will never have to visit the same vertex twice or traverse the same edge twice. For a given budget $B > 0$, the orienteering problem asks to solve the following constrained optimization problem

$$\mathcal{P}^* = \arg \max_{\mathcal{P} \in \Pi} R(\mathcal{P}) \quad \text{s.t. } C(\mathcal{P}) \leq B$$

where Π is the set of all possible paths connecting v_s with v_g . In this problem the space of (feasible or infeasible) solutions Π is a discrete set consisting of $(n - 2)!$ paths from v_s to v_g . In the stochastic version of the problem, the cost of each edge (v_i, v_j) is not a constant, but rather a continuous random variable $\xi_{i,j}$ with a known probability density function (pdf) with positive support and finite expectation. The availability of these density functions is essential in our method, because we will use an approach similar to SAA to estimate the probability that a candidate solution violates the budget constraint. This assumption is also consistent with MCTS literature where a generative model is assumed to be fully known to implement the rollout step described later on. Note that for the viability of the method we propose, it is not necessary for these edge pdfs to be independent. All that is needed is being able to draw independent identically distributed samples from these pdfs, as per the SAA method described by Eq. (2). This assumption also matches the process described above to turn an incomplete graph into a complete graph by adding missing edges. Edges added to the graph have a random cost equal to the sum of

the random costs of the edges of shortest the path associated with the edge being added. The pdfs of these random costs will be in general not independent, but as just pointed out this dependency does not invalidate the applicability of the method we propose.¹ In the following, for the stochastic version of the problem $c(v_i, v_j)$ is the expectation of the random variable $\xi_{i,j}$ associated with the edge (v_i, v_j) . In this case, for a given path $\mathcal{P} \in \Pi$ the corresponding path cost $C(\mathcal{P})$ is therefore a random variable given by the sum of the random variables associated with the edges appearing along the path that will be written as $C(\mathcal{P}, \xi)$, following the notation introduced in the previous subsection. Given a fixed failure probability P_f , the SOPCC asks to solve the following constrained optimization problem:

$$\begin{aligned} & \max_{\mathcal{P} \in \Pi} R(\mathcal{P}) \\ & \text{s.t. } \Pr[C(\mathcal{P}, \xi) > B] \leq P_f \end{aligned} \quad (3)$$

i.e., we now constrain the probability that the cost of the path exceeds the budget B . Problem (3) is evidently an instance of the equivalent formulation of problem (1) discussed above.² *Remark:* in the definition of the stochastic orienteering problem with chance constraints P_f is a parameter that must be set according to the risk aversion of the end user, i.e., it represents the accepted probability of violating the assigned budget constraint. In the orienteering scenarios considered in the introduction, this is the probability that the robot runs out of energy before being able to reach the goal vertex v_g where batteries can be recharged or swapped. Risk averse users will prefer low values for P_f , while risk tolerant users may be willing to consider higher values, in return for larger rewards. The P_f value will in turn influence Π , i.e., the set of possible solution paths, with smaller values corresponding to smaller sets. In section VI we will solve the same problem instances for different values of P_f and this will illustrate how rewards and computational time vary. In general, it shall be noted that the assumption that the pdfs for the edge costs have finite expectations does not allow to set $P_f = 0$. This is for example the case when edge costs are distributed according to exponential distributions, as we do in section VI. In this instance, one cannot assume an upper bound on the edge travel cost, and therefore setting $P_f = 0$ will yield an empty solution set Π making the problem unfeasible. These aspects will be further expanded in section VI.

In practical instances, one is of course not only interested in the value of the objective function $R(\mathcal{P})$ but also in the optimal path $\mathcal{P}$. When solving this problem, one can compute the solution offline, i.e., before its execution starts, or online, i.e., it may update the path based on the available residual budget. In [6–8] we proposed an online algorithm where we computed a *path-policy* that guides the robot through the vertices while being aware of the remaining budget. In these works the policy is computed off-line but it includes

a family of paths, and the selection of the path to follow is performed online based on the realizations of the random variables associated with the already traversed edges. The method presented in [15] is instead a fully offline solution where the path $\mathcal{P}$ is computed beforehand and then executed irrespective of the realizations of the stochastic travel costs. Alternatively, one can opt for a fully online approach, where the path is continuously refined based on the time spent by the agent while traversing the edges. This can be implemented with the MCTS approach discussed next.

C. Monte Carlo Tree Search

MCTS is an approach to solving decision making problems in an online fashion, where planning and execution alternate. It belongs to the family of receding-horizon (also called rollout) methods [26], whereby one solves the planning problem using a finite time-horizon, but then executes just the first action in the plan, and then re-plans from scratch based on the outcome of the first action. In MCTS planning, the algorithm builds a rooted tree whose root node represents the current state, and whose edges connect states that can be reached through the execution of a single action. Key elements in MCTS algorithms are the following:

- 1) a selection process to move from the root of the tree down to a leaf following a so-called *tree policy*;
- 2) an *expansion* step executed to add leaf nodes to the tree;
- 3) a *rollout policy* to be executed from a leaf to estimate how “good” a leaf is;
- 4) a *backup policy* to be executed from the leaves back to the root to guide the eventual selection of the best action from the root.

After the tree is built, an action is selected among those available in the root node. The action is executed, and the tree is discarded and rebuilt having as root the vertex reached executing the selected action. The reader is referred to [27] (chapter 8 and references therein) for more details. As pointed out in [28], different tree policies (step 1) and backup policies (step 4) may have a dramatic impact on the performance of MCTS based planning. In particular, while UCT (Universal Confidence bound for Trees) [16] is often considered the standard tree policy, it is not directly applicable to our problem because actions yielding high values (adding a high reward for the path in the orienteering problem) may also increase the probability of violating the chance constraint $\Pr[C(\mathcal{P}, \xi) > B] \leq P_f$ if they have high edge costs. For this reason, we propose an alternative tree policy based on UCT, but factoring in also failure probabilities (we call this tree policy UCTF – UCT with Failures). Similarly, backup strategies based on plain Monte Carlo averaging are not applicable because they do not consider whether constraints are violated or not. Inspired by the complex backup strategies studied in [28], in this work we instead propose a backup policy that explicitly considers failure constraints.

¹For completeness, one should add that the *shortest path* in this case is determined considering the expectations of the edges’ random costs, which we assumed to be finite.

²While (1) is formulated as a minimization problem, (3) is formulated as a maximization problem for consistency with the orienteering literature, but the two solutions are obviously equivalent.

IV. AN ONLINE MCTS ALGORITHM FOR STOCHASTIC ORIENTEERING WITH CHANCE CONSTRAINTS

A. Using trees to represent orienteering solutions

The MCTS approach sketched in the previous section can be used to model and solve an instance of the SOPCC problem as follows. To each vertex $v \in V$ we associate a set of actions, i.e., the set of vertices that can be directly reached from v . Hence, each action corresponds to an edge in G . The tree $\mathcal{T}$ is rooted at the vertex where the robot is currently positioned, and is parametrized by the available budget B . Therefore, all quantities stored in $\mathcal{T}$ are relative to the available budget B . As the robot moves from location to location, the available budget B is decreased to account for the already incurred travel costs. There is a one-to-one correspondence between nodes in the tree $\mathcal{T}$ and vertices in the graph. Each node in the tree may have from 0 to $n - 1$ children. Vertex v_j can be a child of v_i in the tree only if there is an edge connecting v_i with v_j , i.e., if there is an action from v_i that leads to v_j . Throughout the remainder of this section, when considering a tree $\mathcal{T}$ we ignore nodes associated with vertices in G that have already been visited by the robot, because they cannot be part of an optimal solution as there is never value in revisiting an already visited vertex. Figure 2 shows a tree associated with a simple graph with five vertices.

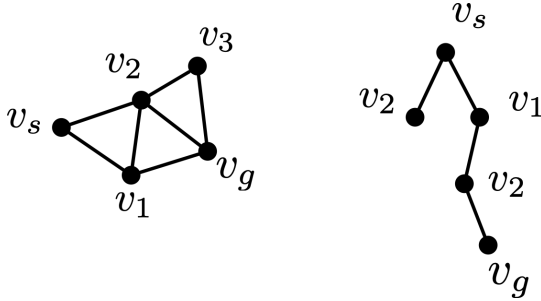


Fig. 2: The right side of the figure shows a possible MCTS tree $\mathcal{T}$ associated with the simple graph on the left and rooted in v_s (start vertex). Vertices v_1 and v_2 are children of v_s because they are directly connected to it. Executing action v_1 from v_s means moving from v_s to v_1 . Vertex v_3 , not appearing in the tree, cannot be a child of v_s because it is not directly connected to it. Vertex v_2 appears as a child of both v_s and v_1 because it is connected to both, but it occurs along two different paths starting from the root node v_s . All paths in $\mathcal{T}$ from v_s to a leaf encode possible paths in G . In this simple example there are two paths, namely v_s, v_2 , and v_s, v_1, v_2, v_g . Note that while the MCTS is being built not all paths must end at the goal vertex v_g .

