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A Monte Carlo Tree Search for the Optimisation of Flight Connections

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Declaration of Authorship

I, **Arnaud Da Silva**, hereby declare that this thesis entitled, **A Monte Carlo Tree Search for the Optimisation of Flight Connections**, is all my own work, except as indicated in the text.

The report has been not accepted for any degree and it is not being submitted currently in candidature for any degree or other reward.

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Abstract

Kiwi.com has proposed a real-world NP-hard optimisation problem, focused on air transport services, which involves determining the cheapest connection between specific zones. Despite some similarities with the classic TSP problem, the problem is more complex. It is an asymmetric, time-constrained and generalised (i.e. it involves zones that contain sets of cities, only one of which is visited) TSP. In addition, infeasibility adds further complexity to the problem as there are no flights available between specific points in the network on certain days. Exact methods often fail in solving these computationally difficult problems, particularly as the size of the problem instance increases; alternative approaches, such as heuristics, are therefore preferred in solving the problems.

To tackle this challenge, we implemented a Monte Carlo Tree Search (MCTS), a tree search algorithm typically used in board games. We adapted and tuned it with various parameters and functions, successfully solving six out of eight instances and establishing a new state-of-the-art solution.

Acknowledgements

(TODO) Thanking anyone who has helped you in any way

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Abbreviations

AK Ahmed Kheiri

MS Management Science

Dedicate this to someone here.

Chapter 1

Introduction

1.1 Background

The number of flight connections keep increasing every year [3], more than 38 million flights have been scheduled in 2023 - therefore, creating a challenge for traveler's to find the best and cheapest flight connections for their specific journey, especially when one has to visit a big number of cities. Consequently, travel agencies have deployed online trip planner algorithms in order to find flights connection that match the traveler's requirements. Example of these are, Google Flights, OpenFlights.org, Skyscanner, Kayak and Kiwi.com.

These agencies have launched different challenges to create and build powerful trip planner algorithms. For instance, as mentionned in [4], OpenFlights.org launched the Air Travelling Salesman project. Furthermore, Kiwi.com has launched a project in 2017, called Traveling Salesman Challenge, where the current algorithm used by Kiwi.com was developed. In 2018, Kiwi.com launched a new challenge, the Traveling Salesman Problem 2.0 which is the focus of this study.

The given problem is a variant of the Traveling Salesman Problem. It can be characteristed as a generalised, assymetric and time dependant TSP. A traveler has to visit a list of areas, one per day, given a starting airport and all the possible flight connections between these areas at different days. The goal is to determine what is the cheapest flights connection for the traveler to come back to the starting area. Regarding the number of possible journeys, solving this problem by exploring every single potential solution is impossible. This is why a heuristic approach is often used to solve such TSP problem. In this paper, the Kiwi.com challenge is solved using a Monte Carlo Tree Search.

1.2 Research objectives

The goals of this dissertation are:

- The implementation of a Python innovative solution to solve the Kiwi.com Traveling Salesman problem 2.0 with no focus on the time limit.
- Focus on instances $(I_1, \ldots I_8)$ that represent more realistic scenarios.
- Try to find better solutions than the state of the art for the considered instances.

1.3 Academic publication

- International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE)

1.4 Dissertation structure

The dissertation is structured as follow:

- Section 2 is the litterature review where the Air Travel optimisations problem are introduced, TSP and its variants are redefined and finally the Monte Carlo Tree Search and an example are presented.
- Section 3 is the problem and instances description to highlight the problem complexity in detail.
- Section 4 is the methodology of our algorithm implementation, where we explain the code's structure, explain the general flow of the algorithm.
- Section 5 is the result and performance of our implementation compared to the state of the art solution and further analysises regarding the MCTS' parameters.

Chapter 2

Literature Review

2.1 Optimisation in Air Travel

In this section, we discuss some common challenges faced by airline companies and demonstrate the importance of optimisation in decision-making for the success and competitiveness of airline companies.

2.1.1 Fleet Assignment Problem

The Fleet Assignment Problem (FAP), as discussed in [5] involves assigning different types of aircraft, to flights based on their capabilities, operational costs, and revenue potential. This decision greatly influences airline revenues and is a vital part of the overall scheduling process. The complexity of FAP is driven by the large number of flights an airline manages daily and its interdependencies with other processes like maintenance and crew scheduling.

2.1.2 Crew Scheduling Problem

The Crew Scheduling Problem (CSP), as discussed in [6], involves assigning crews to a sequence of tasks, each with defined start and end times, with the primary objective of ensuring that all tasks are covered while adhering to regulations on maximum working hours for crew members.

This problem is particularly critical for low-cost airlines, for example in the United Kingdom in 2023, low-cost flights comprise 48% of the scheduled capacity (total number of seats offered) [7], which rely heavily on optimised crew schedules to maintain competitiveness. Efficient crew scheduling is essential not only for low cost carriers and for cost minimisation but also for ensuring operational reliability and flexibility in response to unexpected disruptions. [8]

2.1.3 Disruption Management

Disruptions in airline operations, as noted in [9], can occur due to various factors, including crew unavailability, delays from air traffic control, weather conditions, or mechanical failures. Given that flight schedules are typically planned months in advance [10], effective disruption management is crucial to minimise the impact on passengers and overall airline operations.

The two mains drivers of disruption management are aircraft and crew recovery.

- Aircraft recovery: Optimisation tools help manage the complex logistics of matching available aircraft with rescheduled flights, considering factors like airport availability and maintenance requirements.
- Crew recovery: Optimisation tools are used to adjust crew schedules, taking into account factors such as legal working hours, crew availability, and the need to cover all flights efficiently. These tools help in developing feasible and compliant crew rosters that adapt to the new flight schedules.

These optimisation strategies, supported by advanced software, for instance [11] and [12], are crucial for reducing the impact of disruptions and boosting operational resilience in the airline industry.

2.1.4 Airline adaptation to new demand

Airline companies must continuously adapt their schedules to meet evolving market demands, particularly with the growing dominance of leisure travel over business travel, which has introduced new patterns of demand as shown on Figure 2.1 in Europe. This seasonality poses a challenge for airlines as they have to balance high demand during peak seasons with the risk of underutilisation during off-peak times.

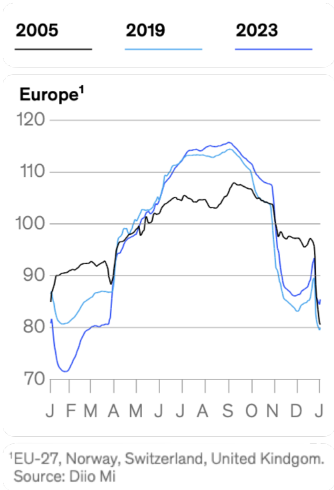


FIGURE 2.1: European demand seasonality [1]

Since travel demand varies throughout the year, airlines use a variety of techniques to achieve operational efficiency while maximising revenue [1]. For instances, airlines sell nearly 65% more seats. To ensure their operatios remain efficient during periods of heightened demand, airline companies make the required allowance for additional aircraft and crew by optimisation models that specify priority routes and requirements for additional flights, alongside effective crew rotation management.

In contrast, winter months pose a different type of problem where demand drops, which can potentially lead to underutilisation of aircrafts. To manage this, airlines are known to turn to ACMI leasing (agreement between two airlines, where the lessor agrees to provide an aircraft, crew, maintenance and insurance [13]) during periods of low demand to temporarily reduce fleet size by outsourcing their capacity. Alongside this, they also increase maintenance activities and incentivise crews to take holidays or undergo training to maximise productivity across the operation. Equally, on a year-round basis, airlines apply dynamic pricing algorithms to vary fares in reaction to real-time demand patterns. In high-demand summer months, fares are tactically set so as to maximise revenues from travelers willing to pay more, while in winter, pricing strategies are aimed at stimulating demand with fare reductions to fill seats that otherwise would have gone empty. Such adaptive strategies are critical to the airlines for effectively beating the seasonal ebbs and flows in the travel industry.

2.2 Traveling Salesman problem and its adapation

The Traveling Salesman Problem is a well known problem in the Operational Research and Computer Science fields. A simple description of the TSP is to find the best roundtrip for a saleman that has to travel around a given number of cities while minimising the overall journey's distance. This problem is characterised as $\mathcal{NP}$-Hard [14]. This means that there is no known polynomial-time algorithm that can solve all instances of the problem efficiently . Regarding time complexity, if we were to solve it exploring all the possible solutions, the time complexity would have been $\mathcal{O}(\frac{(n-1)!}{2})$ where n represents the number of cities.

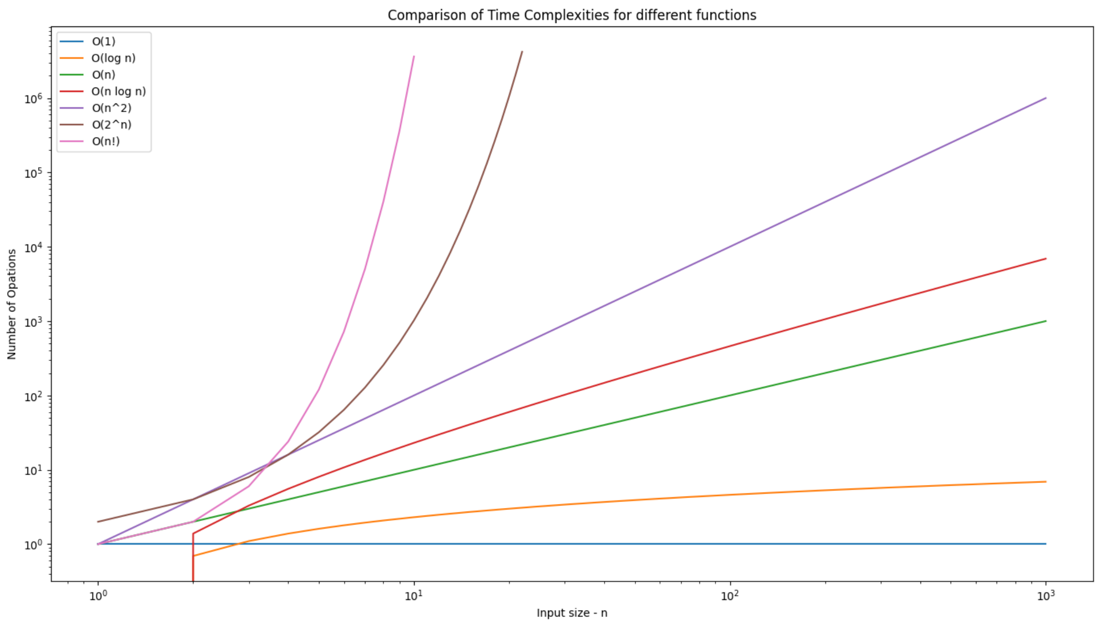


FIGURE 2.2: Time complexity of different functions

On Figure 2.2, different time complexities are compared and demonstrates that the factorial time complexity is the worst. Therefore, these kinds of $\mathcal{NP}$-Hard problem are typically not solved exploiting all the search area but using heuristics algorithms. Heuristics solutions do not guarantee to find the absolute optimal solution but can find near-optimal solutions within more reasonnable timeframes.

The TSP has been studied extensively, and, many variants can be derived from it:

- Symmetric TSP (STSP): The distance between cities are symmetric, meaning that the distance to travel from city A to city B is the same as from city B to city A.

- Assymetric TSP (ATSP): The distance between cities are assymetric, meaning that the distance to travel from city A to city B is different than the distance to travel from city B to city A.[15]
- Multiple TSP (mTSP): Instead of one salesman, multiple salesman are starting from one city, they visit all the cities such that each city is visited exactly once. [16]
- Time Window TSP (TWTSP): Each city has to be visited in a defined time slot. [17]
- Price-collection TSP (PCTSP): Not all the cities have to be visited, the goal is to minimise the overall traveler's distance while maximising the price collected earned when visiting a city. [18]
- Stochastic TSP (STSP): The distances between the cities or the cost of travels are stochastic (ı.e random variables) rather than deterministic. [19]
- Dynamic TSP (DTSP): The problem can change over time, that means that new cities can be added or distances between cities can change while the salesman has already started his journey. [20]
- Generalised TSP (GTSP): The cities are grouped into clusters, the goal is to visit exactly one city from each cluster. [21]
- Open TSP (OTSP): The traveler does not have to end his journey at the starting city. [22]

Multiple algorithms have been developed to address these TSP variants, we can classify them into two categories:

- **Exact Algorithms**: These algorithms aim to find the optimal solution to the TSP by exploring all possible routes or by using mathematical techniques to prune the search space efficiently. Examples include:
  - **Branch and Bound**: This method systematically explores the set of all possible solutions, using bounds to eliminate parts of the search space that cannot contain the optimal solution. It is often used for smaller instances of TSP due to its computational intensity. [23]

  - **Cutting Planes**: This technique adds constraints (or cuts) to the TSP formulation iteratively to remove infeasible solutions and converge to the optimal solution. This approach is particularly effective for symmetric TSPs. [24]
  - **Dynamic Programming**: Introduced by Bellman, this approach breaks down the TSP into subproblems and solves them recursively, which is highly effective for specific TSP variants, though its complexity grows exponentially. [25]

- **Approximation and Heuristic Algorithms**: These algorithms are designed to find near-optimal solutions within a reasonable time frame, specifically for large-scale problems where exact methods are computationally infeasible. Examples include:

  - **Greedy Algorithms**: These algorithms make a series of locally optimal choices in the hope of finding a global optimum. An example is the Nearest Neighbor algorithm, which selects the nearest unvisited city at each step. [26]
  - **Genetic Algorithms**: Inspired by the process of natural selection, these algorithms evolve a population of solutions over time, using operations such as mutation and crossover to explore the solution space. [27]
  - **Simulated Annealing**: This probabilistic technique searches for a global optimum by allowing moves to worse solutions based on a temperature parameter that gradually decreases. It is particularly useful for escaping local optima. [28]
  - **Ant Colony Optimization**: This metaheuristic is inspired by the foraging behavior of ants and uses a combination of deterministic and probabilistic rules to construct solutions, which qre grqdually refined through updates based on pheromone trails. [29]

Some TSP problems (or its variants) have been solved using other algorithms.

2.3 The Monte Carlo Tree Search algorithm

The Monte Carlo Tree Search (MCTS) algorithm can be characterised as less traditionnal than the previously enounced methods in Section 2.2 because MCTS is typically used in games. MCTS' (and its variants) have been successfully implemented across a range of games, such as Havannah [30], Amazons [31], Lines of Actions [32], Go, Chess, and Shogi [33], establishing it as the state-of-the-art algorithm [34], [35], [36]. It is widely used in board games and is increasingly popular since Google DeepMind developed AlphaGo. AlphaGo is a software that was created to beat the best Go's player in the world.

Go is a board game from China where two players take turns placing black or white stones on a grid. The goal is to capture territory by surrounding empty spaces or the opponent's stones. Despite its simple rules, Go is a complex game, with countless possible moves and strategies. It is known for its balance between intuition and logic, hence why it has been a significant focus of artificial intelligence research ,[37]. In 2016, Lee Sedol [38] - the best Go's player in the world was been beaten by AlphaGo 4-1 [39].

MCTS with policy and value networks are at the heart of AlphaGo decision-making process, enabling AlphaGo's to pick the optimal moves in the complex search of Go. [40]

2.3.1 Overview

The MCTS' process is conceptually straightforward. A tree is built in an incremental and assymatric manner (Figure 2.3). For every iteration, a selection policy is used to determine which node to select in the tree to perform simulations. The selection policy, typically balances the exploration (looking into parts of the tree that have not been visited yet) and the exploitation (looking into parts of the trees that appear to be promising). Once the node is selected, a simulation - a sequence of available actions, based on a simulation policy, is applied from this node until a terminal condition is reached e.g no further actions are possible. [41]

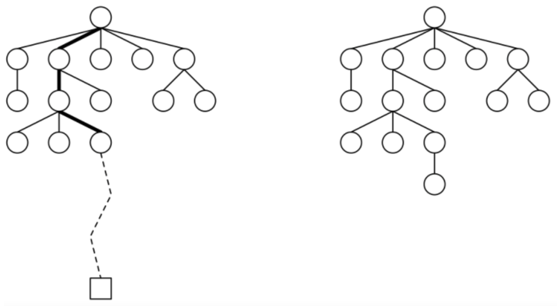


FIGURE 2.3: Assymetrical growth of MCTS - Simulation and Expansion - [2]

To ensure a clearer understanding of MCTS algorithm's stages, we will start by exploring a detailed example [42]. This example will illustrate each component of the algorithm in action. Furthermore, we will generalise the principles discussed, as the methodology of this paper is built on the application of the MCTS algorithm.

2.3.2 Example

Let's say we are given a maximisation problem. When beginning the game, you have two possible actions a_1 and a_2 from the node $S_0^{0,0}$ in the tree $\mathcal{T}$. Every node is defined like so: $S_i^{n_i,t_i}$ where n_i represents the number of times node i has been visited, t_i the total score of this node. Moreover, for every node - we can compute a selection metric, for instance the UCB value: $UCB(S_i^{n_i,t_i}) = \bar{V_i} + 2\sqrt{\frac{\ln N}{n_i}}$ where $\bar{V_i} = \frac{n_i}{t_i}$ represents the average value of the node, n_i the number of times node i has been visited, $N = n_0$ the number of times the root node has been visited (which is also equal to the number of iterations).

Before the first iteration, none node have been visited - $\forall i \in \mathcal{T}, S_i^{0,0}$. At the beginning

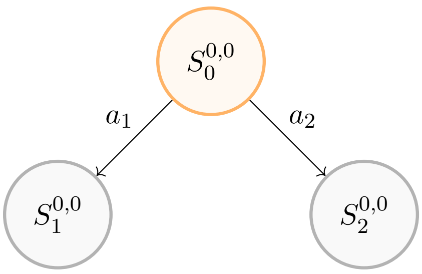


FIGURE 2.4: Selection - $I1$

of $I1$, we have to choose between these two child nodes (or choose between taking a_1 or a_2). After, we have to calculate the UCB value for these two nodes and pick the node that maximises the UCB value (as we are dealing with a maximisation problem).

In Figure 2.4, neither of these have been visited yet so $UCB(S_1^{0,0}) = UCB(S_2^{0,0}) = \infty$. Hence we decide to choose randomly $S_1^{0,0}$.

$S_1^{0,0}$ is a leaf node that has not been visited - then we can simulate from this node, which means selecting actions from this node based on the simulation policy to a terminal state as shown on Figure 2.5:

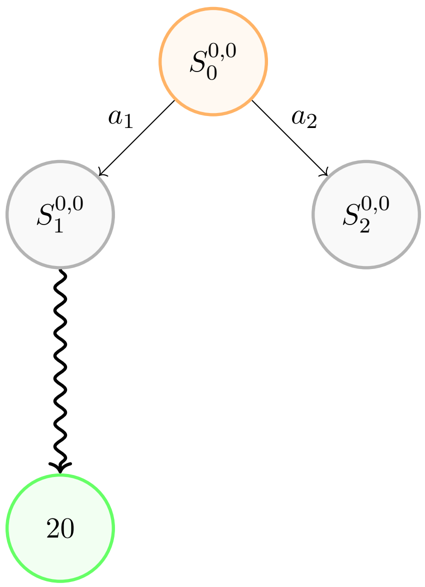


FIGURE 2.5: Simulation - $I1$

The terminal state has a value of 20, we can write that the rollout/simulation from node $S_1^{0,0}$ node is $\mathcal{R}(S_1^{0,0}) = 20$. The final step of $I1$ is backpropagation. Every node that has been visited in the iteration is updated. Let $\mathcal{N}_{\mathcal{R},j}$ be the indexes of the nodes visited during the $j-th$ iteration of the MCTS:

- Before backpropagation:
$$\forall i \in \mathcal{N}_{\mathcal{R},j}, S_{i,old}^{n_i,t_i} \tag{2.1}$$
- After backpropagation:
$$\forall i \in \mathcal{N}_{\mathcal{R},j}, S_{i,new}^{n_i+1,t_i+\mathcal{R}(S_{i,old}^{n_i,t_i})} \tag{2.2}$$

We can then define a backpropagation function:

$$\begin{array}{cccc} \mathcal{B} & : & \mathcal{N}_{\mathcal{R},j} & \rightarrow & \mathcal{N}_{\mathcal{R},j} \\ & & S_i^{n_i,t_i} & \mapsto & S_i^{n_i+1,t_i+\mathcal{R}(S_i^{n_i,t_i})} \end{array}$$

Then, back to the example on Figure 2.6 we update the nodes $\mathcal{B}(S_1^{0,0}) = S_1^{\mathbf{1,20}}$ and $\mathcal{B}(S_0^{0,0}) = S_0^{\mathbf{1,20}}$.

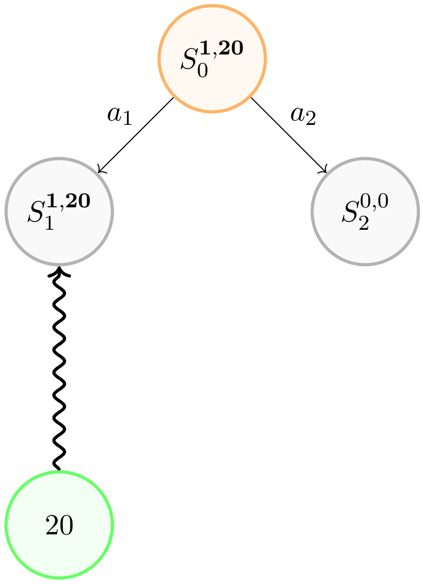
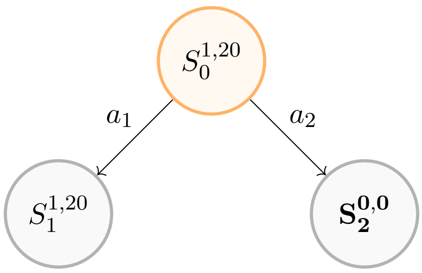


FIGURE 2.6: Backpropagation - I1

The fourth phase of the algorithm has been done for $I1$. Therefore, we can then start the 2^{nd} iteration $I2$. On Figure 2.7, we can either choose a_1 or a_2. When a child node



$$UCB(S_1^{1,20}) = 20 + 2\sqrt{\frac{\ln 1}{1}} = 20$$
$$UCB(S_2^{0,0}) = \infty$$

FIGURE 2.7: Selection - I2

has not been visited yet, you pick this node for the Selection or you can compute the UCB value, it leads to the same conclusion.

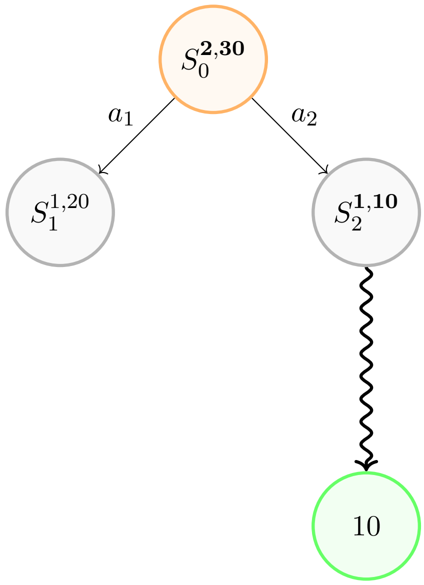


FIGURE 2.8: Simulation and Backpropagation - I2

We can simulate (Figure 2.8) from the chosen node $S_2^{0,0}$ and $\mathcal{R}(S_2^{0,0}) = 10$ and back-propagate all the visited nodes: $\mathcal{B}(S_2^{0,0}) = S_2^{1,10}$ and $\mathcal{B}(S_0^{1,20}) = S_0^{2,30}$. Next, we start the 3^{rd} iteration, based on the UCB score we decide to choose a_1.

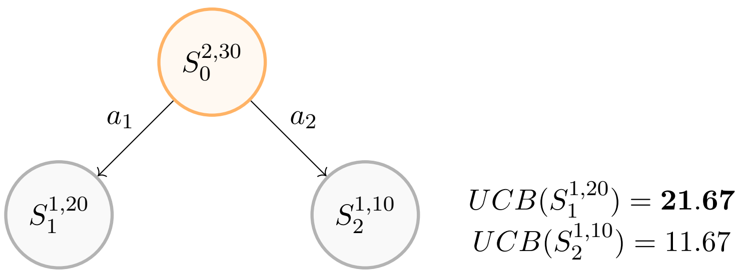


FIGURE 2.9: Selection - I3

$S_1^{1,20}$ is a leaf node and has been visited so we can expand this node.

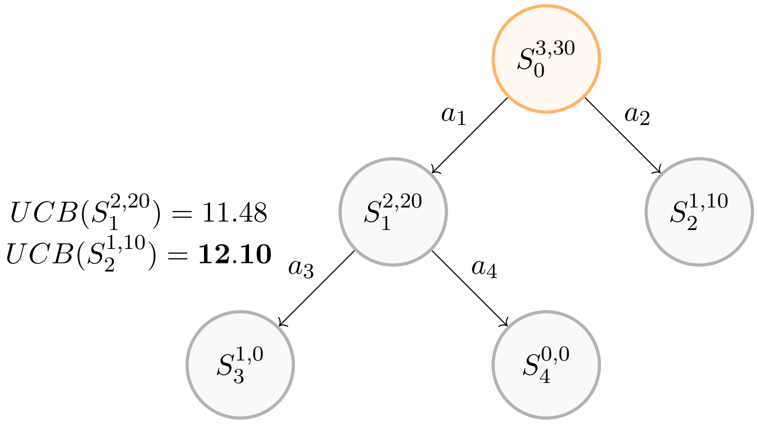


Figure 2.10: Selection and Expansion - I3

Based on UCB score we decide to simulate from $S_3^{0,0}$ on Figure 2.11

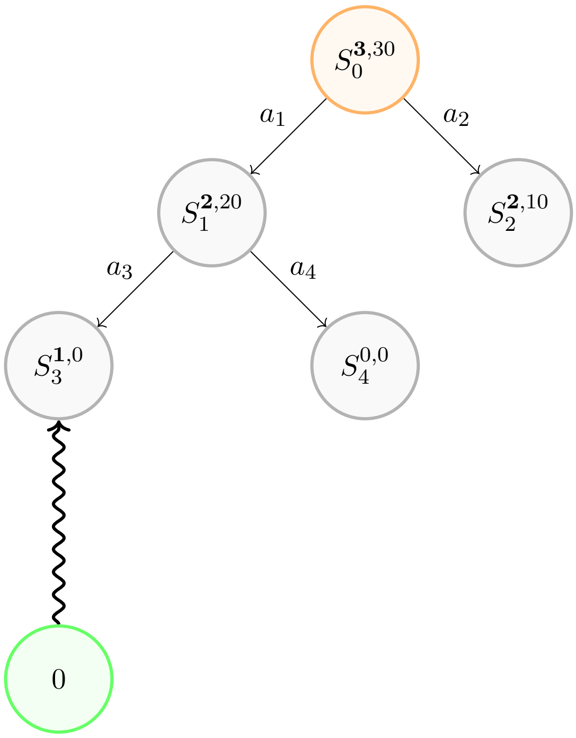


Figure 2.11: Simulation and Backpropagation - I3

This is the fourth iteration $I4$ represented on Figure 2.12:

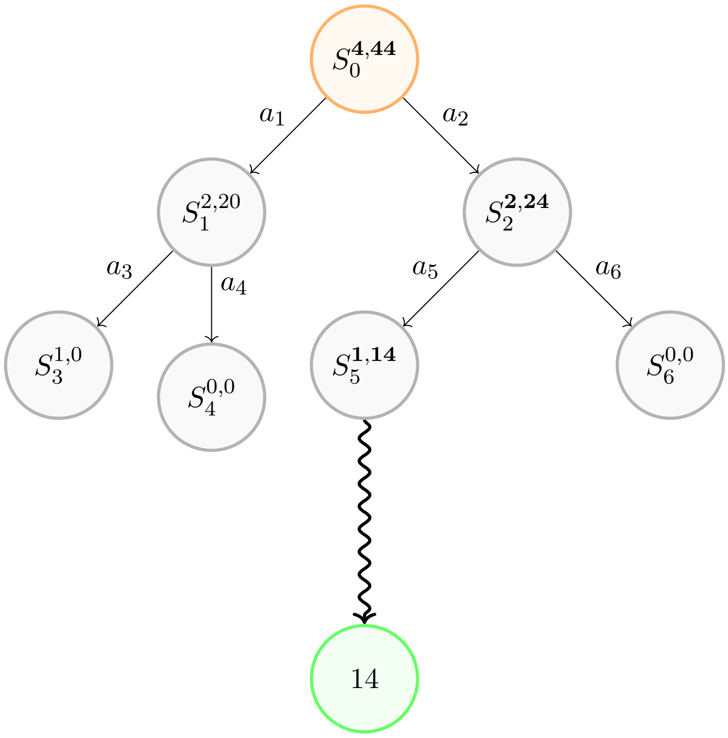


FIGURE 2.12: Selection - Simulation - Backpropagation - I4

The MCTS algorithm can either be stopped because you are running out of time or because you have no more available actions. For instance, if we were to stop at this stage of the algorithm, the best action to undertake is a_2 because it has the higher average value: $\bar{V_1} = \frac{20}{2} \leq \bar{V_2} = \frac{24}{2}$.

2.3.3 The different parameters in the MCTS

As outlined in the previous example, node's selection is crucial in the MCTS process and can significantly influence the performance of the algorithm. The selection function traditionnaly used is the Upper Confidence Bound 1 (UCB). However, there are a lot of different MCTS' selection functions as mentionned in this survey [43]. Every selection function, is based on the upper confidence bound principle, which balances the dual aspect of exploration and exploitation in the tree search.

The UCB and is variants, the UCB1-Tuned are defined as follow:

$$UCB = \overline{X}_i + C_p\sqrt{\frac{2\ln N}{n_i}} \tag{2.3}$$

$$UCB\text{-Tuned} = \overline{X}_i + \sqrt{\frac{\ln N}{n_i}\min\left(\frac{1}{4}, \mathrm{Var}(X_i) + \sqrt{\frac{2\ln N}{n_i}}\right)} \tag{2.4}$$

Where:

- $\overline{X}_i$: Average reward of node i.
- N: Total number of visits to the root node.
- n_i: Number of visits to node i.
- C_p: Exploration parameter
- $\mathrm{Var}(X_i)$: Variance of the rewards at node i, representing the variability of the rewards.

The UCB balances its exploration with the coefficient C_p, empirically $C_p = \sqrt{2}$. The term $C_p\sqrt{\frac{2\ln N}{n_i}}$ adds a confidence interval to the average reward, which encourages exploring less-visited nodes when $C_p > 0$. When $C_p = 0$, the tree search explores less but exploits more of the known part that seems promising for the problem in the tree. The UCB1-Tuned balances its exploration with $\min\left(\frac{1}{4}, \mathrm{Var}(X_i) + \sqrt{\frac{2\ln N}{n_i}}\right)$, making the UCB1-Tuned more adaptable to environments with varying reward distributions. The C_p coefficient can also be considered in the UCB1-Tuned's formula. Hence in stochastic environments the UCB1-Tuned is more likely to have a better overall performance.

Other selection policies, such as the Beta policy or Single Player MCTS [43], also play significant roles in various applications of the Monte Carlo Tree Search. However, these policies will not be the focus of this study due to their probabilistic nature, which does not align well with our specific problem context.

2.3.4 Parallelisation

In computer science, parallelisation is a technique that divides a number of tasks into sub-tasks that can be both independently and simultaneously run on mutiple cores of a computer. Due to the nature of the MCTS and its four phases, this algorithm is a good candidate for parallelisation.

For instance, after selecting a node to explore, rather than conducting a single simulation based on the one simulation policy, you can either run simulations using multiple different simulation policies and select the best outcome, or perform multiple simulations using the same policy (if it is stochastic). Then, going back to the fourth iteration of our example in Figure 2.12, if we parallelise simulations on three cores then instead of having $\mathcal{R}(S_5^{0,0}) = 14$ you have a list of simulation results $\mathcal{R}(S_5^{0,0}) = (\mathcal{R}_1(S_5^{0,0}), \mathcal{R}_2(S_5^{0,0}), \mathcal{R}_3(S_5^{0,0})) = (13, 14, 25)$ and one decision policy could be to pick the maximum of this simulation, hence $\max(\mathcal{R}(S_5^{0,0})) = \mathcal{R}_3(S_5^{0,0}) = 25$.

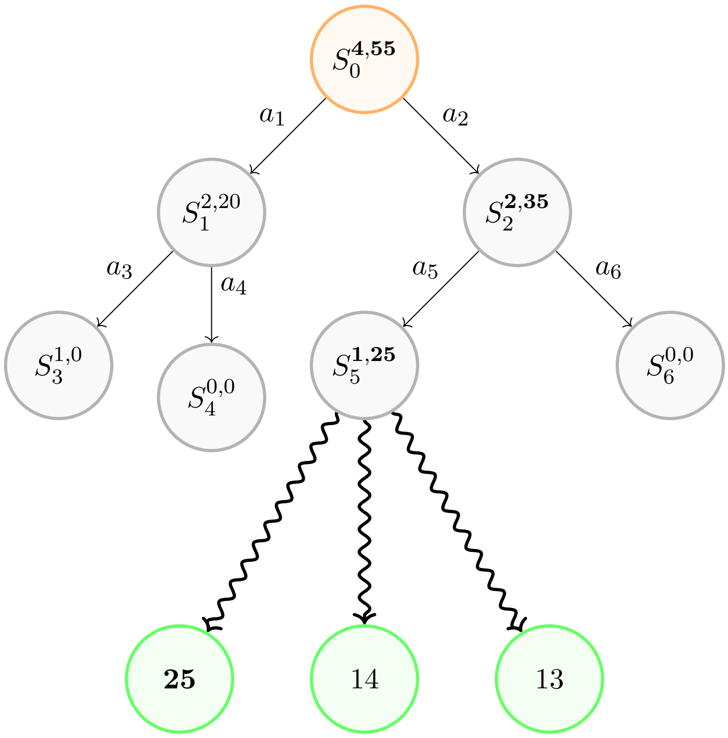


FIGURE 2.13: Example of parrelisation- I4

Multiple parallelisation can be applied in the MCTS. For instance, the multi-tree MCTS aims to build parallelised tree from the root node or the leaf parralelisation where multiple simulations are executed at the same time to get better estimates of the node's value (what is done on Figure 2.13). However, too many modifications of the MCTS can be unproductive and lead to worst results [43].

2.4 Litterature gaps

More than 500 teams registered for Kiwi.com TSP 2.0 challenge, and only 100 teams developed algorithms that were robust enough to go to the second phase of the challenge. The literature on the methods used by the participants is relatively sparse compared to the number of competitors. On the Kiwi.com website, the best instances are showcased. The winners explained their approach during the award ceremony [**?**], they implemented a Breadth-first search (BFS) algorithm in C++. Other participants employed well-known heuristics such as modified Simulated Annealing, Genetic Algorithms and Reinforcement Learning hyper-heuristics. Two papers were published on this challenge, [4] and [**?**] where a Local Search and a Reinforcement Learning (RL) hyper-heuristics algorithms are implemented. The algorithms used by the known participants to solve this challenge are summarised on Table 2.1.

Table 2.1: Kiwi TSP 2.0 - Chosen algorithm of the state of the art solutions

References	Reinforcement Learning	Local search	BFS	SA
Paper 1 [4]	x			
Paper 2 [**?**]		x		
Kiwi's official winner			x	
Other participants	x	x	x	x

Furthermore, Table 2.2 summarises the state of the art solutions.

These points motivate our selection of the Monte Carlo Tree Search as a suitable approach because it has never been implemented for this challenge.

TABLE 2.2: Kiwi TSP 2.0 - State of the art solution

Instance	Kiwi's	Local Search	Reinforcement learning	Best known
I_1	1396	1396	1396	1396
I_2	1498	1498	1498	1498
I_3	7672	7672	7672	7672
I_4	14024	14045	13952	13952
I_5	698	837	690	690
I_6	2159	3021	2610	2159
I_7	31681	32354	30937	30937
I_8	4052	4041	4081	4041
I_9	76372	82242	75604	75604
I_{10}	21667	87462	58304	21667
I_{11}	44153	49453	59361	44153
I_{12}	65447	70082	86074	65447
I_{13}	97859	-	166543	97859
I_{14}	118811	-	198787	118811

Chapter 3

Problem Description

3.1 Overview

Kiwi's traveler wants to travel in N different areas in N days, let's denote A the set of areas the traveler wants to visit:

$$A = \{A_1, A_2, \ldots A_N\}$$

where each A_j is a set of airports in area j:

$$A_j = \{a_{j,1}, a_{j,2}, \ldots, a_{j,k_j}\}$$

where a_{j,k_j} being airports in area j and k_j is the number of airports in area j.

The traveler has to visit one area per day. He has to leave this area to visit a new area by flying from the airport he flew in. He leaves from a known starting airport and has to do his journey and come back to the starting area, not necessarly the starting airport. There are flight connections between different airports, with different prices depending on the day of the travel: we can write c_{ij}^d the cost to travel from $city_i$ to $city_j$ on day d. We do not necessarly have $c_{ij}^d = c_{ji}^d$ neither $c_{ij}^{d_1} = c_{ij}^{d_2}$ if $d_1 \neq d_2$. The problem can hence be characterised as an generalised, assymetric and time dependant TSP - as discussed in Section 2.2.