For a given path from the root to a leaf, one can simulate the time it takes to traverse it by adding random samples drawn from the known pdfs associated with the edges along the path. For every internal tree node v_i we store three attributes for each of its children v_j :

- $N[v_j]$ is the number of times that action v_j was attempted from v_i ;
- $Q[v_j]$ is the expected reward associated with the *feasible* path of maximum reward that selects v_j from v_i , if it exists. Feasible, in this context, means that the estimated failure probability does not exceed the assigned bound P_f (see also Definition 1 below.) If all paths connecting v_i to v_j violate the failure probability P_f , then $Q[v_j]$ is set

to the expected reward associated with the paths starting from v_i and going through v_j .

- $F[v_j]$ is the estimated failure probability of the path defining the value $Q[v_j]$ just defined. Therefore, when the path is feasible $F[v_j] \leq P_f$.

The first two attributed N and Q are borrowed from the classic MCTS definition, while F is specifically introduced to solve the problem we study in this paper. These three quantities are incrementally updated as the tree is being built and expanded, and the specifics will be given when discussing the backup policy. With reference to the tree depicted in Figure 2, the root node v_s , stores the quantities $Q[v_1], Q[v_2], F[v_1], F[v_2], N[v_1]$ and $N[v_2]$ because v_1 and v_2 are connected to v_s . Similarly v_1 stores its own $Q[v_2], F[v_2]$ and $N[v_2]$ because v_2 is a child of v_1 , but these values are different than those stored in v_s because they are associated with a different path from v_s to v_2 .

Definition 1. Let v_i and v_j be two nodes in the tree $\mathcal{T}$ and let v_j be a child node of v_i . We say that v_j is *feasible* for v_i if $F[v_j] \leq P_f$.

In the above definition, $F[v_j]$ is the value stored in v_i , i.e., v_j is feasible for v_i if the estimated probability of failure for a solution path $\mathcal{P}$ going through v_i and then v_j does not exceed the assigned value P_f .

B. Online algorithm alternating planning and execution

The online algorithm we propose alternates planning and execution (see Algorithm 1). Throughout its planning phase, the search tree expansion is conditioned on the residual budget B which is updated after each action is selected and executed. At the first iteration, the algorithm solves the SOPCC with the assigned budget B and root node v set to v_s (line 1.) The solution of SOPCC defines the first action to take, i.e., the robot moves from v_s to the vertex $next_v$ returned by algorithm MCTS-SOPCC (line 3) and incurs a random travel cost ξ_v (line 4.) The budget is then updated by setting B to $B - \xi_v$ (line 5) and the SOPCC is solved again with the updated budget B and starting at vertex v (now set to $next_v$ in line 6.) The process repeats until either the final vertex v_g is reached, or the budget is completely spent. In this last case, the run is considered a failure (line 10).

Algorithm 1: Alternating Planning and Execution

Data: Graph $G = (V, E)$, vertices $v_s, v_g \in V$, budget B

```

1  $v \leftarrow v_s$ 
2 while  $B > 0$  and  $v \neq v_g$  do
3    $next_v \leftarrow \text{MCTS-SOPCC}(v, B)$ 
4   move to vertex  $next_v$  and let  $\xi_v$  be the incurred cost
5    $B \leftarrow B - \xi_v$ 
6    $v \leftarrow next_v$ 
7 if  $B > 0$  then
8   | return Success
9 else
10 | return Failure
```

The first advantage of this solution is that differently from our former works [6–8] it is neither necessary to discretize the

temporal dimension to build a CMDP with a finite state space, nor it is necessary to numerically approximate the transition probabilities between states.

C. MCTS-SOPCC

The MCTS-SOPCC algorithm to solve the SOPCC (line 3 in algorithm 1) customizes the general MCTS approach described in section III as follows.

Tree Policy: The tree policy is used to traverse the tree from the root to a leaf and then select a new node to possibly add to the tree. It is implemented by applying recursively the following strategy inspired by UCT. Assuming v_i is the current vertex, to each of its neighbors³ v_j we associate the following quantity (UCTF stands for UCT with Failure):

$$UCTF(v_j) = Q[v_j](1 - F[v_j]) + z\sqrt{\frac{\log t}{N[v_j]}} \quad (4)$$

where t is the sum of the number of times that the descendants of v_i have been explored already, and z is a constant. The node with the highest UCTF value is then selected and this process is repeated until a vertex not yet in the tree is selected. As commonly done in the basic UCT strategy, if node v_j has not yet been visited its $N[v_j]$ counter is 0 and we then set its UCTF value to ∞ , to make sure all neighbors are visited at least once. The novel term $Q[v_j](1 - F[v_j])$ is the *expected utility* of moving to v_j , obtained by multiplying the estimated utility $Q[v_j]$ by the probability of success $(1 - F[v_j])$. Note that as failure is a binary random variable, this is the expected utility. In this way, given two vertices with similar Q values, the criterion favors the one with the lowest failure probability. The last term in the UCTF formula is borrowed from UCT and encourages the selection of nodes that have been formerly selected fewer times.

Rollout Policy: when a new vertex v_j is added as a child of a node v_i already in the tree (see Figure 3), it is necessary to estimate both: 1) how much reward one will collect by expanding the path through v_j ; 2) the probability of exceeding the available budget before reaching the end vertex v_g .

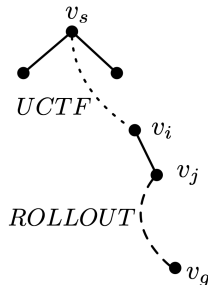


Fig. 3: Assuming the tree is rooted in v_s , the tree policy UCTF repeatedly selects internal vertices in the tree $\mathcal{T}$ until a vertex leaf v_i is reached, and then a child node v_j is added to the tree. Then the rollout algorithm is run from v_j to estimate the values $Q[v_j]$ and $F[v_j]$ to be stored in v_i and then propagated back to the root.

³From the set of neighbors we exclude the set of vertices already visited because revisiting an already visited vertex does not give any reward and is therefore useless. In this context, the terms neighbor and descendant are to be considered synonyms.

These values will be stored in v_i as $Q[v_j]$ and $F[v_j]$, respectively, and are computed by the rollout policy by generating S paths from v_j . Each path is generated using the process sketched in Algorithm 2.

Algorithm 2: Rollout

Data: leaf vertex $v_j \in V$, residual budget B'

```

1 current  $\leftarrow v_j$ 
2 path  $\leftarrow \{v_j\}$ 
3 while true do
4   if random()  $< P_R$  then
5     new  $\leftarrow \text{randomchild}(\text{current})$ 
6   else
7     new  $\leftarrow \text{greedy}(\text{current})$ 
8   if new  $\neq v_g$  then
9     if  $\Pr[C(\text{current}, \text{new}, v_g) < B'] \leq P_f$  then
10      append new to path
11       $B' \leftarrow B' - \text{samplecost}(\text{current}, \text{new})$ 
12      current  $\leftarrow \text{new}$ 
13   else
14     append new to path
15   return path

```

To determine the residual budget B' (input parameter in algorithm 2), we sample the time $t = \xi_1 + \xi_2 + \dots + \xi_k$ it takes to proceed from the root node v_s to the leaf node v_j along the unique path with k edges determined by the tree policy. We then set $B' = B - t$ as the residual budget available when starting from v_j , where B is the budget available at the root node v_s (this value is computed before Algorithm 2 is executed – see algorithm 4). The rollout procedure builds a path from v_j to v_g by iteratively trying to add vertices either randomly (line 5), or greedily (line 7). Random children are added with probability P_R while the greedy strategy is chosen with probability $1 - P_R$. Suitable P_R values are instance dependent and can be identified with a preliminary grid search. This aspect is further discussed in Section VI. The greedy strategy works as follows. For all vertices v_k not yet visited, compute $r(v_k)/c(\text{current}, v_k)$ where *current* is the last vertex added to the path being built. Then, discard the vertices such that $\Pr[c(\text{current}, v_k) + c(v_k, v_g) > B'] > P_f$, and pick the one with the highest ratio. If all vertices are discarded, the greedy step returns v_g . To determine the vertices to discard, we generate M samples for the costs of the edges and use these values to estimate the probability of exceeding the budget B' . This is an instance of the SAA approach described in Section III. The greedy step adds to the path the vertex v_k with the highest ratio between reward and cost, but constrained on having estimated that the probability of moving from v_k to the terminal v_g does not exceed the failure probability P_f . Note that the greedy step may select v_g as the most suitable node to visit next. If the newly selected vertex *new* is the goal vertex v_g , we add it to the path and terminate the rollout returning the path (lines 14 and 15). Otherwise (lines 9 through 12), we consider the path with edges $(\text{current}, \text{new})$ and (new, v_g) and we evaluate if the probability that the cost of this path exceeds B' violates the constraint P_f or not. If it violates the constraint, we reject *new*, otherwise, we add it to the path and update B' . To determine the probability of violating the constraint, we generate M samples, as in the greedy step. It

is easy to see that the rollout step is guaranteed to terminate returning a path.