The aim of the problem is to find the cheapest route for the traveler's journey.

The problem itself had not been mathematically defined in previous research, and we found it particularly valuable in our study to rigorously formulate the problem mathematically, as it provided a clear framework to analyse and understand its complexities.

We can then formulate the problem as follow:

- $\mathcal{A} = \{1, 2, \ldots, N\}$: Set of areas.
- $A_j = \{a_{j,1}, a_{j,2}, \ldots, a_{j,k_j}\}$: Set of airports in area $j \in \mathcal{A}$.
- $\mathcal{D} = \{1, 2, \ldots, N\}$: Set of days.
- $U_d \subseteq \mathcal{A}$: Set of areas that have not been visited by the end of day d.

Parameters

- c_{ij}^d: Cost to travel from airport i to airport j on day $d \in \mathcal{D}$.

Variables

- x_{ij}^d: Binary variable which is 1 if the traveler flies from airport i to airport j on day d, and 0 otherwise.
- v_j^d: Binary variable which is 1 if area j is visited on day d, and 0 otherwise.

Constraints

1. Starting and Ending Constraints:

- The traveler starts at the known starting airport S_0.
- The traveler must return to an airport in the starting area on the final day N.

2. Flow Constraints:

- The traveler must leave each area and arrive at the next area on consecutive days, the next area has not been visited yet.
- Ensure that the traveler can only fly into and out of the same airport within an area.

- Ensure each area is visited exactly once.
- Update the unvisited list as areas are visited.

Objective Function

The goal is to minimise the journey's total travel cost:

$$\min \left(\sum_{d=2}^{N-1} \sum_{i \in \bigcup_{k=2}^{N-1} A_k} \sum_{j \in \bigcup_{k=3}^{N} A_k} c_{ij}^d x_{ij}^d + \sum_{j \in A_1} c_{S_0,j}^1 x_{S_0,j}^1 + \sum_{i \in A_N} \sum_{j \in A_1} c_{ij}^N x_{ij}^N \right)$$

Constraints

- Starting at the known starting airport S_0 at take an existing flight connection:

$$\sum_{j \in A_1} x_{S_0,j}^1 = 1$$

$$\forall d \in \mathcal{D}, c_{S_0,j}^d \in \mathbb{R}^{+*}$$

- Visit exactly one airport in each area each day:

$$\sum_{i \in A_d} \sum_{j \in A_{d+1}} x_{ij}^d = 1 \quad \forall d \in \{1, 2, \ldots, N-1\}$$

- Ensure the traveler leaves from the same airport they arrived at the previous day:

$$\sum_{k \in A_d} x_{ik}^d = \sum_{k \in A_{d-1}} x_{ki}^{d-1} \quad \forall i \in \bigcup_{j=1}^{N} A_j, \forall d \in \{2, 3, \ldots, N\}$$

- Return to an airport in the starting area on the final day with an existing flight connection:

$$\sum_{i \in A_N} \sum_{j \in A_1} x_{ij}^N = 1$$

$$\forall (i,j) \in A_N \times A_1, c_{i,j}^N \in \mathbb{R}^{+*}$$

- Ensure each area is visited exactly once:

$$\sum_{d \in \mathcal{D}} v_j^d = 1 \quad \forall j \in \mathcal{A}$$

- Update the unvisited list:

$$v_j^d = 1 \implies j \notin U_d \quad \forall j \in \mathcal{A}, \forall d \in \mathcal{D}$$

- Ensure a flight on day d between i and j exists only if the cost exists and j is in the unvisited areas on day d:

$$x_{ij}^d \leq c_{ij}^d \cdot v_j^d \quad \forall i, j \in (\bigcup_{j=1}^{N} A_j)^2, \forall d \in \mathcal{D}$$

$$x_{ij}^d \leq v_j^d \quad \forall j \in \bigcup_{j=1}^{N} A_j, \forall d \in \mathcal{D}$$

- Binary variable constraints:

$$x_{ij}^d \in \{0, 1\} \quad \forall (i, j) \in (\bigcup_{j=1}^{N} A_j)^2, \forall d \in \mathcal{D}$$

$$v_j^d \in \{0, 1\} \quad \forall j \in \mathcal{A}, \forall d \in \mathcal{D}$$

3.2 Instances

3.2.1 Description

We are given a set of 14 Instances $I_n = \{I_1, I_2, ..., I_{13}, I_{14}\}$ that we have to solve. Every instances has the same overall structure.

For example, the first few lines of I_4 are:

13 GDN
first
WRO DL1
second
BZG KJ1
third
BXP LB1

That means that the Traveller will visit 13 different areas, starting at airport GDN, that belongs to the starting area. Then we are given the list of airports that are in every zone. For example, the second zone is named second and has two airports: WRO and DL1.

After all the information regarding the areas and the airports we have the flight connections informations. In Table 3.1, few flights are displayed from I_6 for illustrative purposes.

TABLE 3.1: Flight connections sample I6

Departure from	Arrival	Day	Cost
KKE	BIL	1	19
UAX	NKE	73	16
UXA	BCT	0	141
UXA	DBD	0	112
UXA	DBD	0	128
UXA	DBD	0	110

For every instance I_i, we know what connections exist between two airports for a specific day and the associated cost. There might be in some instances flights connections at day 0, this means these connections exist for every day of the journey at the same price. Furthermore, we could have the same flight connections at a specific day but with different prices. Furthermore, we have to consider solely the more relevant connections i.e. the flight connection with the lowest fare, on 3.1 we only consider the flight from UXA to DDB with the associated cost of 110.

3.2.2 General formulation

We decided to formulate the problem mathematically because it was not done in the existing papers, and we found it useful to clearly understand the problem's instances and their characteristics.

An instance I_i can be mathematically defined as follows:

$$I_i = (N_i, S_{i0}, A_i, F_i)$$

where:

- **Number of Areas** N_i:

  $$N_i \in \mathbb{N}$$

  The total number of distinct areas in instance I_i.

- **Starting Airport** S_{i0}:

  $$S_{i0} \in \text{Airports}$$

  The starting airport of the traveller.

- **Airports in Each Area**:

  $$A_i = \{A_{i,1}, A_{i,2}, \ldots A_{i,N_i}\}$$

  where each $A_{i,j}$ is a set of airports in area j for instance i:

  $$A_{i,j} = \{a_{i,j,1}, a_{i,j,2}, \ldots, a_{i,j,k_j}\}$$

  with a_{i,j,k_j} being airports in area j and k_j is the number of airports in area j.

- **Flight Connections**:

  $$F_i = \{F_{i,0}, F_{i,1}, F_{i,2}, \ldots, F_{i,N_i}\}$$

where each flight matrix $F_{i,k}$ represents the flight information of instance i on day k:

$$F_{i,k} = \begin{pmatrix} a^d_{i,k,1} & a^a_{i,k,1} & f_{i,k,1} \\ a^d_{i,k,2} & a^a_{i,k,2} & f_{i,k,2} \\ \vdots & \vdots & \vdots \\ a^d_{i,k,l_{k,i}} & a^a_{i,k,l_{k,i}} & f_{i,k,l_{k,i}} \end{pmatrix}$$

- **Columns**:
  - Departure Airport: $a^d_{i,k,j}$ (Departure airport for the j-th flight on day k)
  - Arrival Airport: $a^a_{i,k,j}$ (Arrival airport for the j-th flight on day k)
  - Cost: $f_{i,k,j}$ (Cost of the j-th flight on day k), where $j \in [1, l_{k,i}]$
- **Rows**: Each row corresponds to a specific flight on day k. The number of rows $l_{k,i}$ depends on the number of flights available on that day.

3.2.3 Kiwi's rules

When solving all the instances, Kiwi's defined time limits constraints based on the nature of the instance. We can summarise these constraints in the Table above:

Table 3.2: Time limits based on the number of areas and airports

Instance	nb areas	Nb Airports	Time limit (s)
Small	≤ 20	< 50	3
Medium	≤ 100	< 200	5
Large	> 100		15

All the useful information about the instances such as the starting airport, the associated area, the range of airports per area, the number of airports and the time limit constraints are defined in Table 3.3.

Table 3.3: Instances and their respective parameters

Instances	Starting Area - Airport	N° areas	Min - Max airport per area	N° Airports	Time Limit (s)
I1	Zona_0 - AB0	10	1 - 1	10	3
I2	Area_0 - EBJ	10	1 - 2	15	3
I3	ninth - GDN	13	1 - 6	38	3
I4	Poland - GDN	40	1 - 5	99	5
I5	zone0 - RCF	46	3 - 3	138	5
I6	zone0 - VHK	96	2 - 2	192	5
I7	abfuidmorz - AHG	150	1 - 6	300	15
I8	atrdruwkbz - AEW	200	1 - 4	300	15
I9	fcjsqtmccq - GVT	250	1 - 1	250	15
I10	eqlfrvhlwu - ECB	300	1 - 1	300	15
I11	pbggaefrjv - LIJ	150	1 - 4	200	15
I12	unnwaxhnoq - PJE	200	1 - 4	250	15
I13	hpvkogdfpf - GKU	250	1 - 3	275	15
I14	jjewssxvsc - IXG	300	1 - 1	300	15

Chapter 4

Methodology

4.1 Monte Carlo Tree Search implementation

4.1.1 General flow

Based on the discussion in Chapter 2, the flow of the Monte Carlo Tree Search algorithm is summarised in Figure 4.1:

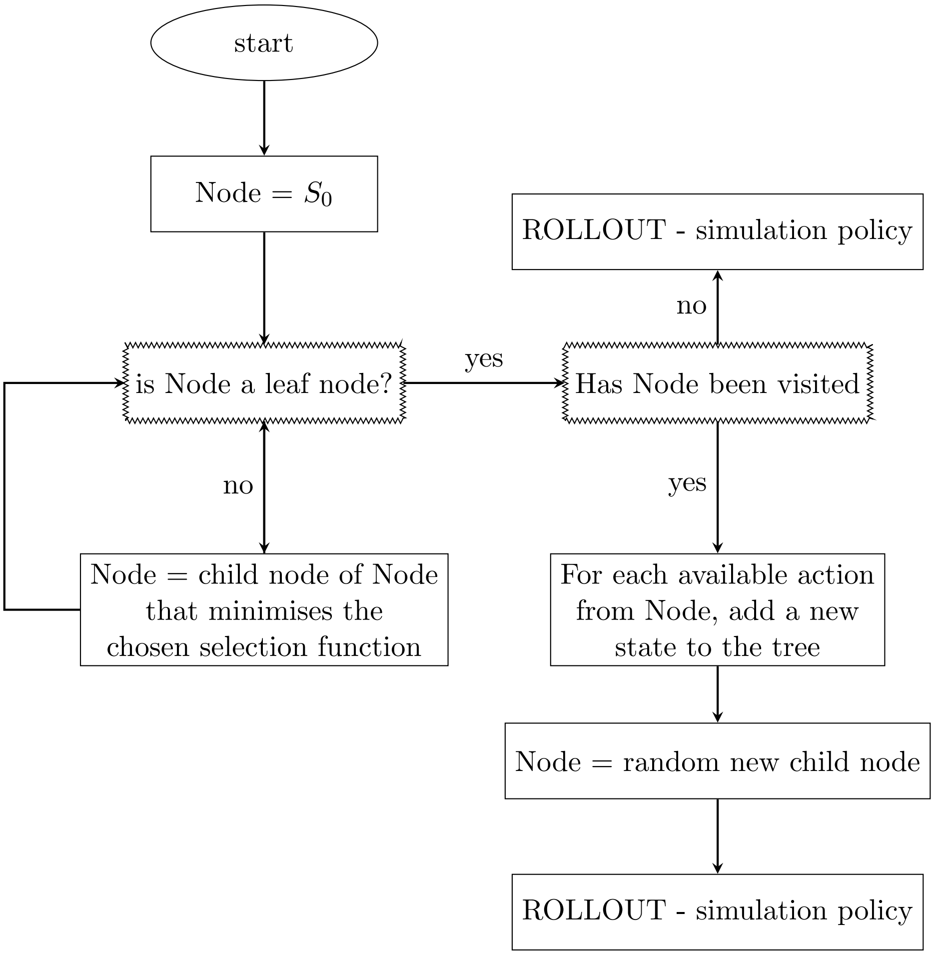


FIGURE 4.1: Flow MCTS

For every iteration of this algorithm, there are four different phases:

1. **Selection:** Starting from the root node (the starting airport S_{i0} for I_i), select successive child nodes (airports that are in unvisited areas) until a leaf node (the airport in the initial area, not necessarily the starting airport) is reached. Use the chosen Selection function to evaluate which node is the most promising. In the illustrative example in Section 2.3.2, the UCB1 function was used for the

selection function. Furthermore, the problem's goal was to maximise the objective function, hence the nodes with the highest UCB1 value was selected. A contrario, in Kiwi's minimisation problem, nodes are evaluated based on the lowest value of the selection function.

2. **Expansion:** If the selected node is not a terminal node, expand the tree by adding all possible child nodes.

3. **Simulation:** From the newly added node, perform a simulation (based on the simulation policy) until a feasible terminal node is reached.

4. **Backpropagation:** Update the values of the nodes along the path from the newly added node to the root based on the result of the simulation.

$$\mathcal{B}(S_i^{n_i,t_i}) = S_i^{n_i+1,t_i+\mathcal{R}(S_i^{n_i,t_i})} \tag{4.1}$$

where $\mathcal{R}(S_i^{n_i,t_i})$ is the cost of the solution found after performing a simulation from node $S_i^{n_i,t_i}$.

4.1.1.1 Data Preprocessing

To implement our MCTS' solution, the first thing to create is a data_preprocessing class to prepare the given instance to the problem at hand. Kiwi's challenge is solved using Python 3.10 on VS Code 1.92.2. Our Python code is structured using object-oriented programming following CamelCase's convention [44]. This data_preprocessing class is represented on Figure 4.2. The input is an instance I_i, as defined in Chapter 3:

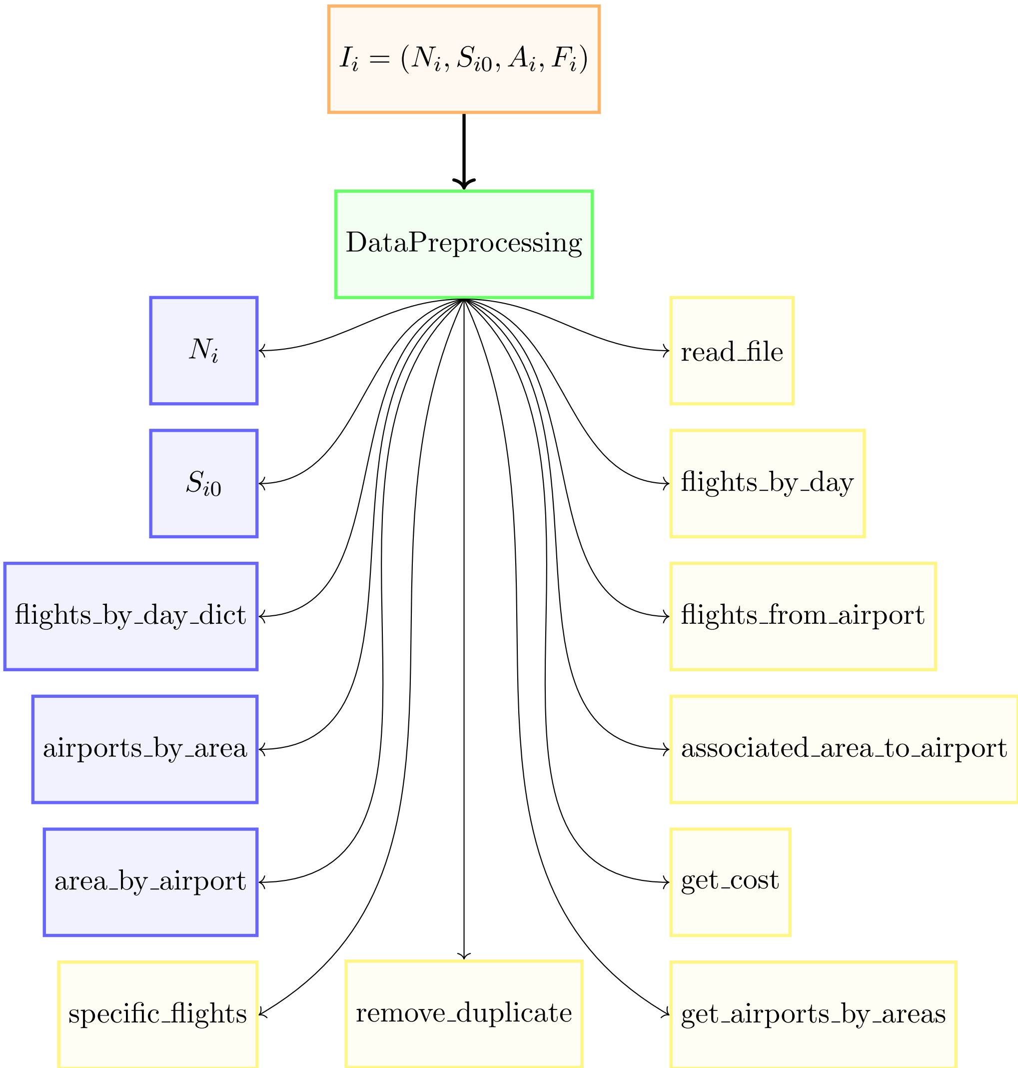


FIGURE 4.2: Explanation of the data preprocessing class

Different useful methods are implemented within the data_preprocessing class to compute and manage various attributes required for the problem at hand. These methods are designed to prepare and structure the data, making it easier to use in subsequent phases of the algorithm. For example, the remove_duplicate method ensures that only the cheapest flight connections are considered between two airports if multiple flight connections exist at different prices, on the same day. Other methods, such as flights_by_day_dict and get_airports_by_areas organise the data. The first method regroups all the flights by their respective days, creating a dictionary where each key represents a day and its corresponding value is a list of available flights. The second method regroups all the airports present in the different areas.

Finally, other methods, such as specific_flights, will be useful for developing the MCTS' algorithm. These give all the possible flight connections from a specific airport on a given day, taking into account the areas visited, so that all possible actions can be obtained from a node.

Given that Python is relatively slower, in terms of computation, compared to other programming languages, dictionnaries are used where possible. Dictionnaries allow for efficient data retrieval based on a key, with an average time complexity of $\mathcal{O}(1)$. This choice improves the performance of the data preprocessing step, enabling the algorithm to run more efficiently despite Python's inherent limitations.

4.1.1.2 Node

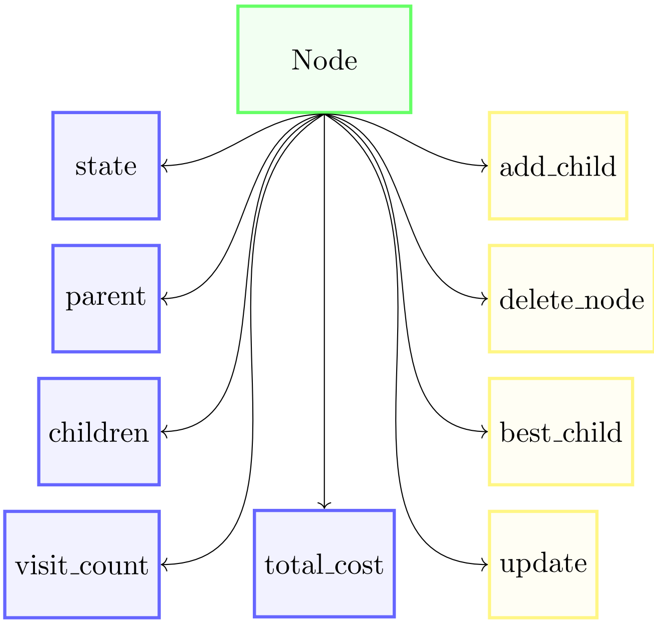


FIGURE 4.3: Explanation of the Node class

As mentionned earlier in Section 2.3.2, a Node structure is used in the algorithm, hence the implementation of a Node class. Each Node has a reference to a parent node (unless it is the root node) and may have one or more child nodes (unless it is a leaf node). These relationships form a tree structure where each node can expand into potential future states, guiding the search process. The visit_count tracks the number of times a node has been visited during the MCTS process. This is crucial for evaluating the node's importance and for calculating the score of the node with the selection function. The state is a dictionnary that contains the node's current information:

- current_airport: The airport where the traveler is at this node.
- current_day: The day of the trip at this node.
- remaining_zones: The zones that still need to be visited to complete the journey.
- visited_zones: The zones that have already been visited to ensure that all zones are visited exactly once during the trip.
- total_cost: It represents the accumulated cost of the current solution path leading to this node.

Additionally, to manage the expansion of child nodes, the add_child method is defined. This method generates new nodes based on the possible actions available from the current node. These new nodes represent the next possible states in the traveler's journey, allowing the search tree to expand and explore different travel routes. Finally, the delete_node method can be used to delete a node from the list of its parent's children.

4.2 The different policies

In the previous section, we outlined the general flow of the MCTS algorithm, focusing on two cores classes, DataPreprocessing and Node, that are central in MCTS' implementation.

In Section 2.3.3, we explored the various selection policies that guide the decision-making process within the MCTS Although there is a limited litterature review, we decided to parameterise not only the selection policy but also the simulation and expansion policies.

4.2.1 Simulation policies

When a simulation is runned from a given node in the tree, the goal is to find a feasible combinaison of airports that could be a solution to our problem. From this node chosen for simulation, we obtain the current state (defined in section 4.1.1.2). The remaining actions must then be chosen to find a simulated solution based on the simulation policy.

Below is the definition of the three distinct simulation policies:

- Random policy: This policy selects a random action from the set of available actions, introducing variability and exploration in the simulation process.
- Greedy policy: This policy selects the action that corresponds to the cheapest available flight connection, thus prioritising cost minimisation at each step.
- Tolerance policy (with coefficient c): This policy selects an action randomly from a subset of actions that are within a certain tolerance level of the minimum cost action. The tolerance level is defined by a coefficient c. The tolerance policy is defined as follows:
  - Identify the cheapest flight connection among the available actions c_{min}.

- Filter the actions to include only those with a cost less or equal than $c_{min}(1+c)$.
- Randomly select an action from this filtered set.

4.2.2 Expansion policies

When expanding a node, it's theoretically possible to expand all available child nodes i.e. add to the tree all the possible flight connections from this airport (that are in the available actions based on the visited areas). However, in practice, this can be computationally expensive and time-consuming, particularly in problems with a large number of possible actions. To address this, heuristic approaches often involve compromises that enhance the efficiency of the search process by selectively expanding certain nodes rather than all possible ones.

Firstly, we defined `number_of_children`, a parameter of our MCTS algorithm which regulates the maximum number of children that can be expanded from any given node. This limitation controls the size of the search tree, as expanding too many children for every selected node could make the algorithm computationally exhaustive.

In our implementation we defined two expansion policies:

- **Top-K Actions Policy**: This policy expands the nodes corresponding to the cheapest flight connections available. Specifically, it sorts all possible actions based on their associated costs and selects the top k actions with the lowest costs, where k is regulated by `number_of_children`. This approach ensures that only the most promising actions, in terms of cost efficiency, are considered during expansion. This policy narrows down the search space but can increase the chance to reach a leaf node.
- **Ratio Best-Random Policy**: This policy takes a more balanced approach by combining the selection of the best actions with a degree of randomness. First, it calculates the number of top actions to select based on a predefined ratio, $c \in [0, 1]$, which reflects the proportion of Top-K Actions within the allowed `number_of_children`. After selecting these best actions, the policy randomly selects $(1 - c) * number\_of\_children$ actions from the remaining pool to reach the desired number of children. This policy is designed to explore a broader range of possibilities while still prioritising cost-effective options.

4.2.3 Notations

After definining the different parameters of the MCTS, a MCTS function can be defined as follow:

$$\mathcal{MCTS} \quad : \quad S_p(C_p), E_p(c), R_p, N_c \quad \mapsto \quad \mathcal{MCTS}(S_p(C_p), E_p(c), R_p, N_c)$$

where:

- $S_p(C_p)$: Selection policy (UCB or UCB1-T) with exploration parameter C_p (defined in Section 2.3.3).
- $E_p(c)$: Expansion policy (Top-K ratio or best random) with proportion c (defined in Section 4.2.2).
- R_p: Rollout/simulation policy (random, tolerance, or greedy) (defined in Section 4.2.1).
- N_c: Maximum number of children added during node expansion.

4.2.4 Pseudo-code

In this section, the implementation of the algorithm in practice is explored by examining the different functions of our MCTS class. The search function of the MCTS is defined:

Algorithm 1 Search_Function

```
Initialise Root_Node with Initial_State
while Tree is not fully explored do
    Node ← Select(Root_Node)
    if Node is not fully expanded then
        Node ← Expand(Node)
    end if
    Cost ← Simulate(Node)
    Backpropagate(Node, Cost)
end while
return Best_Leaf_Node
```

The `Search` function represents the general flow of the algorithm as mentionned on Figure 4.1.

The `Select` function (Algorithm 2), which selects the node to visit, returns two arguments: a boolean and a node. The boolean indicates to the expansion function whether expansion is necessary (True means no expansion needed, False means expansion needed).

Algorithm 2 Select_Function

Input: $Node$
$Current \leftarrow Node$
while $Current.Children$ is not empty **do**
  if Current is not fully expanded **then**
    $UnvisitedChildren \leftarrow$ Children with $VisitCount = 0$
    if $UnvisitedChildren$ is not empty **then**
      $SelectedChild \leftarrow$ Randomly select from $UnvisitedChildren$
      return $True, SelectedChild$
    end if
  else
    $Current \leftarrow$ BestChild($Current$)
  end if
end while
if $Current.Children$ is empty **and** $Current.State["current\_day"] == N_{Areas}$ **then**
  return $False, Current$
else if $Current.Children$ is empty **and** $Current.State["current\_day"] <> N_{Areas}$ **then**
  return $False, Current$
else if $Current.State["current\_day"] == N_{Areas} + 1$ **then**
  return $True, Current$
end if

There are special cases to handle, when one approaches the final solution because one has to communicate the right information to the `Expand Node` function.

After simulating, the backpropagation function updates the node's attributes. The new node becomes the parent of this node, and so on until `Node` is `None`, i.e., all the information is backpropagated up to the root node.

Algorithm 3 Backpropagate_Function

```
while Node is not None do
    Node.Update(Cost)
    Node ← Node.Parent
end while
```

The transition function modifies the states of a node by updating the current airport, the visited zones, remaining zones, etc.

Algorithm 4 Transition_Function

```
New_State ← Copy of State
New_State.Current_Day ← State.Current_Day + 1
New_State.Current_Airport ← Action[0]
New_State.Total_Cost ← State.Total_Cost + Action[1]
Update(New_State.Path, New_State.Current_Airport)
Remove_Visited(New_State.Remaining_Zones, New_State.Current_Airport)
Add_Visited(New_State.Visited_Zones, New_State.Current_Airport)
return New_State
```

Finally, the Best Child function, defined in the Node class is based on the selection function UCB and UCB1_Tuned. They both, compute the score of the visited nodes and pick the one that minimises the selection function.

Algorithm 5 Best Child

```
Require: Selection_Function
Visited_Children ← Children with visitCount > 0
Choices_Weights ← [Selection_Function(child) for child in Visited_Children]
Best_Child_Node ← Child with minimum Choices_Weights
return Best_Child_Node
```

Chapter 5

Results and performance

5.1 Hypothesis

As mentionned in Section 1.2, the primary objective was to implement a new algorithm to find solutions without imposing time constraints. Only instances $(I_1, \ldots, I_8)$ are studied because they represent realistic scenarios.

Hence, simulations for every instances have been conducted, testing different combinations of parameters in what is called a grid search. Each combination of parameters was run 10 times to ensure the reliability and consistency of the results. One challenge, is that the computational budget is limited when using Python. Especially for the more complex instances, $(I_7 \ldots I_{14})$ where the time to find a solution for a given set of parameters is more than 20 minutes. It becomes practically impossible to perform for each instance, 10 simulations for every combination of parameters in the grid search. Hence, the size of the grid search for the more complex instances were reduced as shown in Table 5.1.

Table 5.1: Grid search

	$(I_1 \ldots I_6)$	$(I_7 \ldots I_8)$	$(I_9 \ldots I_{14})$
selection_policy	top_k, ratio_k	top_k, ratio_k	-
simulation_policy	random, greedy, tolerance	greedy	-
selection_policy	UCB, UCB1T	UCB, UCB1T	-
C_p	0, 1.4, 2.8	1.4	-
N_children	5, 10, 15	10	-
Ratio c	0, .3, .5, .8, 1	.5	-

5.2 Results analysis

5.2.1 Overview

After running the various simulations with the grid search parameters defined in Table 5.1, our results were compared with those of Kiwi and RL (Reinforcement Learning) [4] - the only two official publications about this challenge.

TABLE 5.2: Best results vs State of the art

Instance	Best known	Best found	Gap (%)	Mean	Std
I_1	1396	**1396**	0	0	0
I_2	1498	**1498**	0		
I_3	7672	**7672**	0		
I_4	13952	15101	8.24		520.8
I_5	690	-	-		-
I_6	2159	-	-		-
I_7	30937	-			
I_8	4052	**4037**	-0.52		

A solution was found for I_1, I_2, I_3, I_4, I_7 and I_8. The results shown in table 5.2 are the best found costs' solution within the grid search. The results of the simulations for I_1, I_2, I_3 are displayed in Section C and the detailed path-solution for $I_1, \ldots, I_8$ (except I_5, I_6) can be found in Section D.

5.2.2 Analysis

5.2.2.1 I_1, I_2, I_3 and I_4

For these instances, solutions were found and the various simulations were carried out successfully. Therefore, the influence of the parameters on the $\mathcal{MCTS}$ function and final solution was investigated. For I_3, the analysis focuses on the C_p parameter, the influence of the expansion ratio and finally, the study will investigate the overall correlation matrix.

Analysis on C_p

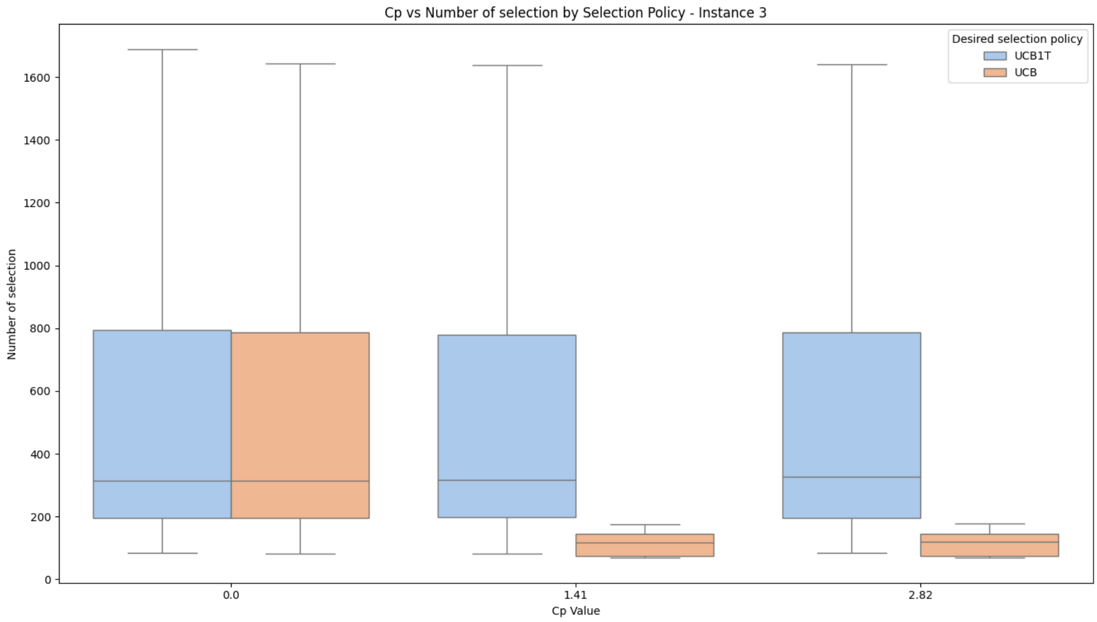


FIGURE 5.1: C_p vs Number of selection

In Figure 5.2, the box plots illustrate the relationship between the exploration constant C_p and the number of selection phases under the UCB and UCB1T selection policies:

- $C_p = 0$ **lead to the same performance:** When the $C_p = 0$, the selection policy of the UCB and the UCB1T are equal (cf equation 2.3 and 2.4).
- **Higher C_p values lead to faster convergence for UCB:** As C_p increases from 0.0 to 2.82, the median number of selection phases under the UCB policy decreases.

- **UCB1T encourages more exploration:** UCB1T consistently results in a higher number of selection phases compared to UCB, especially at higher C_p values. This is consistent with UCB1T's definition to promote broader exploration before converging.

Although a higher exploration parameter C_p may lead to faster convergence under the UCB selection policy, it often results in worse outcomes compared to the UCB1T algorithm, as shown in Figure 5.2. While UCB1T may require more time to converge, it

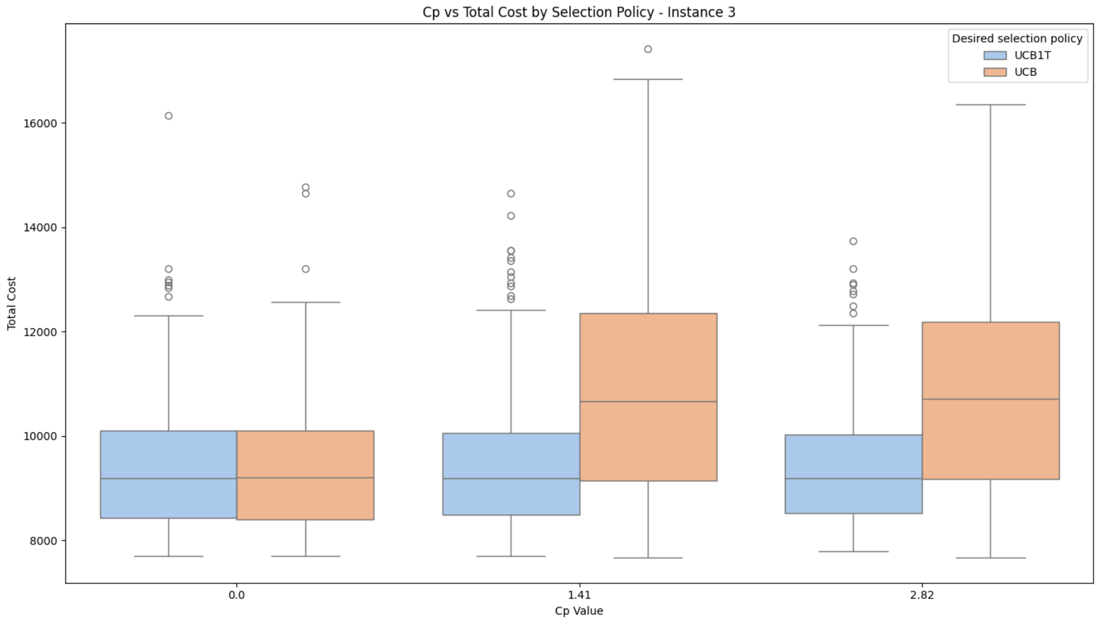


FIGURE 5.2: C_p vs Total cost

generally explores the search tree more effectively, leading to better overall performance. One can notice that C_p's correlation with the UCB1T selection policy for I_3 is low.

Analysis of Expansion ratio

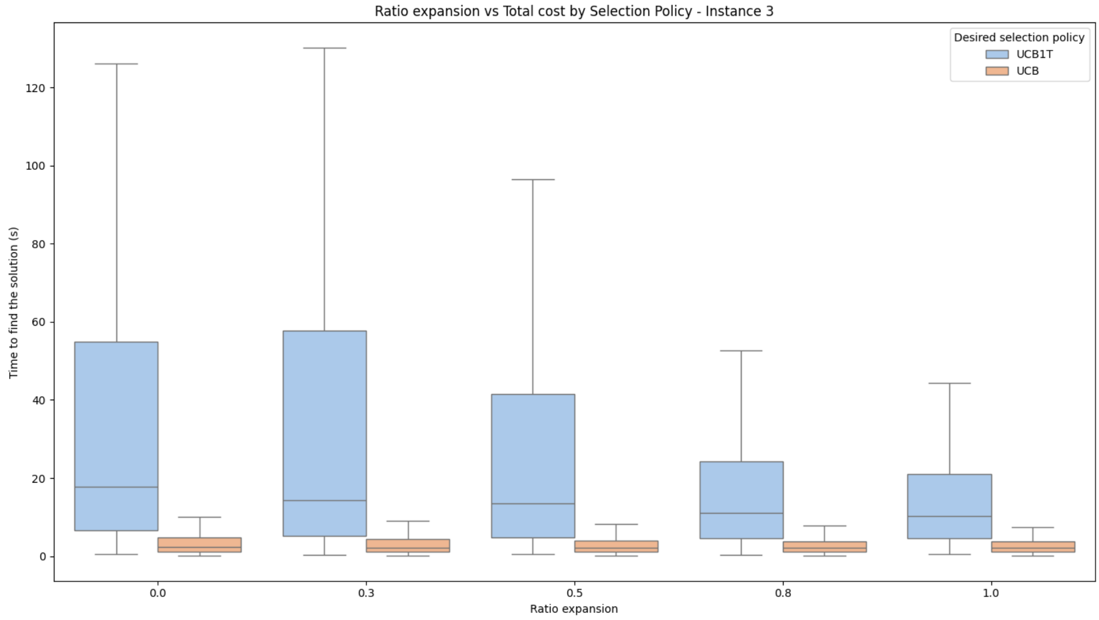


FIGURE 5.3: Ratio expansion vs Time to find the solution

The box plots show the relationship between ratio expansion (the proportion of expanded child nodes that has the cheapest flight connection over the chosen number of children) and the time to find a solution for the UCB and UCB1T policies:

- **UCB finds solution faster than UCB1T:** Across all ratio expansion values, the UCB policy consistently finds solutions more quickly than UCB1T. This suggests that UCB, being less aggressive in exploration, converges on solutions faster.
- **Higher ratios lead to a faster convergence:** For both policies, the time to find a solution generally decreases as the ratio expansion increases, indicating a more efficient search process when expanded nodes are less chosen randomly from the set of available actions. However, in more complex instances, it is crucial to have a ratio $r \in [0.3, 0.7]$ to escape potential leaf node.