Backup Policy: After the S paths from v_j have been generated by the rollout procedure, we can compute the expected return $Q[v_j]$ and estimate $F[v_j]$, i.e., the probability of failure of expanding the route from v_i through v_j . The values are computed by averaging the rewards and failures⁴ associated with the S paths returned, as per the SAA approach. These values must then be propagated upwards through the tree towards the root, as the paths generated from v_j are subpaths of paths starting from the root and therefore influence the values for the Q and F labels associated with the children of the root node. In MCTS without constraints, this is often done by averaging the returns, but the case considered in this work is different because of the need to eventually select actions leading to paths whose probability of violating the budget constraint does not exceed P_f . The backup step is then applied from node v_j backwards towards the root considering the relationship between the Q and F labels of the newly added node v_j , and the Q and F labels of its parent node v_i . The step also involves the parent of v_i , if it exists (called v_k in the following). We refer to figure 4 while explaining the process, and algorithm 3 sketches the procedure (for the sake of brevity the algorithm just shows the updates Q and F , as updates for N are just increases by one.) After the values are propagated from v_j to v_i , the process is recursively repeated backward starting from v_i , then from v_k , and so on until the root node is reached.

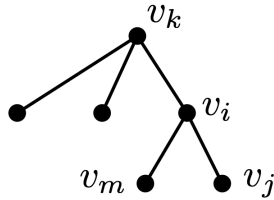


Fig. 4: When backing up the values $F[v_j]$ and $Q[v_j]$ stored at node v_i , it is necessary to consider their relationships with the values $F[v_i]$ and $Q[v_i]$ stored with v_k .

The backup step at node v_i is as follows (refer to algorithm 3). If v_i is the root, then v_k does not exist, and the backup step does not perform any operation because the values $F[v_j]$ and $Q[v_j]$ are already stored with v_i (the loop in line 3 is never executed.) If v_k exists, it has its labels $F[v_i]$, $Q[v_i]$ initialized already, and it may be necessary to propagate the F and Q values upwards if a better path from root to leaf has been found. We distinguish the following cases:

- if $F[v_i] < P_f$ (this value is stored in v_k – test at line 4) it means v_i is feasible for v_k . The new F and Q values determined for v_j should be propagated up only if the new path extending from v_i through v_j is both 1) feasible; 2) provides a better return. The first condition is checked in line 5, while the second condition is checked in line 6. To this end, we compare the value $Q[v_i]$ stored in v_k with the expected value of the new path found, which is $r(v_i)$

(reward obtained visiting v_j) plus $Q[v_j]$ (reward obtained from v_i onwards).

- if $F[v_i] > P_f$ it means that the best path from v_k through v_i violates the chance constraint. In this case, if $F[v_i] > F[v_j]$ then a better path from v_k through v_i has been determined, irrespective of the Q values, because it lowers the failure probability (possibly bringing it below P_f .) In this case, the values of the new path from v_k to v_i and then to v_j are propagated to v_k (lines 10 and 11.)

After the values are propagated from v_i to its parent v_k , the same mechanism is recursively applied one level up (lines 12 and 13).

Algorithm 3: Backup

Data: $v_j, Q[v_j], F[v_j]$

```

1  $v_i \leftarrow v_j.parent$ 
2  $v_k \leftarrow v_i.parent$ 
3 while  $v_k$  is not null do
4   if  $v_k.F[v_i] < P_f$  then
5     if  $v_i.F[v_j] < P_f$  then
6       if  $v_k.Q[v_i] < v_i.Q[v_j] + r(v_i)$  then
7          $v_k.Q[v_i] \leftarrow v_i.Q[v_j] + r(v_i)$ 
8          $v_k.F[v_i] \leftarrow v_i.F[v_j]$ 
9     else if  $v_k.F[v_i] > v_i.F[v_j]$  then
10       $v_k.F[v_i] \leftarrow v_i.F[v_j]$ 
11       $v_k.Q[v_i] \leftarrow v_i.Q[v_j] + r(v_i)$ 
12    $v_k \leftarrow v_k.parent$ 
13    $v_i \leftarrow v_i.parent$ 

```

Action Selection: After the tree $\mathcal{T}$ has been built, the best action available from the root node v is selected. The best action is defined as the feasible node v_j with the highest value $Q[v_j]$ (recall definition 1). If among the children of the root node no feasible node is found (i.e., all nodes connected to the root have an F value exceeding the failure probability P_f), then action selection returns v_g , i.e., it tries to move the robot to the final vertex v_g in the orienteering graph V .

Algorithm 4 shows how the components described above are put together. As in MCTS algorithms, the tree is expanded through a fixed number of iterations K . At each iteration, the UCTF criterion is used as a tree policy to move from the root of the tree to a node v_j (line 3) that is added to the tree if it is not already present. Then, S paths are generated from v_j (line 4) using the rollout process formerly described (line 7). At each rollout step, the algorithm considers a different residual budget B' obtained by sampling the time t to move from the root of the tree to the new node v_j (line 5). After the S samples are collected, the values $Q[v_j]$ and $F[v_j]$ for v_j can be computed (line 8) and propagated back to the root with the backup procedure (line 13). As the last step, the actions counter N is also propagated back to the root (line 14.) Finally, the algorithm returns the action from the root with the highest Q value among the feasible ones (line 15). If no feasible action is found, *ActionSelection* returns the goal vertex v_g . Alternatively, when no action is found, one could further extend the tree by running SOPCC again and extending the current tree rather than restarting from scratch, though this is not done in the experiments we consider in this paper.

⁴To estimate $F[v_j]$ we take the ratio between the number of paths with cost exceeding the budget and the total number of paths S .

Algorithm 4: MCTS-SOPCC

Data: start vertex v , budget B

```

1 Initialize tree  $\mathcal{T}$  with root equal to  $v$ 
2 for  $K$  iterations do
3    $v_j \leftarrow UCTF(v)$ 
4   for  $S$  iterations do
5      $t \leftarrow \text{SampleTraverseTime}(v, v_j)$ 
6      $B' \leftarrow B - t$ 
7      $path \leftarrow \text{rollout}(v_j, B')$ 
8     compute  $Q[v_j]$  and  $F[v_j]$  based on the  $S$  rollouts
9   if  $v_j$  is not a child node of  $v$  then
10    add  $v_j$  as child node of  $v$  with  $Q[v_j]$  and  $F[v_j]$ 
11  else
12    update estimates of  $Q[v_j]$  and  $F[v_j]$  stored in  $v$ 
13  Backup( $v_j, Q[v_j], F[v_j]$ )
14  BackupN( $v_j$ )
15 return ActionSelection( $\text{root}(\mathcal{T})$ )

```

V. THEORETICAL PROPERTIES

In this section we provide some theoretical properties of the algorithm we proposed. We start asserting the asymptotic probabilistic convergence of the method we defined, and then analyze the error probability as a function of the finite number of iterations K .

A. Asymptotic Convergence

The following theorem characterizes the asymptotic behavior of the MCTS-SOPCC algorithm, i.e., its performance for large values of the number of independent rollouts S . The results build upon the fact that all iterations of the loop at line 4 in algorithm 4 are independent, and therefore the Q and F values computed in line 8 are independent random variables.