Finally, the UCB policy is more correlated to the expansion ratio than the UCB1T as shown in Figure 5.4. UCB's overall performance is worst than UCB1T because it relies heavily on the exploitation compared to UCB1T that even if it converges slower gives better results.

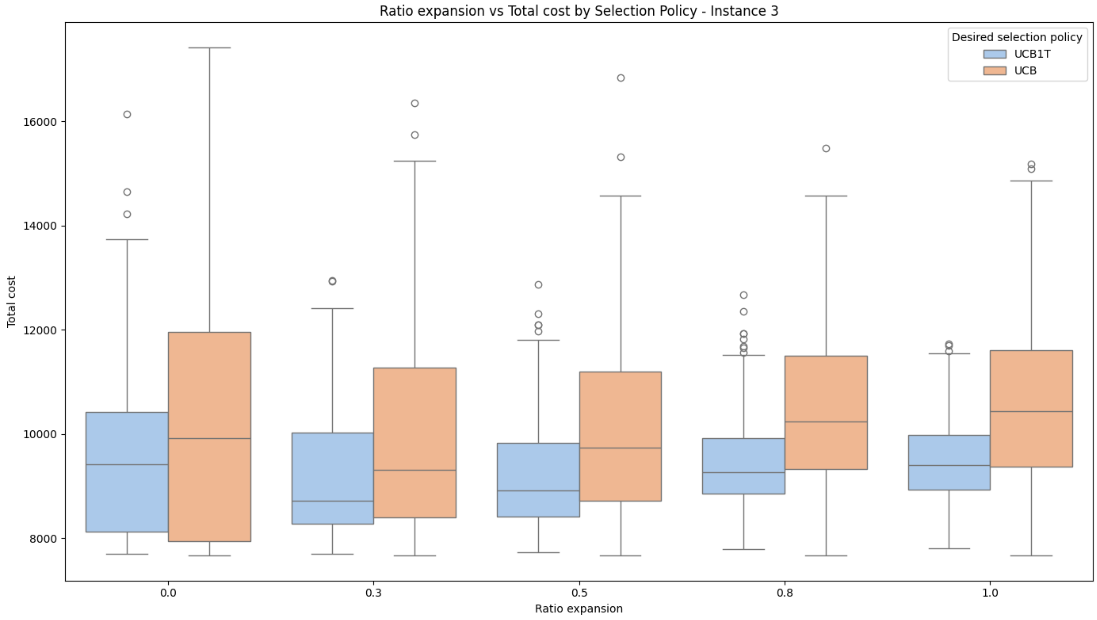


FIGURE 5.4: Expansion ratio vs Total cost

Analysis of simulations performances

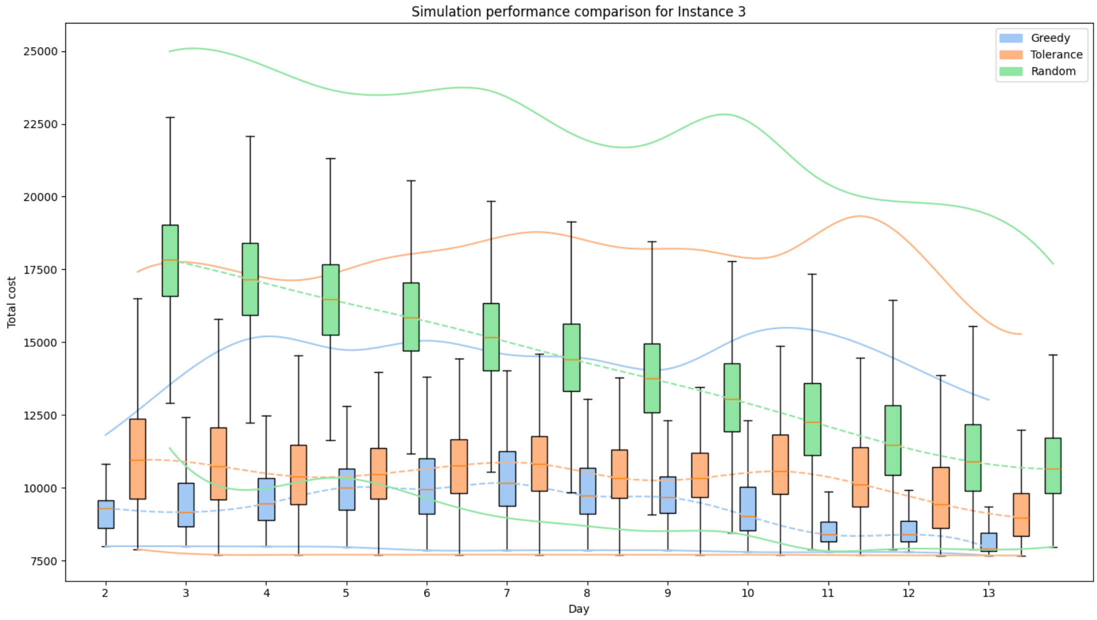


FIGURE 5.5: Simulation performance - Instance 3

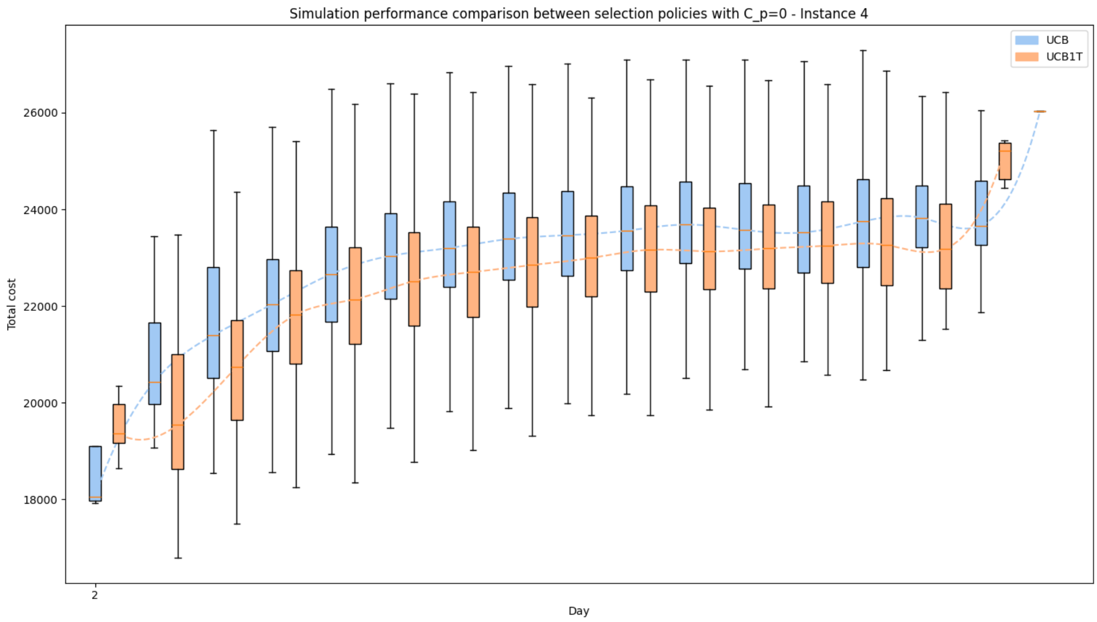


FIGURE 5.6: Simulation performance $C_p = 0$ - Instance 4

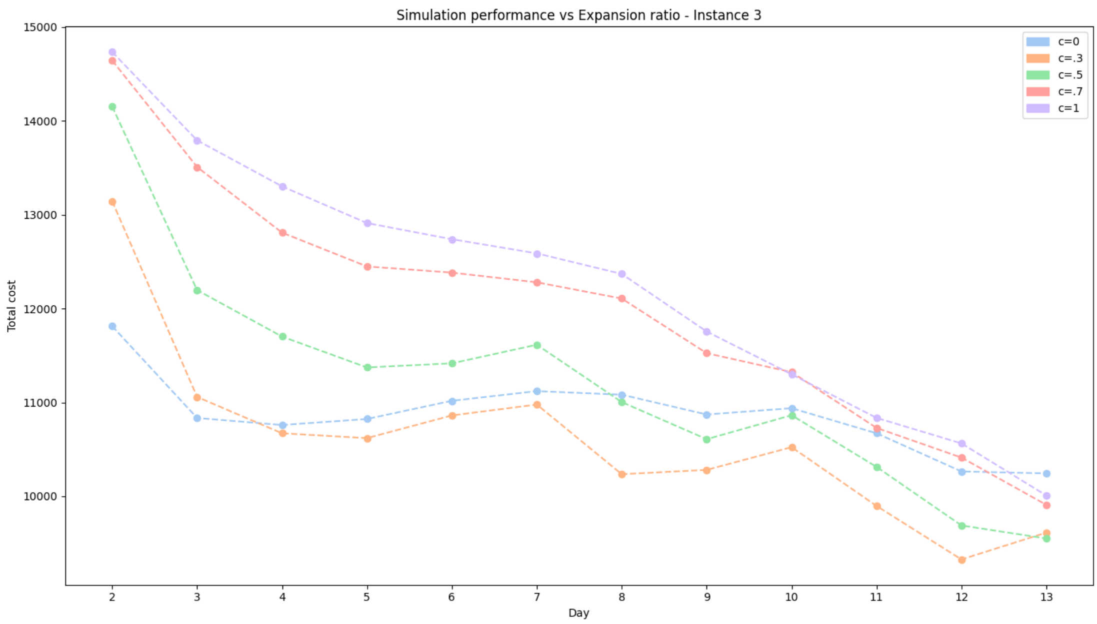


FIGURE 5.7: Simulation performance vs Expansion Ratio - Instance 3

5.2.3 Parrelisation

The parametrisation of this MCTS is not efficient for the considered instance, hence the search process do not converge towards the minimum found cost. These two distributions

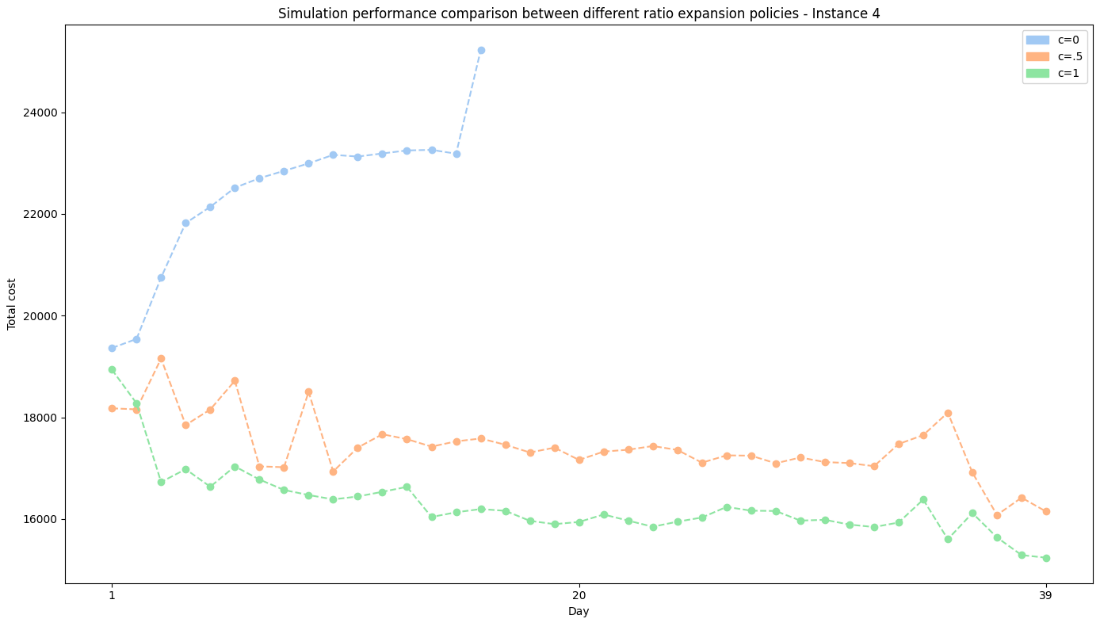


FIGURE 5.8: Simulation performance vs Expansion Ratio - Instance 4

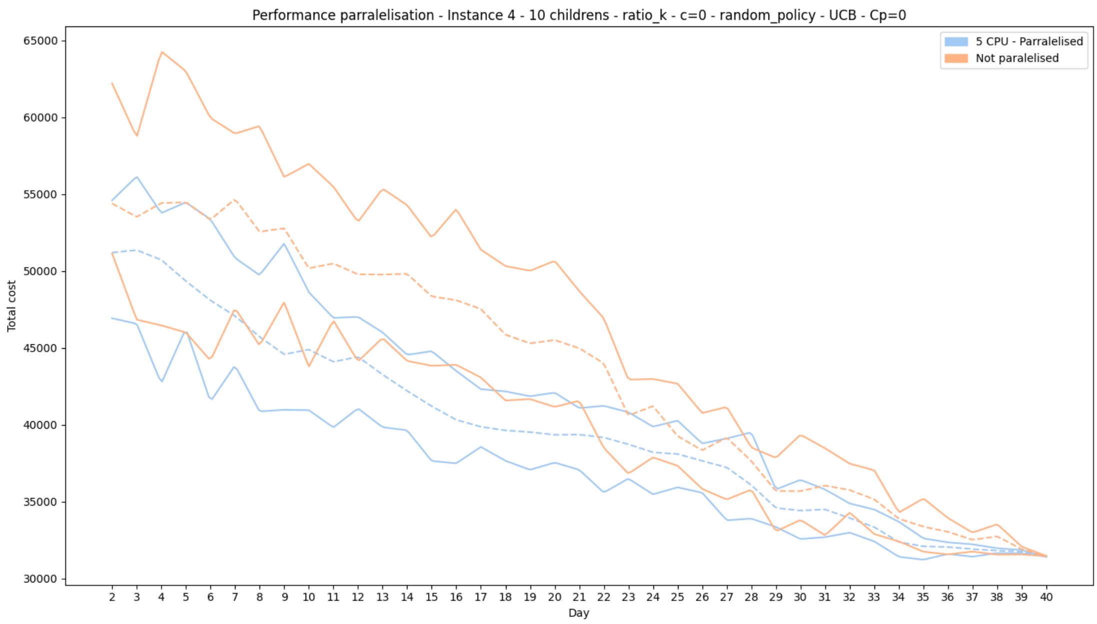


FIGURE 5.9: Performance Parrelisation vs no - Instance 4

have a similar behavior, having $C_p = 0$ indicates a similar decision-making process when using the UCB and UCB1T selection policy.

In Figure 5.14, the median distributions for the different scenarios have been plotted. One can observe that having a value c too close to 1, does not on average converge to

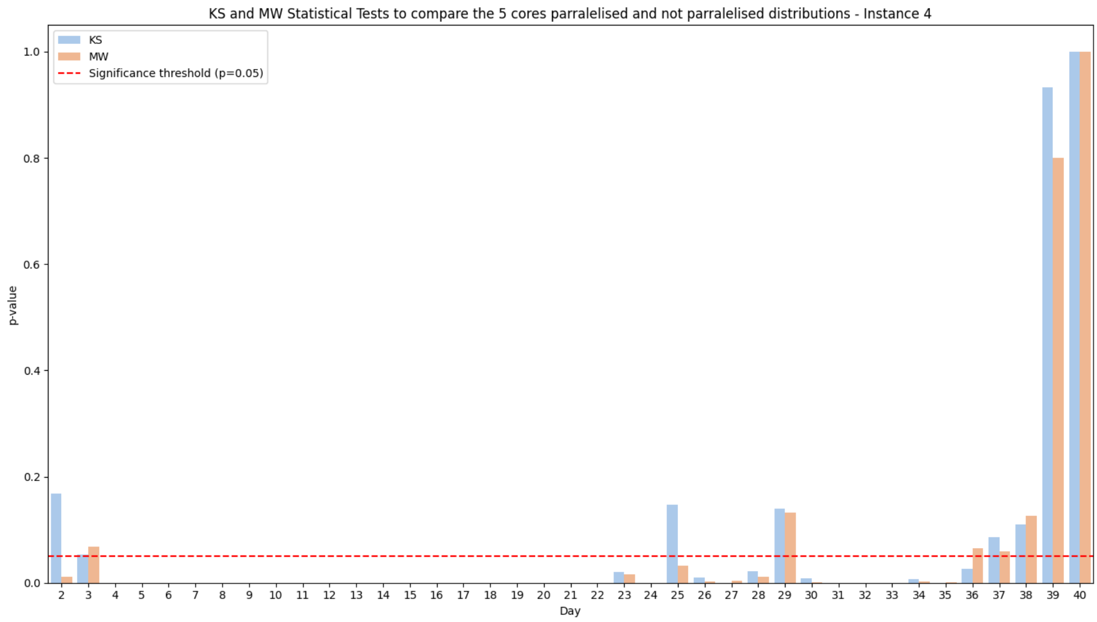


Figure 5.10: Stats test Performance Parrelisation vs no - Instance 4

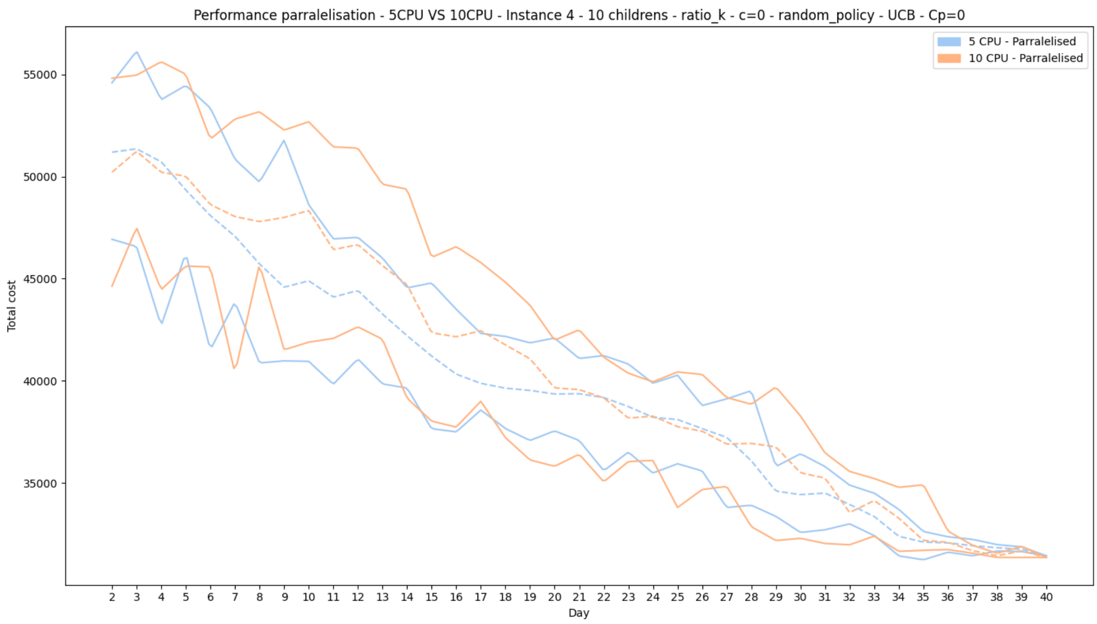


Figure 5.11: test Performance 5 and 10 Parrelisation vs no - Instance 4

this minimum-cost solution. A contrario, lower c values appears to guide the tree search more effectively during the first days of simulations, which is crucial to not overexpand the size of the tree, which can lead to an inefficient and time-consuming MCTS.

These conclusions can be drawn for small instances, however for I_4, we can clearly see

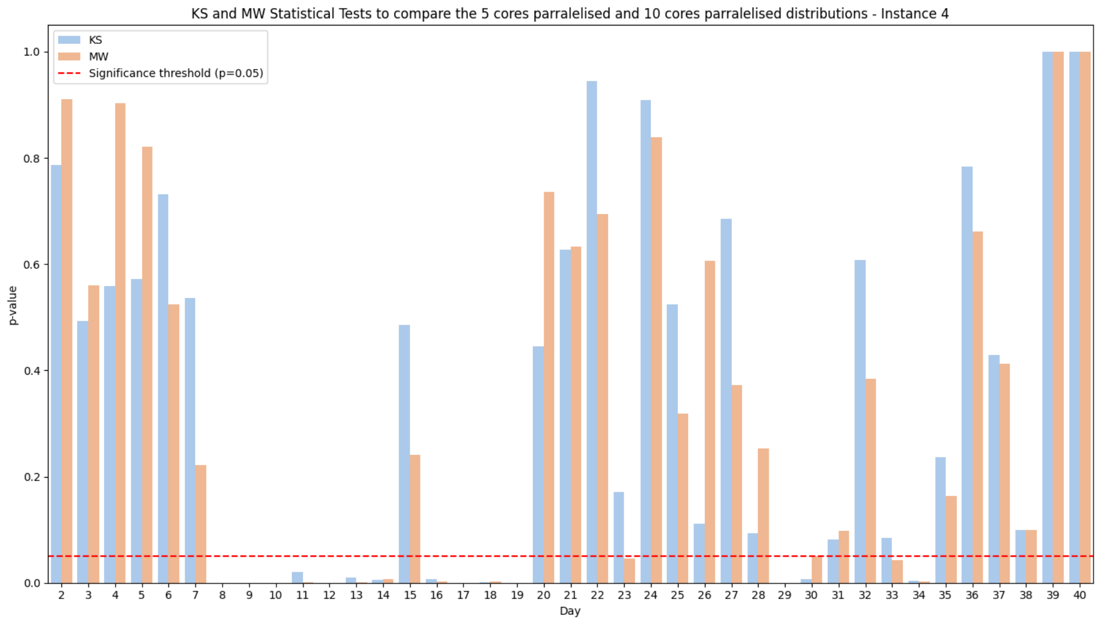


FIGURE 5.12: Stats test Performance 5 and 10 Parrelisation vs no - Instance 4

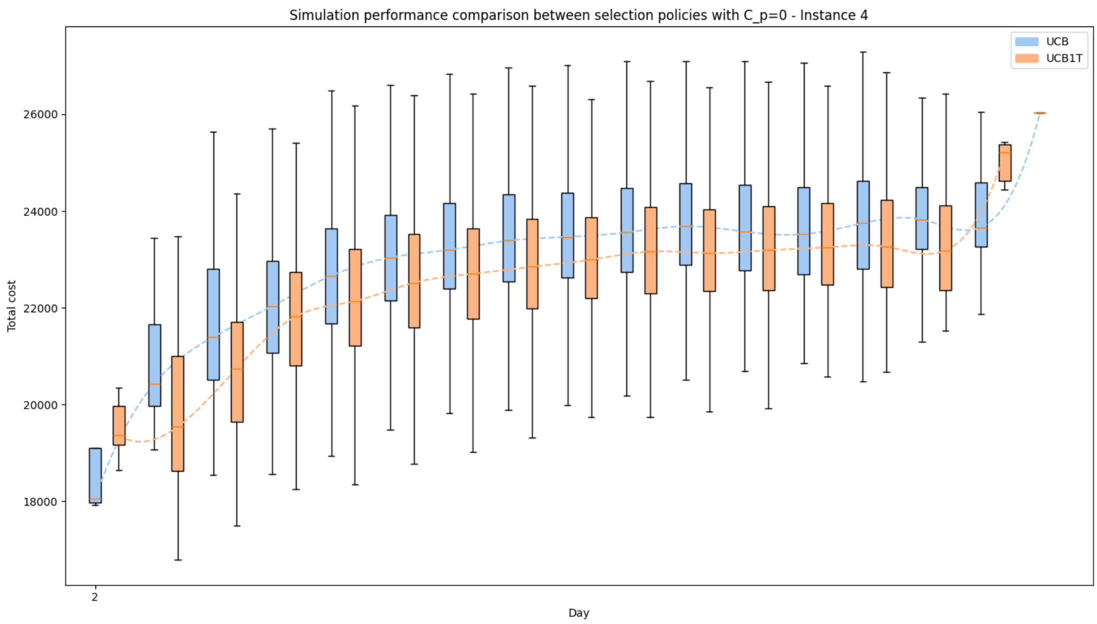


FIGURE 5.13: Simulation performance $C_p = 0$ - Instance 4

in Figure 5.15 that having $c = 0$ for a greedy selection policy is inefficient in this tree search because it diverges from the min-simulated cost. The tree search is therefore unable to find a solution after 10 minutes. Based on the median comparison, $c = 1$ is a more optimal parameter for guiding the tree search (for I_3).

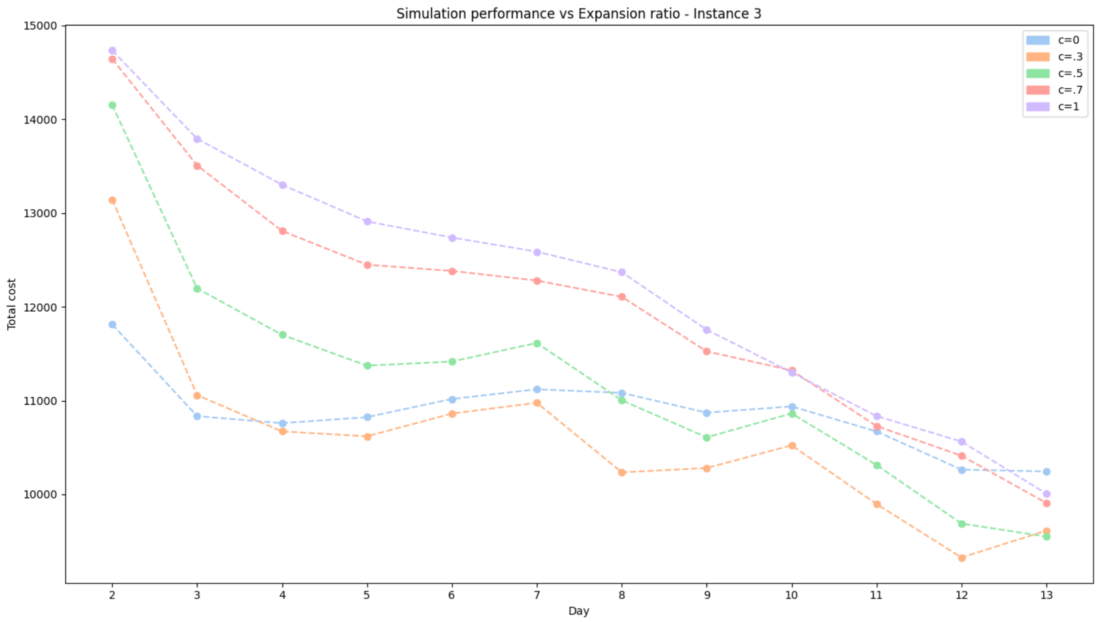


FIGURE 5.14: Simulation performance vs Expansion Ratio - Instance 3

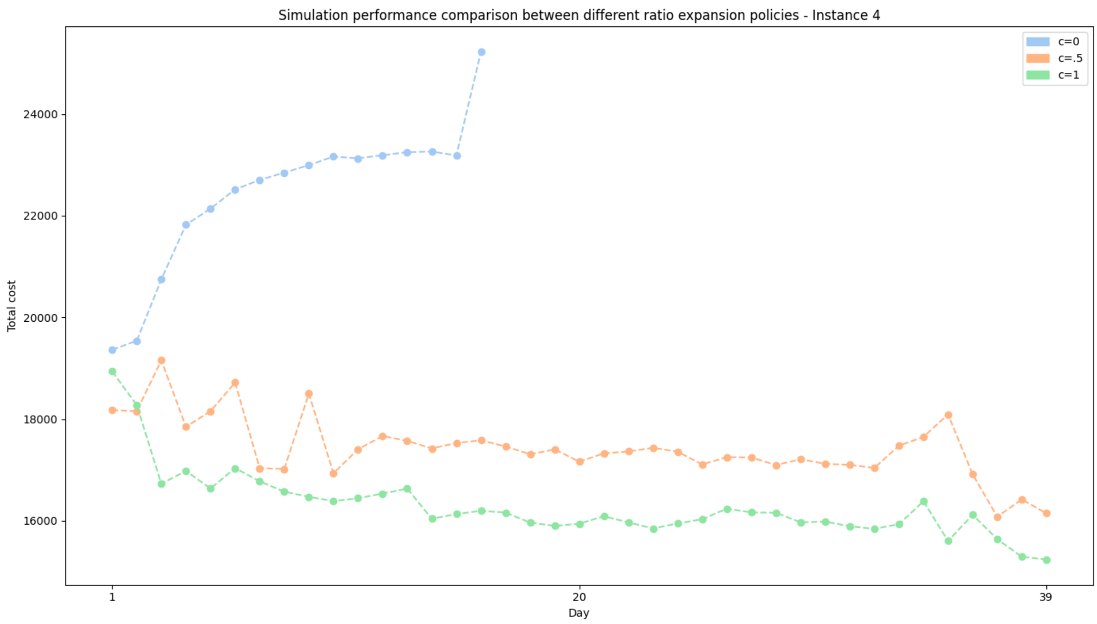


FIGURE 5.15: Simulation performance vs Expansion Ratio - Instance 4

Correlation

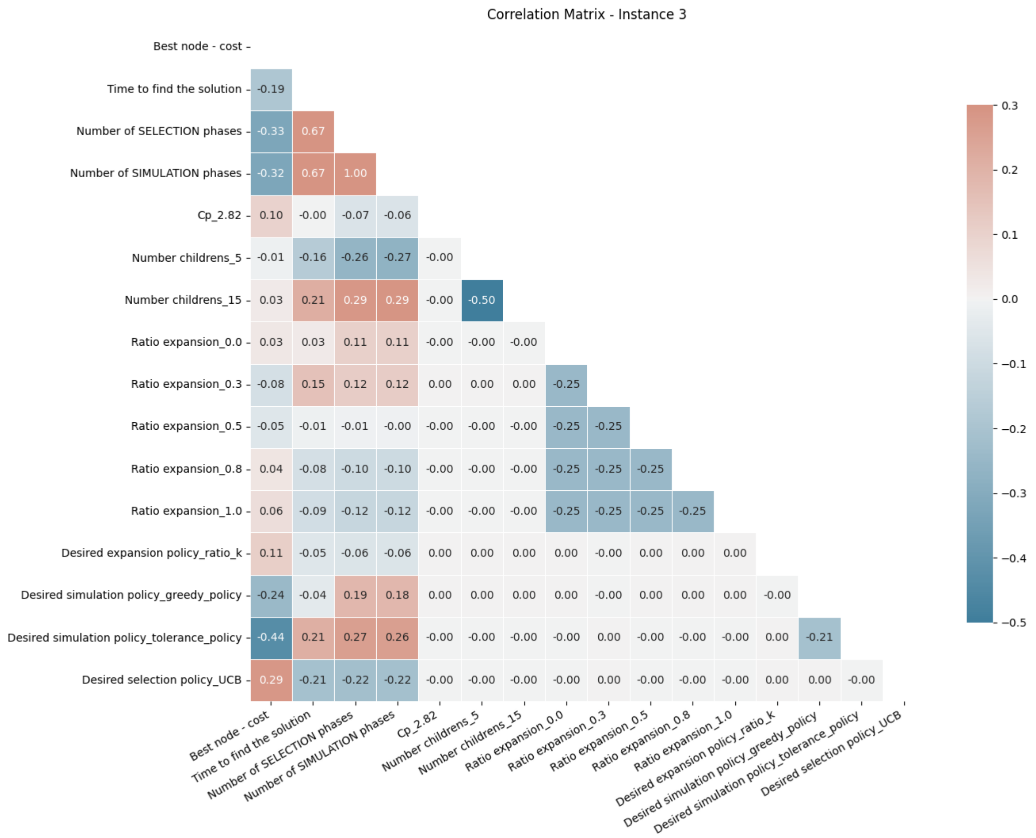


FIGURE 5.16: Correlation matrix - Instance 3

5.2.4 Parallelisation

As discussed in Section 2.3.4, parallelisation can be implemented to better estimate one selected node's value. In our implementation, for I_4, we parallelisation a $\mathcal{MCTS}(S_p(C_p = 0) = "UCB", E_p(c = 0) = "ratio\_k", R_p = "random", N_c = 10)$ on five cores. The set of parameters has been chosen to represent the behavior of parallelisation in a stochastic environment. The parralelisation has been implemented during the simulation process. Therefore, we chose the minimum outcome of the five simulations.

In Figure 5.17, the five cores parallelised's distribution better performs than the non-parralelised approach. It confirms that parallelisation guides the MCTS more effectively in the first days of the tree search.

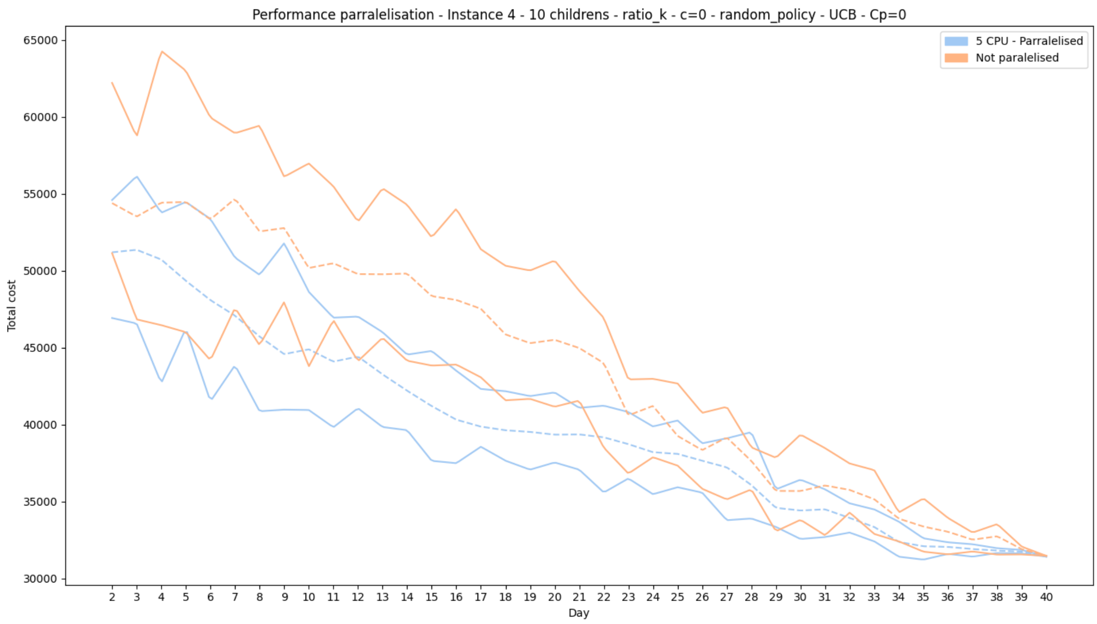


FIGURE 5.17: Performance Parrelisation vs no - Instance 4

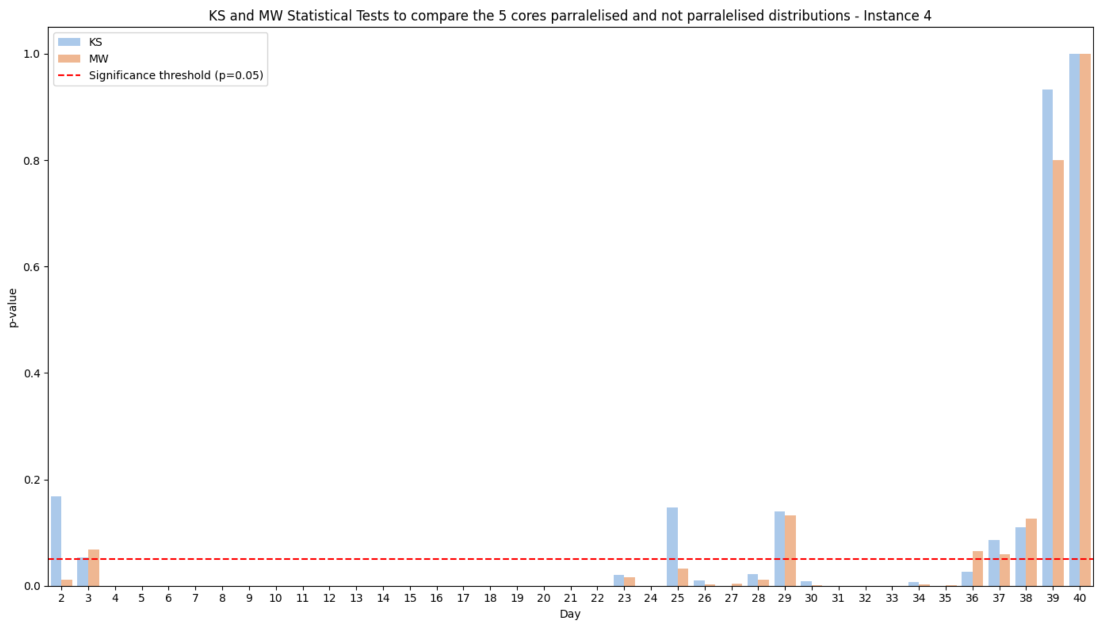


FIGURE 5.18: Stats test Performance Parrelisation vs no - Instance 4

The Mann-Whitney and the Kolmogorov-Smirnov statistical tests have been implemented. These tests compute p-values that test the null hypothesis that the two groups have the same distribution. Hence, from Figure 5.18 there is enough statistical evidence to say that a five core parallelised MCTS with a stochastic simulation policy better performs with parralelisation at a 5% level.