Theorem 1. *For $\lim_{S \rightarrow \infty}$, if the MCTS-SOPCC algorithm returns a feasible node v_j , then with probability $1 - F[v_j]$ there is a solution to the SOPCC with expected value $Q[v_j]$.*

Proof. First, observe that by the weak law of large numbers as the number of independent rollouts S increases, the computed values for F and Q converge in probability to their expected values. More specifically, since F is the indicator variable for the event “exceeding the budget B ,” its expectation is then equal to the probability of the associated event.

By construction, the node v_j returned by MCTS-SOPCC is always an immediate descendant of the node v stored at the root of the tree $\mathcal{T}$. To prove the claim we separately consider the cases where v_j is a leaf node or not. The theorem applies only to the case where the algorithm returns a feasible node v_j . If the root has no feasible child, then the algorithm returns v_g , as discussed when describing how action selection is implemented.

If the feasible node v_j is a leaf node in the tree, the values $Q[v_j]$ and $F[v_j]$ were stored when v_j was added to the tree and were never modified because v_j has no descendants. These values, by construction, were obtained with S independent rollouts from v_j (loop at line 5, and line 8 in algorithm 4), and therefore the claim directly holds by the law of large numbers, as stated above.

If v_j has one or more descendants, we need to distinguish two cases. If the Q and F values were never modified after v_j was added, then we are in the same case as above and the statement therefore holds. If the Q and F values were modified (one or more times), then that happened during a call to the *Backup* function. In *Backup*, the Q and F are modified only to either 1) increase the Q value while ensuring that v_j remains feasible (lines 7 and 8 in algorithm 3), or 2) decrease the F value while v_j is infeasible (lines 10 and 11 in algorithm 3). However, since the node is feasible, the last update must have been an update of the first type and the stored F value converges to its mean as S increases. $\square$

True to the MCTS spirit, the presented algorithm is an anytime algorithm, i.e., by increasing the value of the parameters K and S the quality of the returned solution increases. This is in contrast to our former works where a solution is produced only after the whole state space for the CMPD has been constructed and the associated linear program solved. In section VI we will assess how K influences the quality of the solution and the computation time. The other relevant parameter is S , the number of samples used to estimate the failure probability of a path from the root to a leaf. Obviously, the larger the number of samples, the more accurate the estimate and the associated computation time. As common for these types of algorithms, the probability of not finding the solution (if it exists) tends to 0 as the values of K and S increase. The convergence velocity is influenced by the size of the search space, i.e., by the average branching factor in the tree.

B. Error Rates

While theorem 1 provides a guarantee regarding the asymptotic behavior of the algorithm, it is interesting to reason about the performance and error rates for finite values of K , i.e., the number of iterations. In particular, we are interested in the probability that the final step in algorithm 4 selects the wrong action, i.e., it picks a suboptimal vertex. To this end, it is useful to draw a comparison with bandit algorithms and the concept of regret. In bandit algorithms, one is interested in balancing exploration and exploitation while bounding the cumulative regret. However, in the problem we consider there is no cost for exploration (done thorough simulation), and the only cost to consider is the so called *simple regret*, i.e., the cost incurred by making the wrong choice based on the data available. Hence, the problem we consider is related to a special class of bandit problems known as *pure exploration* problems (see [29], chapter 33, as well as our recent paper [30] for more details.) Without loss of generality, assume that after $\mathcal{T}$ has been built the optimal choice is v_1 , and the values $F[v_1]$ and $Q[v_1]$ are stored in the root node. The function ActionSelection($\text{root}(\mathcal{T})$) will return the wrong action in two mutually exclusive cases:

- when $F[v_1] > P_f$, i.e., when the estimate of the failure probability of action v_1 exceeds the assigned failure probability. Note that since v_1 is the optimal choice, it must be feasible, and therefore its failure probability must

be smaller than P_f . Hence this condition corresponds to an overestimation of such failure probability.

- when $F[v_1] \leq P_f$ but there is another suboptimal feasible vertex, say v_2 , such that $Q[v_2] > Q[v_1]$.

We now separately study both these conditions. We start observing that *failure*, i.e., overrunning the budget, is a binary condition, and is therefore modeled by a Bernoulli random variable with parameter p . The return associated with an action is instead a non-negative random variable estimated by $Q[v_i]$.

The following theorem characterizes the probability of wrongfully estimating that the optimal action v_1 is infeasible, i.e., it provides a bound on $\Pr[F[v_1] > P_f]$ as a function of the number of times $N[v_1]$ that action v_1 has been tried (the first condition defined above). Let us define $f(v_1)$ as the parameter p describing the Bernoulli variable modeling the binary event *failure after selecting* v_1 . Therefore $F[v_i]$ is a random variable estimating $f(v_i)$. Let $\Delta = P_f - f(v_1)$ and since v_i is feasible, it follows that $\Delta > 0$. Intuitively, $\Pr[F[v_1] > P_f]$ should shrink as $N[v_1]$ grows because more samples lead to a more accurate estimate, and it should grow when Δ decreases because when $f(v_1)$ approaches P_f even small estimation errors may lead to wrongly decide v_1 as unfeasible. The following theorem formalizes these intuitions.

Theorem 2. *Let $F[v_1]$ be the estimate of $f(v_1)$ after the tree $\mathcal{T}$ has been built with K iterations with $N[v_1]$ attempts for action v_1 ; let $\Delta = P_f - f(v_1)$. Then*

$$\Pr[F[v_1] > P_f] \leq \sqrt{\frac{f(v_1)(1-f(v_1))}{2\pi N[v_1]\Delta^2}} e^{\left(-\frac{N[v_1]\Delta^2}{2f(v_1)(1-f(v_1))}\right)}$$

Proof. We start recalling the Cramér-Chernoff method (see e.g., [29], chapter 5). Let X be a random variable with $\mu = \mathbb{E}[X]$ and finite variance σ^2 . If $\hat{\mu} = \frac{1}{n} \sum_{i=1}^n X_i$ where the X_i s are a sequence of independent identically distributed samples of X , then for $\varepsilon > 0$

$$\Pr[\hat{\mu} \geq \mu + \varepsilon] \leq \sqrt{\frac{\sigma^2}{2\pi n \varepsilon^2}} e^{\left(-\frac{n\varepsilon^2}{2\sigma^2}\right)} \quad (5)$$

Next, observe that $F[v_1]$ is the estimate of $f(v_1)$ obtained through $N[v_1]$ independent simulations. Moreover, the Bernoulli variable modeling the *failure* event has variance $f(v_1)(1-f(v_1))$. Note furthermore that because of how we defined Δ the event $F[v_1] > P_f$ is equivalent to the event $F[v_1] > f(v_1) + \Delta$. Substituting these values in Eq. (5), the claim follows. $\square$

We finally turn to the second source of error, i.e., the case where the algorithm correctly estimates that the optimal action v_1 is feasible but selects a different feasible action v_2 because it estimates that it has a higher return. We start observing that while the failure probability is modeled by a Bernoulli random variable, returns are random variables with positive support that in general do not have a known distribution. Consequently, in the analysis the set of tools we can use is much more limited. Chebychev's inequality, stated below, is applicable for any random variable X , and for any $\varepsilon > 0$ states

$$\Pr[|X - \mathbb{E}[X]| \geq \varepsilon] \leq \frac{\mathbb{V}[X]}{\varepsilon^2}$$

where $\mathbb{E}[x]$ is the expectation of X and $\mathbb{V}[X]$ is its variance. Mirroring the notation introduced above, let $Q[v_1]$ and $Q[v_2]$ be the random variables estimating the expected return when selecting v_1 and v_2 , respectively. Moreover, $q(v_1)$ and $q(v_2)$ are the expected returns when selecting v_1 and v_2 .

Theorem 3. *Let v_1 be the optimal feasible action and let v_2 be a suboptimal feasible action. Then, the probability P_{ERR} that v_2 is selected instead of v_1 is bounded by*

$$P_{ERR} \leq \frac{\sigma_z^2}{\min\{N[v_1], N[v_2]\}G}$$

where: σ_z^2 is the variance of the random variable $z = q(v_2) - q(v_1)$ and $G = q(v_1) - q(v_2)$.