A comparison between five-core and ten-core parallelisations of the considered Monte Carlo Tree Search (MCTS) is shown in Figure 5.19 and 5.20. There are no statistical improvments in increasing the number of cores. As discussed in [43], too many modifications to the MCTS can lead to undesirable behaviour.

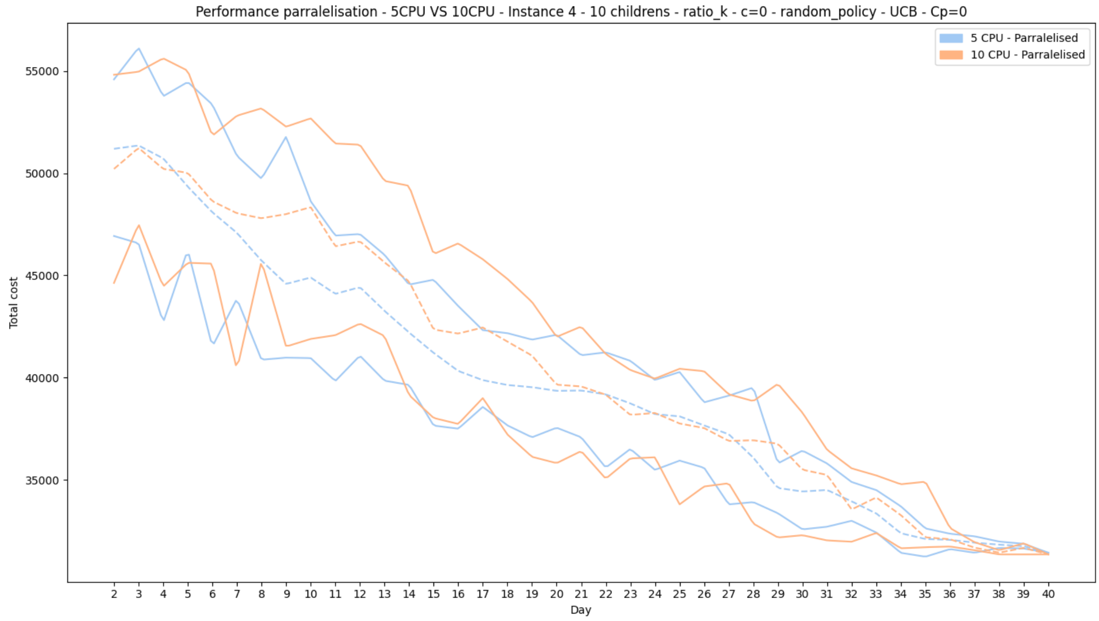


FIGURE 5.19: test Performance 5 and 10 Parrelisation vs no - Instance 4

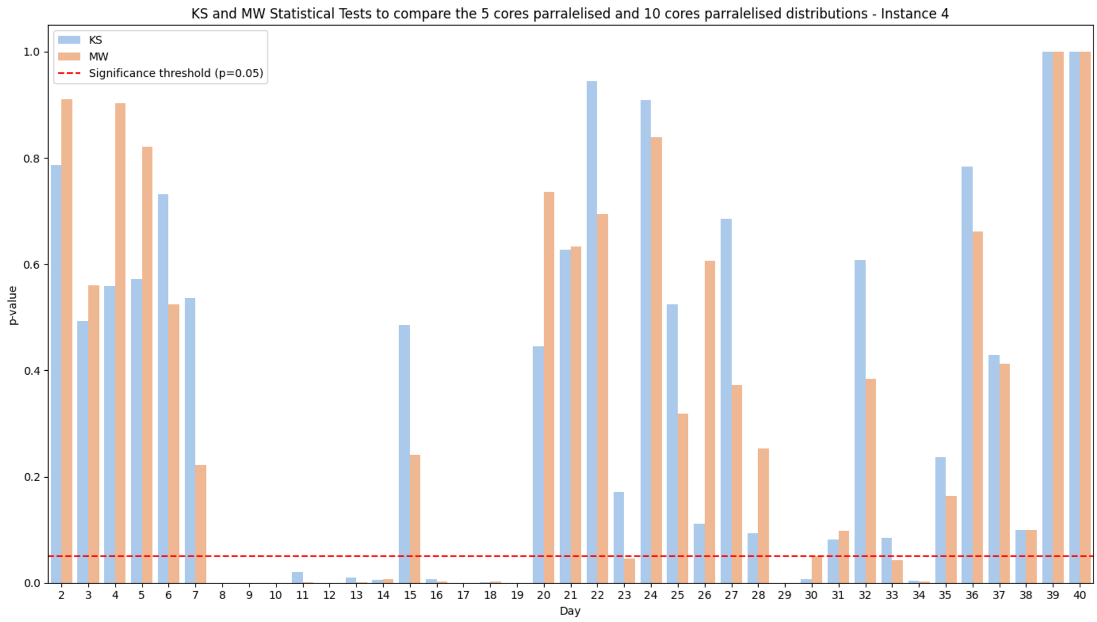


FIGURE 5.20: Stats test Performance 5 and 10 Parrelisation vs no - Instance 4

5.2.4.1 I_5 and I_6

The challenge faced with these two instances is that with the defined grid search, the $\mathcal{MCTS}$ function was not able to conduct the tree search effectively.

Chosen nodes for the simulation that reached final states, under random or tolerance policies, failed to progress further the expansion of the tree because of the randomness of these simulations. Hence, as decided during the implementation of the algorithm, if a simulation from a node cannot reach a final state, this node would be deleted.

5.2.4.2 $I7$ and I_8

For these instances we have found

Chapter 6

Conclusion

6.1 Summary

In this dissertation, we implemented a Monte Carlo Tree Search (MCTS) solution for the Kiwi.com Traveling Salesman Problem 2.0, focusing on the first eight instances without imposing time constraints. Although MCTS is traditionally employed in board games, we adapted it to address this asymmetric, time-dependent, and generalized TSP variant proposed by Kiwi.com. In certain situations, the paper comes close to the state of the art solution, or achieves the state of the art solution, and finally, in certain situations, the paper beats the state of the art solutions.

Regarding the selection policy, the UCB1-Tuned outperformed the classic UCB, guiding the tree search more accurately by taking into account the variability of the simulations. Regarding the expansion ratio, for small instances I_1, I_2, I_3 a lower ratio was prefered because the problem is less complex. However, for other instances, a balanced ratio of 0.5 was effective in allowing new potential candidates within the solution space. We compared the greedy, tolerance and random simulation policies. The greedy approach is best suited for relatively straightforward problems with a low risk of the search getting stuck in local optima, while the tolerance policy provides a balance, introducing potential candidates to bypass these local optima. The random policy, although it sometimes reached acceptable solutions, never achieved a state-of-the-art result and is generally less favorable. Finally, we recommend developing parallelisation within the MCTS, which is particularly beneficial when employing random simulations to better estimate node values and guide the tree search more effectively.

6.2 Areas for expansion

After completing this work, here are a few suggestions for deepening our study.

- **Code a solution in a faster programming language**: The problem with our implementation is the time taken to first, preprocess the data and then find solutions. One enhancement can be to speed up the code to preprocess the instances, where it can take up to 20 minutes to preprocess the data for $I_6, \ldots I_{14}$. An implementation in C or C++ could drastically enhance the performance of the code, hence allowing to test our implementation on $I_9, \ldots, I_{14}$.
- **Implement efficient paralelisation**: We demonstrated that a leaf paralelisation method enhanced the guidance of the tree search, however it was not integrated across all simulations for the parameters in the grid search. One can explore other parallelisations methods such as multi-tree MCTS (as defined in Section 2.3.4).
- **Redefine parameters of the MCTS**: Other parameters can be considered, for example instead of having a number of children $N_c = (5, 10, 15)$ one could have used adaptive parameters, such as setting the number of children N_c based on a percentage of available actions (e.g., 50%). The search process could thus be better adapted to the specifics of the problem at different stages.

Chapter 7

Draf

Selec policy	Exp policy	Simu policy	N° childrens	Ratio	Cp	Best cost	Mean	Std	T(s)
UCB	ratio k	tolerance	10.0	0.0	1.4	1396.0	1396.0	0.0	0.0

- Background

  Methodology Previous studies - Litterature gaps Just expand on the motivation I tried my mathematical formulation

  Careful between I1 and I_1

  Delete instances that are not studied

  Computational time - good to report Try to do significant tests Add diminution of objective function plots

  Submitted

  Instutional for Electric

Appendix A

Code Listings

A.1 Data preprocessing

```
import numpy as np
from copy import deepcopy


class data_preprocessing:
    def __init__(self, instance_path):
        self.instance_path = instance_path

        self.info, self.flights = self.read_file(f_name=self.instance_path)
        self.number_of_areas, self.starting_airport = (
            int(self.info[0][0]),
            self.info[0][1],
        )

        self.flights_by_day_dict =
self.flights_by_day(flight_list=self.flights)

        self.flights_by_day_dict = self.remove_duplicate(
            flights_by_day=self.flights_by_day_dict
        )

        self.list_days = [k for k in range(1, self.number_of_areas)]

        self.airports_by_area = self.get_airports_by_areas()
```

```
        self.area_to_explore = self.which_area_to_explore(
            airports_by_area=self.airports_by_area
        )
        self.area_by_airport =
self.invert_dict(original_dict=self.airports_by_area)

        self.starting_area = self.associated_area_to_airport(
            airport=self.starting_airport
        )
        self.list_airports = self.get_list_of_airports()
        self.list_areas = list(self.airports_by_area.keys())
        self.areas_connections_by_day = (
            self.possible_flights_from_zone_to_zone_specific_day()
        )

    def read_file(self, f_name):
        dist = []
        line_nu = -1
        with open(f_name) as infile:
            for line in infile:
                line_nu += 1
                if line_nu == 0:
                    index = int(line.split()[0]) * 2 + 1
                if line_nu >= index:
                    temp = line.split()
                    temp[2] = int(temp[2])
                    temp[3] = int(temp[3])
                    dist.append(temp)
                else:
                    dist.append(line.split())
            info = dist[: int(dist[0][0]) * 2 + 1]
            flights = dist[int(dist[0][0]) * 2 + 1 :]
        return info, flights

    def flights_by_day(self, flight_list):
        # Create an empty dictionary to hold flights organized by day
        flights_by_day = {}

        # Iterate over each flight in the input list
        for flight in flight_list:
            # Extract the day from the flight entry
```

```
            day = flight[2]

            # Create a flight entry without the day
            flight_without_day = flight[:2] + flight[3:]

            # Add the flight to the corresponding day in the dictionary
            if day not in flights_by_day:
                flights_by_day[day] = []
            flights_by_day[day].append(flight_without_day)

        return flights_by_day

    def flights_from_airport(self, flights_by_day, from_airport,
considered_day):
        flights_from_airport = []
        for day, flights in flights_by_day.items():
            if day == considered_day:
                for flight in flights:
                    if flight[0] == from_airport:
                        flights_from_airport.append(flight)
                return flights_from_airport
            else:
                return None

    def invert_dict(self, original_dict):
        inverted_dict = {}
        for key, value_list in original_dict.items():
            for value in value_list:
                if value in inverted_dict:
                    inverted_dict[value].append(key)
                else:
                    inverted_dict[value] = key
        return inverted_dict

    def get_cost(self, day, from_airport, to_airport):
        # Retrieve flights for the specified day and day 0
        flights_day = self.flights_by_day_dict.get(day, [])
        flights_day_0 = self.flights_by_day_dict.get(0, [])

        # Find the cost for the specified day
        cost_day = next(
```

```
            (
                flight[2]
                for flight in flights_day
                if flight[0] == from_airport and flight[1] == to_airport
            ),
            float("inf"),
        )

        # Find the cost for day 0
        cost_day_0 = next(
            (
                flight[2]
                for flight in flights_day_0
                if flight[0] == from_airport and flight[1] == to_airport
            ),
            float("inf"),
        )

        # Return the minimum cost if either exists, otherwise inf
        if cost_day == float("inf") and cost_day_0 == float("inf"):
            return float("inf")

        return min(cost_day, cost_day_0)

    def possible_flights_from_zone_to_zone_specific_day(self):
        areas_connections_by_day = {}

        for day, flights in self.flights_by_day_dict.items():
            areas_connections_list = []

            for flight in flights:
                connection = f"{self.area_by_airport.get(flight[0])} to
{self.area_by_airport.get(flight[1])}"
                if connection not in areas_connections_list:
                    areas_connections_list.append(connection)

            areas_connections_by_day[day] = areas_connections_list

        return areas_connections_by_day

    def get_airports_by_areas(self):
```

```
        area_num = int(self.info[0][0])
        return {f"{i}": self.info[2 + i * 2] for i in range(0, area_num)}

    def get_list_of_airports(self):
        unique_airports = set()

        # Iterate through each sublist and add elements to the set
        for sublist in self.airports_by_area.values():
            for airport in sublist:
                unique_airports.add(airport)

        return list(unique_airports)

    def associated_area_to_airport(self, airport):
        return next(
            (
                area
                for area, airports in self.airports_by_area.items()
                if airport in airports
            ),
            "Airport not found",
        )

    def remove_duplicate(self, flights_by_day):
        for day, flights in flights_by_day.items():
            unique_flights = {}
            for flight in flights:
                flight_key = (flight[0], flight[1])
                if flight_key not in unique_flights:
                    unique_flights[flight_key] = flight
                else:
                    if flight[2] < unique_flights[flight_key][2]:
                        #
print(flight[0],flight[1],flight[2],flight_key,unique_flights[flight_key][2])
                        unique_flights[flight_key] = flight
                flights_by_day[day] = list(unique_flights.values())
        return flights_by_day

    def possible_flights_from_an_airport_at_a_specific_day(self, day,
from_airport):
        daily_flights = self.flights_by_day_dict.get(day, [])
```

```
        flights_from_airport = []
        for flight in daily_flights:
            if flight[0] == from_airport:

                flights_from_airport.append([flight[1], flight[2]])

        return flights_from_airport

    def
possible_flights_from_an_airport_at_a_specific_day_with_previous_areas(
        self, day, from_airport, visited_areas
    ):
        daily_flights = self.flights_by_day_dict.get(
            day, []
        ) + self.flights_by_day_dict.get(0, [])
        flights_from_airport = []
        for flight in daily_flights:
            # print(self.associated_area_to_airport(airport=flight[0]))
            if (flight[0] == from_airport) and (
                self.associated_area_to_airport(airport=flight[1]) not in
visited_areas
            ):

                flights_from_airport.append([flight[1], flight[2]])

        return flights_from_airport

    def which_area_to_explore(self, airports_by_area):
        return list(
            {
                key: len(value)
                for key, value in airports_by_area.items()
                if len(value) > 1
            }
        )
```