Proof. First observe that $Q[v_1]$ is an estimate of q_1 obtained by averaging $N[v_1]$ independent samples, and that $q(v_1)$ is its expectation. The same relationships hold between $Q[v_2]$ and $q(v_2)$. Next, since we assumed v_1 is optimal and v_2 is suboptimal, it follows that $G = q(v_1) - q(v_2) > 0$. Let us now introduce the new random variable $Z = Q[v_2] - Q[v_1]$. This can be thought as taking the average difference between $\min\{N[v_1], N[v_2]\}$ samples of $Q[v_2]$ and $Q[v_1]$ (as in general the number of samples will be different, we consider the minimum between the two, and discard those in excess.) Therefore, its variance is $\sigma_z^2 / \min\{N[v_1], N[v_2]\}$. From the linearity of expectation, it follows that $\mathbb{E}[Z] = q(v_2) - q(v_1)$. Since ActionSelection returns the feasible action with the highest estimated Q value, it will return v_2 instead of v_1 only if $Q[v_2] > Q[v_1]$, i.e., only if $Z > 0$. We define $P_{ERR} = \Pr[Z > 0]$ as this is the probability that ActionSelection selects the wrong action. Next, consider:

$$Z > 0 \Leftrightarrow Z > q(v_2) - q(v_1) + q(v_1) - q(v_2) \Leftrightarrow Z > \mathbb{E}[Z] + G$$

Hence the claim follows by applying Chebychev's inequality to $\Pr[|Z - \mathbb{E}[Z]| \geq G]$ and recalling that $\mathbb{V}[X] = \sigma_z^2 / \min\{N[v_1], N[v_2]\}$. $\square$

We conclude by observing how the bound provided in theorem 3 depends on the gap G . For small values of G the bound becomes loose. However, small G values mean that the simple regret incurred by selecting the suboptimal vertex v_2 rather than the optimal vertex v_1 is small, and therefore the impact on performance is limited. On the contrary, as G increases (and therefore the simple regret increases), the probability of making the wrong choice decreases. Additionally, the error probability decreases linearly with the smallest number of samples between v_1 and v_2 .

VI. RESULTS

In this section, we provide two types of results. First, we assess the sensitivity of the proposed algorithm to the parameters P_R (balance between random exploration and greedy rollout), K (number of iterations) and S (number of simulations to estimate the failure probability). Next, we make some comparisons with an alternative method formerly proposed in literature solving both our formerly developed problem instances, but also third party benchmark problems.⁵

⁵All code needed to produce these results and charts is available on <https://github.com/ucmrobotics/StochasticOrienteering>.

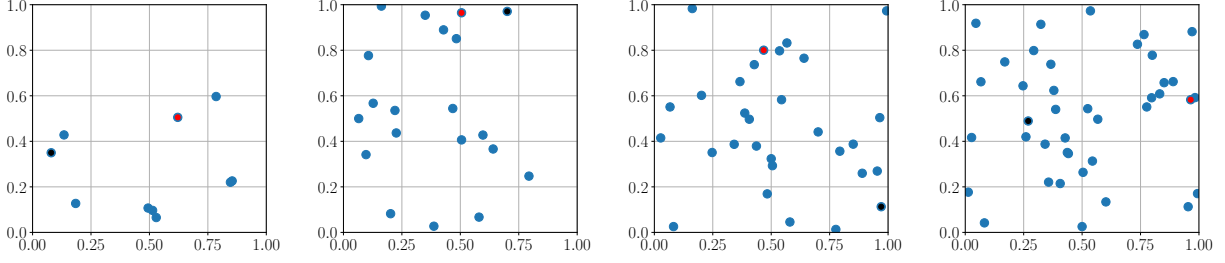


Fig. 5: The four test graphs used for our initial benchmarking. In all graphs the start vertex is marked in red and the end vertex is marked in black.

In all our tests we kept the parameter z (coefficient in the UCTF quantity defined in Eq. (4)) equal to 3. This value was selected after a few preliminary tests showing this is a good compromise between exploration and exploitation. All numerical tests were executed on a system with an Apple M1 Max processor and 32 GB of RAM, and our MCTS code is written in Python.

To ease the comparison with our previous work [6–8] we start considering the same setup to generate test cases. The n vertices in the graph are randomly sampled inside the unit square, and rewards are sampled from a uniform distribution with support $[0, 1]$. All graphs are complete, i.e., $(v_i, v_j) \in E$ for each $v_i \neq v_j$. Figure 5 shows these benchmark cases.

The random cost associated with edge (v_i, v_j) is

$$\kappa d_{i,j} + \mathcal{E}\left(\frac{1}{(1-\kappa)d_{i,j}}\right) \quad (6)$$

where $d_{i,j}$ is the Euclidean distance between v_i and v_j and $\mathcal{E}(\lambda)$ is a random sample from the exponential distribution with parameter λ . This formulation ensures that the expected cost to traverse (v_i, v_j) is equal to $d_{i,j}$ and the cost is non-negative. In all our experiments the parameter κ is set to 0.5. Before discussing the results, it is worth outlining that complete graphs are the most challenging to deal with because every node in the tree has the maximum possible branching factor, and for n vertices there are $\mathcal{O}(n!)$ possible paths⁶ in the space of possible policies.

Our first test aims at identifying a suitable value for the P_R parameter used in Algorithm 2, i.e., the probability of picking a random vertex for path expansion instead of doing a greedy choice. To this end, we performed a grid search for different values of P_R ranging from 0.1 to 0.9 over the four test environments displayed in figure 5. Results are shown in Figure 6 where we display the average normalized reward, i.e., the ratio between the maximum reward obtained in each graph instance and the reward obtained for a given choice of P_R . This normalization is necessary because as the number of vertices varies, the rewards vary, too, and therefore comparing the absolute values can be misleading. This preliminary assessment shows a mild sensitivity on P_R (note the scale of the y axis) and consequently in the following we fixed $P_R = 0.3$ in all our subsequent experiments.

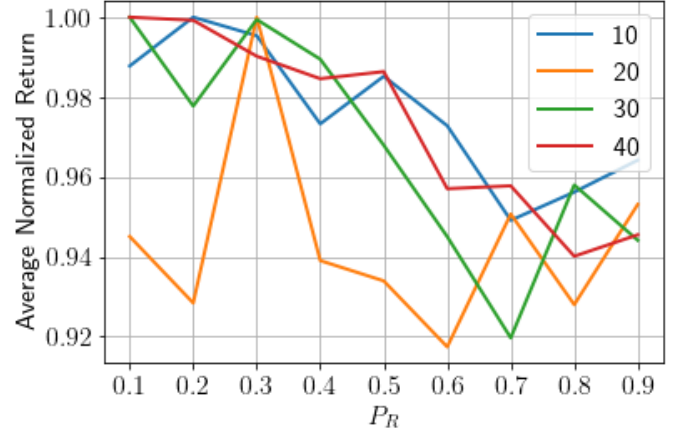


Fig. 6: Average normalized return for different values of P_R on test graphs with the number of vertices ranging from 10 to 40. Averages are computed over 100 independent runs for each P_R value.

Figure 7 shows how the computational time grows with the number of iterations K (red line) as well as the standard deviation. The figure was collected for a problem instance with 20 vertices and averaged over 50 independent executions. The trend is roughly linear, as expected, and therefore one can accordingly tune the number of iterations based on the available time. Variations in the computation time emerge because the produced paths may have more or less vertices depending on the realizations of the stochastic travel times. It is worth observing that this time is not all spent upfront but rather distributed along the path (see algorithm 1).

Next, we investigate how the number of iterations K in algorithm 4 influences the collected reward. Figure 8 shows how the amount of collected rewards changes with K (with all other parameters fixed.) for a graph with 20 vertices (red line) 30 vertices (blue line) and 40 vertices (orange line). Data is averaged over 50 runs with K varying from 200 to 2580. In all instances the reward barely grows with the number of iterations, showing that already with a value of K around 1000 the algorithm displays a good performance. For larger graphs with a larger branching factor, with larger values of K one can expect a continued increase in the accrued reward, but this comes at the cost of increased computational time, as shown in figure 7. Overall, this figure seems to indicate that the reward collected by the algorithm is not too sensitive to the value of K (this would of course not be the case when

⁶The number is less than $n!$ because the start and final vertices are assigned.

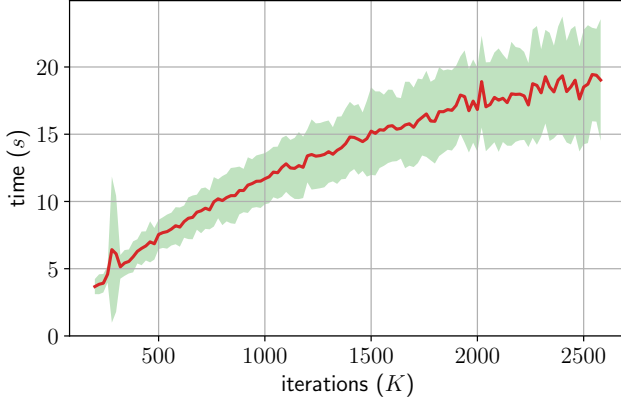


Fig. 7: Computation time as a function of the number of iterations K (red line). The green area shows the standard deviation (data averaged over 50 trials for each value of K). The chart refers to a graph with 20 vertices and $S = 100$ samples.

K is decreased to smaller values now shown in the figure, as it would not have the ability to sufficiently explore the set of paths.)

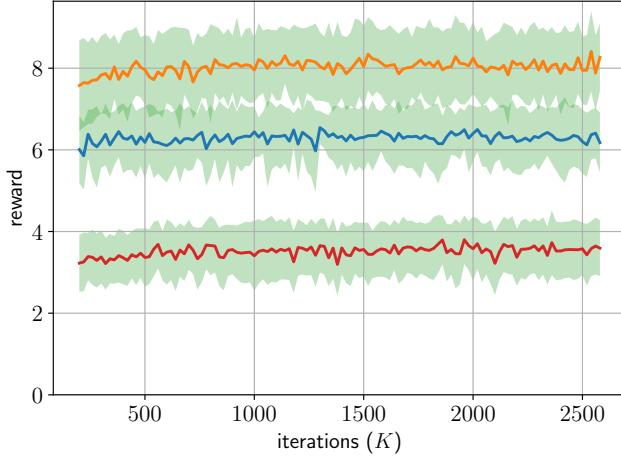


Fig. 8: Reward as a function of the number of iterations K . The orange line shows the trend for 40 vertices, the blue shows the reward trend for 30 vertices and the red shows the trend for 20 vertices. The green area shows the standard deviation (data averaged over 50 trials for each value of K). In all instances $S = 100$ samples.

Finally, figure 9 shows how the probability of exceeding the budget B varies with the number of samples S used to estimate the time to traverse a path. In this specific case, the assigned failure probability was $P_f = 0.1$. As the number of samples increases, the probability of failure decreases, as expected. This will further decrease as the parameter K increases because a larger part of the search space is searched (the chart was produced with $K = 1000$, as per the considerations discussed above.)

Having assessed the sensitivity of the algorithm to its parameters, we next contrast its performance to alternative solutions. In [31] we already showed that the approach presented in this paper outperforms CMDP formulations we studied in [6–

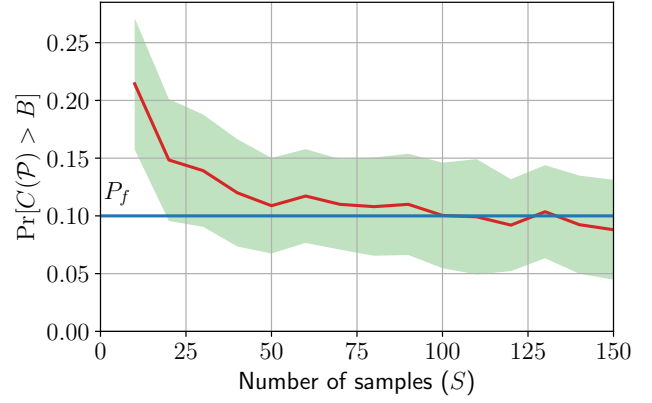


Fig. 9: Probability of failure as a function of the samples size S for a graph with 20 vertices, $K = 1000$ and $P_f = 0.1$. The green area shows the standard deviation (data averaged over 50 trials for each value of S).

$$\begin{aligned}
 & \max_{\pi} \sum_{i,j} \pi_{ij} r(v_i) \\
 & \text{s.t.} \\
 & \pi_{ij} \in \{0, 1\} \quad \forall v_i, v_j \in V \\
 & \sum_j \pi_{ji} \leq 1 \quad \sum_j \pi_{ij} \leq 1 \quad \forall v_i \in V \\
 & \sum_j \pi_{1j} = 1 \quad \sum_j \pi_{jn} = 1 \\
 & \sum_j \pi_{ij} - \sum_j \pi_{ji} = \begin{cases} 1 & \text{if } i = 1 \\ -1 & \text{if } i = n \\ 0 & \text{otherwise} \end{cases} \\
 & s_i \leq s_j - 1 + (1 - \pi_{ij})M \quad \forall v_i, v_j \in V \\
 & s_1 = 1 \quad s_n = n \quad s_i \in [1, n] \quad \forall v_i \in V \\
 & \Pr \left(\sum_{i,j} \pi_{ij} \xi_{ij} \geq B \right) \leq P_f \tag{7}
 \end{aligned}$$

8]. Therefore, in this venue we instead compare it with the method proposed in [15] that uses a MILP formulation to solve the problem. This solution is offline, i.e., it computes the path before its execution. The formulation is given in the subsequent box. In particular, compare Eq. (7) with Eq. (3) and the problem definition provided in section III.

The formulation introduces one binary variable π_{ij} for each edge (v_i, v_j) and aims at maximizing the sum of collected rewards. The reader is referred to [15] for a full discussion of the other variables and constraints. For the sake of comparison, here we focus on Eq. (7) which involves the chance constraint because this influences the comparisons we will present next. As pointed out in [15], this constraint is in general non linear, and therefore the SAA method discussed in Section III is used to turn this nonlinear constraint into a linear deterministic approximation. This approximation turns the optimal formulation given above into a suboptimal one that can be solved

by a MILP solver. The approximation is as follows. First, draw Q samples for each random variable ξ_{ij} . These samples are indicated as t_{ij}^q . Integer variables z^q for each sample are introduced, together with these additional linear constraints:

$$z^q \geq \frac{\sum_{ij} \pi_{ij} t_{ij}^q - B}{B} \quad z^q \in \{0, 1\}$$

Starting from these definitions, the chance constraint in Eq. (7) is substituted with the following

$$\frac{\sum_q z^q}{Q} \leq \beta$$

where, as noted in [15], the value β is set by the user and is smaller than the P_f used in Eq. (7). This approach therefore leaves open the questions of 1) how to choose a Q value; 2) how to pick β .

Our implementation of the MILP solution uses the Gurobi software. After preliminary experiments aiming at finding suitable values for Q and β , in all cases we set $Q = 80$ and $\beta = P_f/2$. Moreover, in all tests we cap the computation time at 600 seconds. If the MILP solver has not found a solution by the deadline, the best solution produced thus far is returned. For the MCTS implementation, instead, we set $K = 350$ (number of tree expansions) and $S = 100$ (number of rollouts per leaf node.) These values were selected based on the results we presented at the beginning of this section.

The comparisons we present span three dimensions. The first is the collected reward, the second is the failure probability, and the third is the computational time. Figure 10 compares the reward collected by the two algorithms. More specifically, it is the ratio between the reward collected by the MCTS algorithm and the MILP algorithm. MCTS results are averaged over 100 independent runs, while MILP results are averaged over 10 runs (we run fewer test cases for MILP because, as it will be shown later, it takes much longer than the MCTS.)

As the MILP algorithm approximates the optimal solution, the ratio is expected to always be below 1 and the closer to 1, the better for the MCTS algorithm. The figure compares two different budgets (top panel $B = 2$ and bottom panel $B = 3$), as well as two different values for P_f . As can be seen, the ratio is always in the range of 0.9 and in some cases closer to 1. A special case to be observed is for $B = 2$ and $P_f = 0.05$, where the MCTS algorithm beats the MILP algorithm and the ratio is therefore larger than 1. While this is in general not possible, one has to keep in mind that in all cases the MILP algorithm was stopped after 600 seconds. Hence in this specific instance, it can be inferred that the MILP algorithm was stopped while the partial solution was still relatively far from the optimal one, so that MCTS managed to find a better one.

Next, we compare the effective failure probability obtained by the two algorithms. Results are shown in figures 11 and 12 for different budgets and failure probabilities. In this test, data are averaged over 50 trials for each algorithm. More precisely, for the MCTS algorithm we consider 50 independent runs, while for the MILP algorithm we consider 10 solutions and run each of these 5 times.

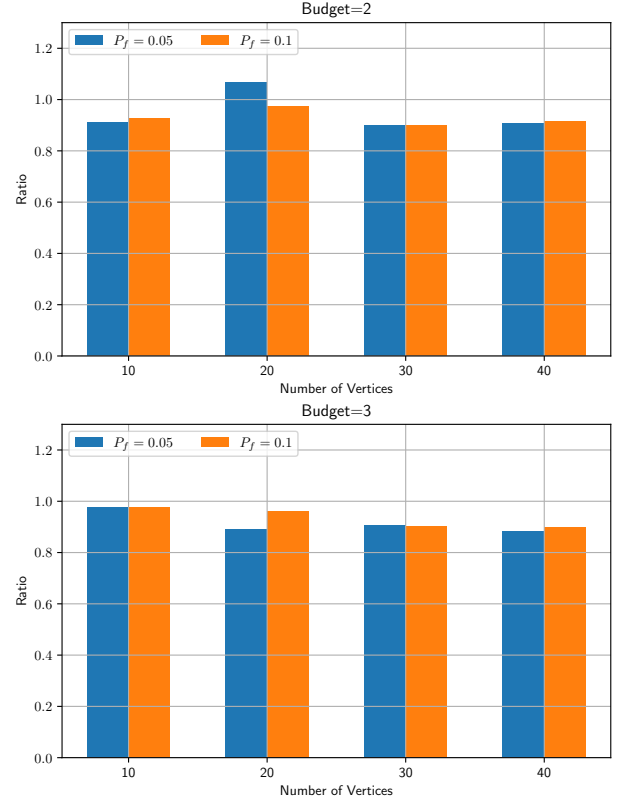


Fig. 10: Ratio between the reward collected by the MCTS and the MILP solutions for different values of P_f . The top panel is for $B = 2$ and the bottom one is for $B = 3$.

In this case, lower is better, and we observe that in 13 out of 16 cases MCTS achieves a lower failure probability than the MILP algorithm. As pointed out by the authors, the MILP algorithm is sensitive to the values selected for Q and β and its failure probability could decrease by increasing Q and decreasing β . However, both changes come at a cost. Increasing Q increases the number of binary variables (and hence computation time) and decreasing β will generate routes collecting less reward. The MCTS algorithm, instead, does not need a careful tuning of the parameters, as pointed out at the beginning of this section.

Finally, we compare the computational time again for the same values for B and P_f . Results are shown in figures 13 and 14.

In this case, we observe that for small problem instances (10 vertices) the time spent by the two algorithms is similar, with the MILP algorithm actually being even faster than the MCTS algorithm. However, as the size of the problem increases, as expected, the MILP algorithm needs much more time, with the exception of the case $B = 2$, $n = 30$, where evidently the structure of the graph allows to quickly prune the search space. In all other cases, the gap is very large.

Overall these results suggest that for large problem sizes the proposed MCTS algorithm allows us to find high quality solutions (albeit suboptimal) spending a fraction of the time and incurring a lower failure rate. In a practical scenario, one could actually implement both algorithms, and use MILP for small problem instances, and MCTS for large ones.

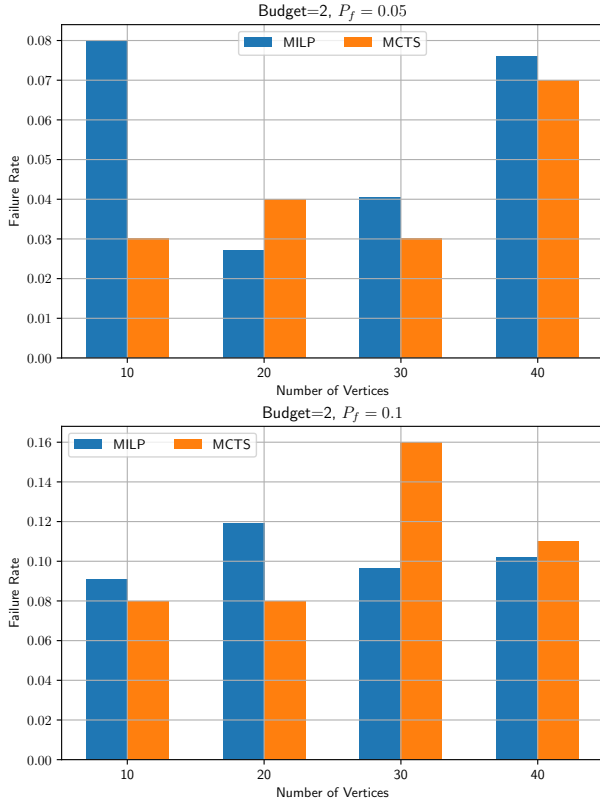


Fig. 11: Failure rates incurred by the MILP algorithm (blue) and MCTS algorithm (orange) for the case $B = 2$. The top panel is for $P_f = 0.05$ and the bottom one is for $P_f = 0.1$.

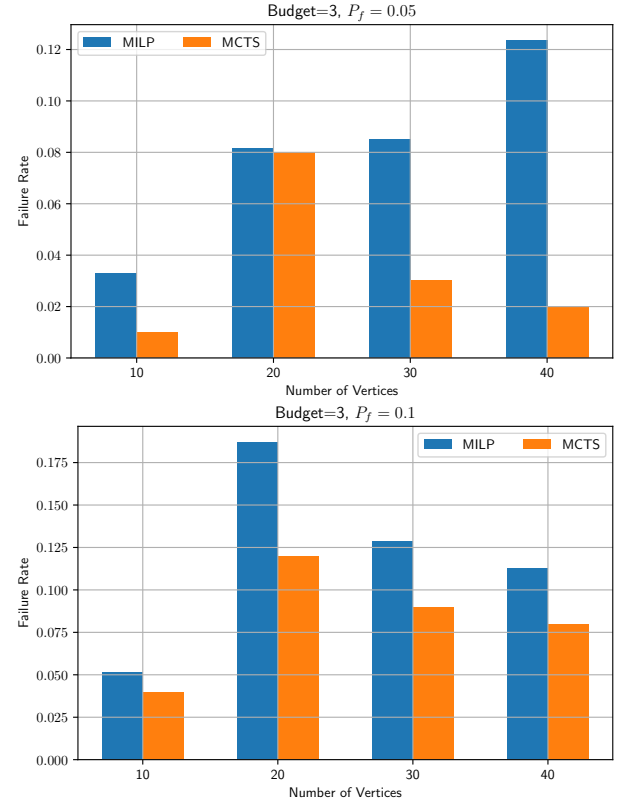


Fig. 12: Failure rates incurred by the MILP algorithm (blue) and MCTS algorithm (orange) for the case $B = 3$. The top panel is for $P_f = 0.05$ and the bottom one is for $P_f = 0.1$.

Having assessed that the algorithm we propose favorably compares to the state of the art when solving instances we generated on our own, we conclude this experimental evaluation by further comparing them on benchmark instances used by the traveling salesman problem (TSP) research community and freely available online.⁷ The instances we use have a number of vertices ranging from 16 to 70 and we used the same noise distribution given in Eq. (6) to describe the edge cost noise. As TSP problem instances do not include vertex rewards, we assigned rewards using a uniform distribution over the range $[1, 4]$. Figure 15 shows these additional problem instances, while Table I displays the results. Note that for the MILP approach in this case we had to increase the Q value to 120, otherwise the failure probability exceeds the assigned P_f threshold. In this case we observe that, as expected, as the number of vertices grows, the performance gap between the approximate MCTS approach and the MILP solution grows, too, but never drops below 0.72. At the same time, in all cases MCTS is always at least 50 times faster than the MILP solution. It is also worthwhile mentioning that for both algorithms one could perform a grid search to determine the optimal parameter values, but this has not been done. Overall, these additional benchmark problems show that the results we obtained with our own problem instances generalize also to other test cases.

VII. CONCLUSIONS AND FUTURE WORK

In this paper, we have presented a new algorithm to solve the stochastic orienteering problem with chance constraints. The main novelty is in using an MCTS approach to explore the space of possible policies and a generative model for the travel times across the edges to prune away realizations that violate the assigned bound on the probability of failure. To the best of our knowledge, this approach is novel. The proposed algorithm offers various advantages. By being an anytime algorithm, it can produce results within a given pre-assigned computational time, while previous methods will not produce any results until the associated linear program is built and solved. In addition, we have shown that in a variety of test cases our method produces high quality solutions in a fraction of the time.

There are various venues for further research. First, the current rollout policy relies on a simple greedy strategy. It would be interesting to explore whether different rollout policies (e.g., policies using some of the heuristic methods formerly proposed for the orienteering problems) would produce better results (either in terms of speed or collected rewards).

From an application standpoint, it would also be interesting to consider the case of stochastic rewards, for both cases when edge costs are deterministic or stochastic. With stochastic rewards and deterministic edge costs, one could consider a chance constraint on the minimum reward to collect. In this case, the proposed method would be mostly applicable “as is” after having replaced the rollout method with one sampling collected reward values, rather than travel costs. The case with

⁷<http://webhotel4.ruc.dk/~keld/research/LKH-3/>

Test case	Budget	P_f	MCTS			MILP			Ratios	
			Reward	P_f	Time(s)	Reward	P_f	Time(s)	Reward	Time
ulysses16	50	0.05	38.55	0.05	2.44	39.41	0.064	374.21	0.98	153.20
ulysses16	50	0.1	39.32	0.08	2.46	40.68	0.095	600.29	0.97	243.58
ulysses22	50	0.05	54.67	0.02	3.17	59.36	0.0465	600.71	0.92	189.09
ulysses22	50	0.1	54.63	0.05	3.08	59.86	0.078	600.59	0.91	194.74
att48	25000	0.05	104.14	0.08	7.67	134.36	0.0590	600.75	0.77	78.29
att48	25000	0.1	104.79	0.1	8.21	136.09	0.0815	600.74	0.77	73.17
berlin52	5000	0.05	109.28	0.06	8.01	141.74	0.0735	600.84	0.77	74.99
berlin52	5000	0.1	110.99	0.08	8.21	142.52	0.0875	669.16	0.78	81.42
st70	500	0.05	125.83	0.02	11.54	173.50	0.0745	629.03	0.72	54.50
st70	500	0.1	126.65	0.02	11.96	174.77	0.0785	622.38	0.72	52.00

TABLE I: Comparison between the proposed MCTS approach and the MILP solution. For both algorithms we show the collected reward, the experimental failure probability P_f and the time spent to find the solution. The tenth column shows the ratio between the reward obtained by MCTS and the reward obtained by MILP. In this case values closer to one are desirable. The eleventh column shows the ratio between the time spent by MILP and the time spent by MCTS. In this case, larger values indicate more significant speedups. For the MCTS approach we consider averages over 100 runs, while for the MILP approach we consider averages over 10 runs.

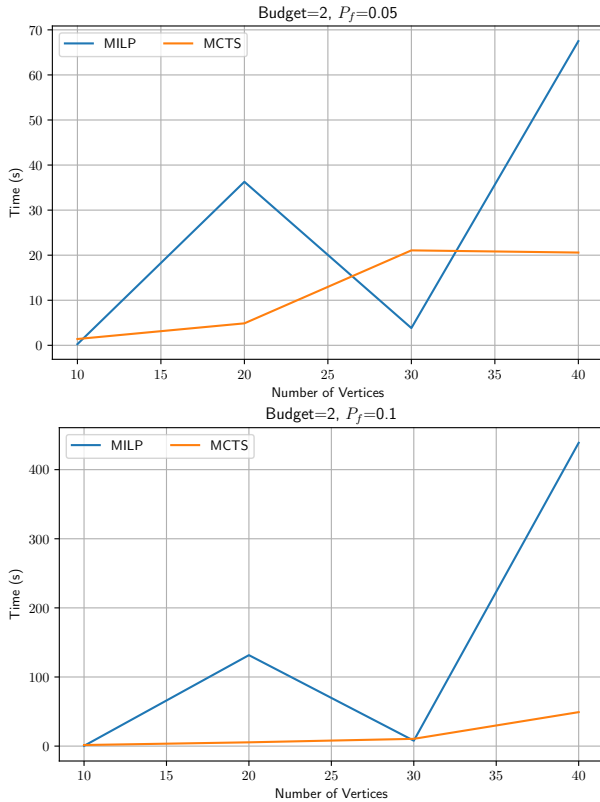


Fig. 13: Average time spent to find the solution by the MILP algorithm (blue) and MCTS algorithm (orange) for the case $B = 2$. The top panel is for $P_f = 0.05$ and the bottom one is for $P_f = 0.1$.

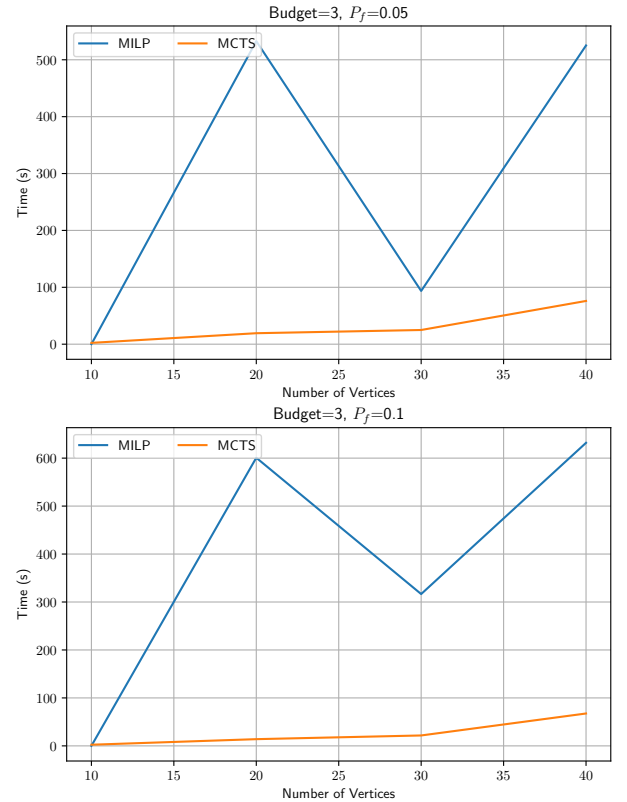


Fig. 14: Average time spent to find the solution by the MILP algorithm (blue) and MCTS algorithm (orange) for the case $B = 3$. The top panel is for $P_f = 0.05$ and the bottom one is for $P_f = 0.1$.

both stochastic rewards and stochastic edge costs, appears to be more complex, as one could define separate chance constraints for both. In this case, one could extend the proposed method with rollouts sampling both stochastic quantities, but it would also be necessary to revise the problem formulation accounting for multiple constraints. These extensions will be considered in future iterations of this research.

Finally, it will be interesting to investigate whether this approach could be extended to study other planning problems with chance constraints where building a finite state space is disadvantageous because of the need to discretize continuous dimensions, such as time.

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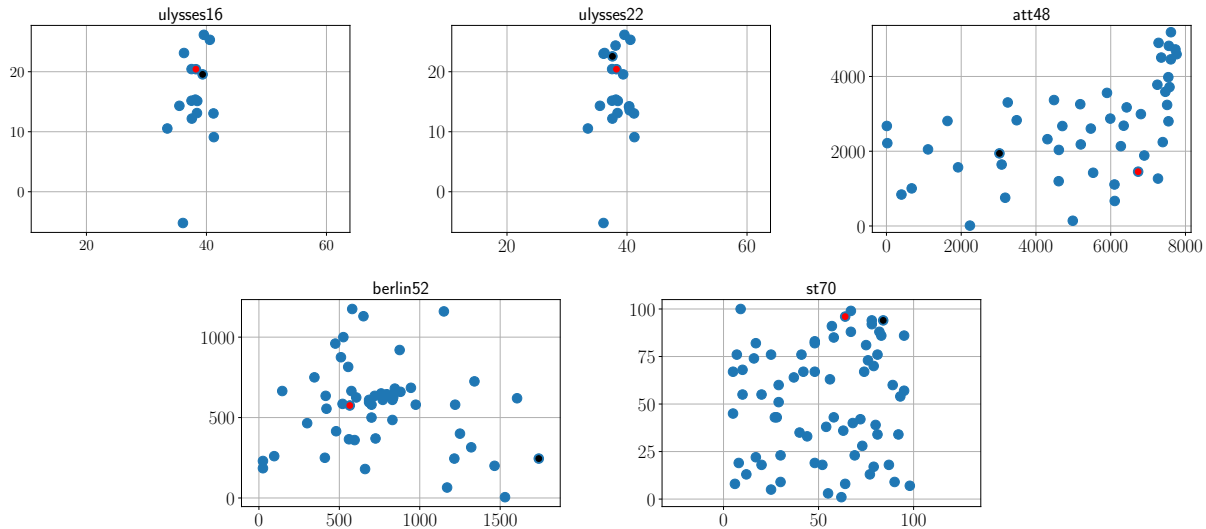


Fig. 15: The five additional benchmark problems borrowed from the TSP research community. The number of vertices varies from 16 to 70 (the numeric suffix in the benchmark name gives the number of vertices).

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