A.2 Node

```
import numpy as np
import random
from scipy.stats import (
kstest,
norm,
beta,
expon,
gamma,
lognorm,
weibull_min,
uniform,
pareto,
t,
chi2,
)


class Node:
def __init__(self, state, desired_selection_policy, cp, parent=None):
self.cp = cp
self.desired_selection_policy = desired_selection_policy
self.state = state  # State is a dictionary representing the current situation
self.parent = parent  # Parent node
self.children = []  # List of child nodes
self.visit_count = 0  # Number of times this node has been visited
self.total_cost = 0  # Total cost accumulated in simulations from this node
self.scores = []

def add_child(self, child_state):
child_node = Node(
state=child_state,
desired_selection_policy=self.desired_selection_policy,
cp=self.cp,
parent=self,
)
self.children.append(child_node)
return child_node
```

```
def is_fully_expanded(self):
# if self.parent is None:
#    return False
return len(self.children) > 0 and all(
child.visit_count > 0 for child in self.children
)

def update(self, result):
self.visit_count += 1
self.total_cost += result
self.scores.append(result)

def UCB(self, c_param):
epsilon = 0

visited_children = [child for child in self.children if (child.visit_count >
    0)]

sorted_children = sorted(
visited_children,
key=lambda child: child.total_cost / (child.visit_count + epsilon),
)
scores = {child: rank + 1 for rank, child in enumerate(sorted_children)}
total_scores = sum(scores.values())

def normalized_score(child):
return scores[child] / total_scores

choices_weights = [
normalized_score(child)
+ c_param
* (2 * np.log(self.visit_count) / (child.visit_count + epsilon)) ** 0.5
for child in visited_children
]

best_child_node = self.children[np.argmin(choices_weights)]

return best_child_node

def SP(self):
```

```
visited_children = [child for child in self.children if child.visit_count > 0]
D = 1

def sp_mcts_score(child):
mean_cost = np.mean(child.scores) if len(child.scores) > 0 else 0
variance = np.var(child.scores) if len(child.scores) > 0 else 0
possible_deviation = np.sqrt(variance + (D / child.visit_count))
return mean_cost - self.cp * possible_deviation

choices_weights = [sp_mcts_score(child) for child in visited_children]

best_child_node = self.children[np.argmin(choices_weights)]
return best_child_node

def Bayesian(self):
visited_children = [child for child in self.children if child.visit_count > 0]
N = self.visit_count

def bayesian_uct_score(child, use_variance=False):
mean_cost = np.mean(child.scores) if len(child.scores) > 0 else 0
exploration_term = np.sqrt(2 * np.log(N) / child.visit_count)

if use_variance:
variance = np.sqrt(np.var(child.scores)) if len(child.scores) > 0 else 0
exploration_term *= variance

return mean_cost + exploration_term

# Select which Bayesian UCT formula to use
use_variance = True  # Change this to ‘False‘ to use the first formula
choices_weights = [
bayesian_uct_score(child, use_variance=use_variance)
for child in visited_children
]

best_child_node = self.children[np.argmin(choices_weights)]
return best_child_node

def UCB1_tuned(self, c_param):
visited_children = [child for child in self.children if child.visit_count > 0]
```

```
def ucb1_tuned_score(child):
mean_cost = np.mean(child.scores) if len(self.scores) > 1 else 0
variance = np.var(self.scores) if len(self.scores) > 1 else 0
# UCB1-Tuned formula
exploration_term = np.sqrt(
(np.log(self.visit_count) / child.visit_count)
* min(
0.25,
variance
+ np.sqrt(2 * np.log(self.visit_count) / child.visit_count),
)
)
return mean_cost + c_param * exploration_term

choices_weights = [ucb1_tuned_score(child) for child in visited_children]

best_child_node = self.children[np.argmin(choices_weights)]
return best_child_node

def thompson_sampling(self, c_param):
visited_children = [child for child in self.children if child.visit_count > 0]

def best_fit_distribution(scores):
distributions = {
"normal": norm,
"beta": beta,
"exponential": expon,
"gamma": gamma,
"lognormal": lognorm,
"weibull_min": weibull_min,
"uniform": uniform,
"pareto": pareto,
"t": t,
"chi2": chi2,
}
p_values = {}
for dist_name, dist in distributions.items():
try:
params = dist.fit(scores)
d_statistic, p_value = kstest(scores, dist_name, args=params)
p_values[dist_name] = p_value
```

```
except Exception as e:
p_values[dist_name] = (
0  # Handle the error and skip this distribution
)
print(f"Skipping {dist_name} due to fitting issues: {e}")

best_dist_name = max(p_values, key=p_values.get)
best_p_value = p_values[best_dist_name]

if best_p_value < 0.05:
return None, None

best_dist = distributions[best_dist_name]
best_params = best_dist.fit(scores)

return best_dist, best_params

sampled_values = []
for child in visited_children:
if len(child.scores) > 1:
best_dist, best_params = best_fit_distribution(child.scores)
if best_dist is not None:
sampled_value = best_dist.rvs(*best_params)
sampled_values.append(sampled_value)
else:
return self.UCB(
c_param
)  # Fallback to UCB if no good distribution is found
else:
sampled_values.append(np.mean(child.scores))

best_child_node = visited_children[np.argmin(sampled_values)]
return best_child_node

def randomized_ucb(self, c_param, random_factor=0.1):
visited_children = [child for child in self.children if child.visit_count > 0]

def randomized_ucb_score(child):
mean_cost = np.mean(child.scores) if len(child.scores) > 0 else 0
exploration_term = np.sqrt(
(2 * np.log(self.visit_count) / (child.visit_count))
```

```
)
random_term = random_factor * np.random.rand()
return mean_cost + c_param * exploration_term + random_term

choices_weights = [randomized_ucb_score(child) for child in visited_children]

best_child_node = visited_children[np.argmin(choices_weights)]
return best_child_node

def epsilon_greedy(self, epsilon):
visited_children = [child for child in self.children if child.visit_count > 0]

if np.random.rand() < epsilon:
# Explore: randomly select a child
best_child_node = np.random.choice(visited_children)
else:
# Exploit: select the child with the best average cost
best_child_node = min(
visited_children,
key=lambda child: (
np.mean(child.scores) if len(child.scores) > 0 else float("inf")
),
)

return best_child_node

def best_child(self):
if self.desired_selection_policy == "UCB":
return self.UCB(c_param=self.cp)
if self.desired_selection_policy == "UCB1T":
return self.UCB1_tuned(c_param=self.cp)
if self.desired_selection_policy == "SP":
return self.epsilon_greedy(self.cp)
if self.desired_selection_policy == "Bayesian":
return self.Bayesian()

else:
raise ValueError(
f"Unknown Selection policy: {self.desired_selection_policy}"
)
```

```
def delete_node(self):
self.parent.children = [
child for child in self.parent.children if child != self
]
```

A.3 MCTS

```
    import numpy as np
import random
from copy import deepcopy
import logging
import time
import os
import shutil
import glob

from Data_Preprocessing import data_preprocessing
from Node import Node


class MCTS(data_preprocessing):
    def __init__(
        self,
        instance,
        instance_number,
        number_childrens,
        desired_expansion_policy,
        ratio_expansion,
        desired_simulation_policy,
        desired_selection_policy,
        cp,
        number_simulation,
    ):
        self.instance_number = instance_number
        self.number_childrens = number_childrens
        self.desired_simulation_policy = desired_simulation_policy
        self.desired_expansion_policy = desired_expansion_policy
        self.ratio_expansion = ratio_expansion
        self.number_simulation = number_simulation
        self.desired_selection_policy = desired_selection_policy
        self.cp = cp

        self.expanded_nodes = []
        self.simulations_dict = {}

        self.start_time = time.time()
```

```
        super().__init__(instance_path=instance)
        self.end_time_data_preprocessing = time.time() - self.start_time
        self.simulation()
        # self.organise_log_files_in_folder(
        #     folder_path=os.path.dirname(self.instance_path)
        # )
        # self.collect_all_nodes()

    def configure_logging(self):
        log_file =
f"{self.instance_path}_{self.number_childrens}_{self.desired_simulation_policy}_{self.desi
        log_file = self.get_unique_log_file(log_file)

        # Clear any existing handlers
        for handler in logging.root.handlers[:]:
            logging.root.removeHandler(handler)

        # Configure the logger
        logging.basicConfig(
            level=logging.DEBUG,  # Set the log level to DEBUG to capture all
types of logs
            format="%(asctime)s - %(name)s - %(levelname)s - %(message)s",
            handlers=[
                logging.FileHandler(
                    log_file, mode="w"
                ),  # 'w' to overwrite the log file each run, 'a' to append
                # logging.StreamHandler(),  # Optional: to also print logs to
the console
            ],
        )
        logger = logging.getLogger(__name__)
        return logger

    def get_unique_log_file(self, base_log_file):
        """
        Check if the log file exists and if so, create a new file with a
unique suffix.
        """
        base_name, extension = os.path.splitext(base_log_file)
        counter = 0  # Start with 0 to have the first file as _0
        while True:
```

```
            new_log_file = f"{base_name}_{counter}{extension}"
            if not os.path.exists(new_log_file):
                return new_log_file
            counter += 1

    def organise_log_files_in_folder(self, folder_path):
        """
        Organize log files in the specified folder by moving files with the
    same base name into a dedicated directory.

        :param folder_path: Path to the folder containing the log files.
        """
        # Change to the target directory
        os.chdir(folder_path)

        # Find all log files in the directory
        log_files = glob.glob("*.log")

        # Track which files have already been moved to avoid duplication
        processed_bases = set()

        for log_file in log_files:
            # Extract the base name (up to the first '_')
            base_name = (
                log_file.rsplit("_", 1)[0]
                if "_" in log_file
                else log_file.rsplit(".", 1)[0]
            )

            if base_name not in processed_bases:
                # Mark this base as processed
                processed_bases.add(base_name)

                # Create a pattern to match all similar files
                pattern = f"{base_name}*.log"

                # Find all files matching this pattern
                matching_files = glob.glob(pattern)

                if matching_files:
                    # Create a directory for these files
```

```
                folder_name = os.path.join(folder_path, base_name)
                os.makedirs(folder_name, exist_ok=True)

                # Move each matching file into the directory
                for file in matching_files:
                    shutil.move(file, folder_name)

                # print(
                #     f"Moved files with base '{base_name}' into folder:
{folder_name}"
                # )

def initialise_root_node(self):
    return {
        "current_day": 1,
        "current_airport": self.starting_airport,
        "remaining_zones": [
            x for x in self.list_areas if x != self.starting_area
        ],  # Exclude the starting area
        "visited_zones": [self.starting_area],  # Exclude the starting area
        "total_cost": 0,
        "path": [self.starting_airport],
    }

def transition_function(self, state, action):
    new_state = deepcopy(state)
    new_state["current_day"] += 1
    new_state["current_airport"] = action[0]
    new_state["total_cost"] += action[1]
    new_state["path"].append(action[0])
    # self.logger.info(
    #     f"Airport {action[0]},
{self.associated_area_to_airport(airport=action[0])} to remove in
{new_state['remaining_zones']}"
    # )
    new_state["remaining_zones"].remove(
        self.associated_area_to_airport(airport=action[0])
    )
    new_state["visited_zones"].append(
        self.associated_area_to_airport(airport=action[0])
    )
```

```
        return new_state

    def random_policy(self, actions):

        if not actions:
            return None
        return random.choice(actions)

    def greedy_policy(self, actions):

        # self.logger.info(f"Actions: {actions}")
        if not actions:
            return None
        # Select the action with the lowest cost
        best_action = min(actions, key=lambda x: x[1])
        # self.logger.info(f"Chosen action based on heuristic policy:
    {best_action}")
        return best_action

    def tolerance_heuristic_policy(self, actions):
        # self.logger.info(f"Actions: {actions}")

        if not actions:
            return None

        # Find the minimum cost
        min_cost = min(actions, key=lambda x: x[1])[1]

        # Filter actions within the tolerance level
        best_actions = [
            action
            for action in actions
            if action[1] <= min_cost * (1 + self.ratio_expansion)
        ]

        # Select a random action from the best actions
        best_action = random.choice(best_actions)

        # self.logger.info(f"Chosen action based on tolerance policy:
    {best_action}")
```

```
        return best_action

    def get_unvisited_children(self, node):
        queue = [node]
        unvisited_children = []
        while queue:
            current_node = queue.pop(0)
            for child in current_node.children:
                if child.visit_count == 0:
                    unvisited_children.append(child)
                else:
                    queue.append(child)

        return unvisited_children

    def backpropagate(self, node, cost):
        while node is not None:

            node.update(cost)

            # self.logger.info(
            #     f"Backpropagating Node: {node.state}, Visit Count:
    {node.visit_count}, Total Cost: {node.total_cost}, Scores: {node.scores}"
            # )

            node = node.parent

    def collect_all_nodes(self):
        nodes = []
        queue = [self.root]
        while queue:
            node = queue.pop(0)
            nodes.append(node)
            queue.extend(node.children)
        return nodes

    def get_final_nodes(self):
        day = self.number_of_areas + 1
        nodes = [
            node
            for node in self.collect_all_nodes()
```

```
            if node.state.get("current_day") == day
        ]

        # Initialize variables to track the best nodes for this day
        min_cost_child = None
        robust_child = None
        min_cost_robust_child = None
        secure_child = None

        # Values to compare against
        min_cost = float("inf")
        max_visit_count = -float("inf")
        max_secure_value = -float("inf")

        for node in nodes:
            # Min-Cost Child: Select the root child with the lowest total_cost
            if node.total_cost < min_cost:
                min_cost = node.total_cost
                min_cost_child = node

            # Robust Child: Select the most visited root child (visit_count)
            if node.visit_count > max_visit_count:
                max_visit_count = node.visit_count
                robust_child = node

            # Min-Cost-Robust Child: Among the nodes with the lowest
    total_cost, select the one with the highest visit_count
            if node.total_cost == min_cost and node.visit_count >=
    max_visit_count:
                min_cost_robust_child = node

            # Secure Child: Select the child that minimizes a lower confidence
    bound
            if (
                node.visit_count > 0
                and node.parent is not None
                and node.parent.visit_count > 0
            ):
                secure_value = (node.total_cost / node.visit_count) - self.cp
    * (
                    (node.parent.visit_count / node.visit_count) ** 0.5
```

```
                )
                if secure_value > max_secure_value:
                    max_secure_value = secure_value
                    secure_child = node

        # Logging the results for the current day
        if min_cost_child:
            self.logger.info("\n\n")
            self.logger.info(f"Best Node: {min_cost_child.state}")
        if robust_child:
            self.logger.info(
                f"Robust Child (Day {day}): State={robust_child.state}, Visit
Count={max_visit_count}"
            )
        if min_cost_robust_child:
            self.logger.info(
                f"Min-Cost-Robust Child (Day {day}):
State={min_cost_robust_child.state}, Cost={min_cost}, Visit
Count={min_cost_robust_child.visit_count}"
            )
        if secure_child:
            self.logger.info(
                f"Secure Child (Day {day}): State={secure_child.state}, Secure
Value={max_secure_value}"
            )

    def display_all_nodes(self, nodes):
        for node in nodes:
            print(
                f"State: {node.state}, Visit Count: {node.visit_count}, Total
Cost: {node.total_cost}"
            )
            self.logger.info(
                f"State: {node.state}, Visit Count: {node.visit_count}, Total
Cost: {node.total_cost}"
            )

    def print_execution_times(self):
        self.logger.info(
            f"\n\n\n Time to preprocess the data:
{self.end_time_data_preprocessing:.4f} seconds"
```

```
        )
        self.logger.info(
            f"\n\n\n Time to find the solution: {self.end_search_time:.4f}
seconds"
        )
        self.logger.info(
            f"\n\n\n Total time:
{self.end_time_data_preprocessing+self.end_search_time:.4f} seconds \n\n"
        )

    def get_simulation_policy(self):
        if self.desired_simulation_policy == "greedy_policy":
            return self.greedy_policy
        elif self.desired_simulation_policy == "random_policy":
            return self.random_policy
        elif self.desired_simulation_policy == "tolerance_policy":
            return self.tolerance_heuristic_policy
        else:
            raise ValueError(
                f"Unknown simulation policy: {self.desired_simulation_policy}"
            )

    def get_expansion_policy(self):
        if self.desired_expansion_policy == "top_k":
            return self.top_k_actions

        if self.desired_expansion_policy == "ratio_k":
            return self.ratio_best_random

        else:
            raise ValueError(
                f"Unknown expansion policy: {self.desired_expansion_policy}"
            )

    def top_k_actions(self, actions):
        sorted_actions = sorted(actions, key=lambda x: x[1])
        return sorted_actions[: self.number_childrens]

    def ratio_best_random(self, actions):
        # Determine the number of best actions to take based on the ratio
        ratio = self.ratio_expansion
```

```
        num_best = int(self.number_childrens * ratio)
        num_random = self.number_childrens - num_best

        # Sort actions to get the best ones
        sorted_actions = sorted(actions, key=lambda x: x[1])
        best_actions = sorted_actions[:num_best]

        # Select the remaining random actions from the remaining pool
        remaining_actions = sorted_actions[num_best:]

        # Ensure we don't try to sample more than available actions
        num_random = min(num_random, len(remaining_actions))

        # If num_random is zero or there are no remaining actions, we skip the
    sampling
        if num_random > 0 and remaining_actions:
            random_actions = random.sample(remaining_actions, num_random)
        else:
            random_actions = []

        # Combine the best actions and the random actions
        final_actions = best_actions + random_actions
        random.shuffle(final_actions)

        return final_actions

    def delete_node(self, node):
        if node.parent:
            for _ in node.parent.children:
                pass
                # self.logger.info(
                #     f"before deletion: {len(node.parent.children)},{_.state}"
                # )
            node.parent.children.remove(node)
            for _ in node.parent.children:
                pass
                # self.logger.info(
                #     f"after deletion: {len(node.parent.children)},{_.state}"
                # )

    def print_characteristics_simulation(self):
```

```
        self.logger.info(f"\n\nSimulation dictionnary:
    {self.simulations_dict}")
        self.logger.info(f"Number of childrens: {self.number_childrens}")
        self.logger.info(f"Desired expansion policy:
    {self.desired_expansion_policy}")
        self.logger.info(f"Ratio expansion: {self.ratio_expansion}")
        self.logger.info(f"Desired simulation policy:
    {self.desired_simulation_policy}")
        self.logger.info(f"Desired selection policy:
    {self.desired_selection_policy}")
        self.logger.info(f"Cp: {self.cp}")
        self.logger.info(f"Instance: {self.instance_number}")

    def simulation(self):
        for _ in range(self.number_simulation):
            self.logger = None
            self.logger = self.configure_logging()
            self.root = Node(
                self.initialise_root_node(),
                desired_selection_policy=self.desired_selection_policy,
                cp=self.cp,
            )
            self.best_leaf = None
            self.best_leaf_cost = float("inf")
            self.search()
            self.end_search_time = time.time() - self.start_time
            self.print_execution_times()
            self.get_final_nodes()
            self.print_characteristics_simulation()

    def select(self, node):
        self.logger.info("\nSELECTION\n")
        current_node = node
        self.logger.info(f"Starting selection at node: {current_node.state}")

        while current_node.children:
            self.logger.info(f"Current node: {current_node.state}")
            self.logger.info(f"Childrens: {current_node.children}")

            if not current_node.is_fully_expanded():
                # Select a random unvisited child if there are any
```

```
            unvisited_children = [
                child for child in current_node.children if
child.visit_count == 0
            ]
            self.logger.info(f"Unvisited children:
{len(unvisited_children)}")
            if unvisited_children:
                selected_child = random.choice(unvisited_children)
                self.logger.info(
                    f"Randomly selected unvisited child: {selected_child}"
                )
                return True, selected_child

        else:
            current_node = current_node.best_child()
            self.logger.info(f"Moving to best child: {current_node.state}")
            # return True, current_node

    if (not current_node.children) and (
        current_node.state["current_day"] == self.number_of_areas
    ):
        self.logger.info("Final day selected")
        return False, current_node

    elif (not current_node.children) and (
        current_node.state["current_day"] != self.number_of_areas
    ):
        self.logger.info(f"The node {current_node.state} has no children")
        return False, current_node

    elif current_node.state["current_day"] == self.number_of_areas + 1:
        return True, current_node

def expand_node(self, node):
    if node not in self.expanded_nodes:
        self.expanded_nodes.append(node)

        actions =
self.possible_flights_from_an_airport_at_a_specific_day_with_previous_areas(
            node.state["current_day"],
            node.state["current_airport"],
```

```
                node.state["visited_zones"],
            )

            if node.state["current_day"] == self.number_of_areas:
                node.state["visited_zones"] = node.state["visited_zones"][1:]
                node.state["remaining_zones"].append(
                    self.associated_area_to_airport(self.starting_airport)
                )

                actions =
    self.possible_flights_from_an_airport_at_a_specific_day_with_previous_areas(
                    node.state["current_day"],
                    node.state["current_airport"],
                    node.state["visited_zones"],
                )

            expansion_policy = self.get_expansion_policy()
            actions = expansion_policy(actions)

            if actions:
                self.logger.info("Start expansion")
                for action in actions:
                    self.logger.info(f"{action}")
                    new_state = self.transition_function(node.state, action)
                    node.add_child(new_state)
                self.logger.info("End expansion")
            else:
                self.logger.info(f"No actions possible")
                return None

            return node

        else:
            self.logger.info("INFINITE LOOP")
            return None

    def search(self):
        while True:
            node_to_explore = self.select(self.root)

            self.logger.info(f"Node to explore: {node_to_explore[1].state}")
```

```
        if node_to_explore[1].state["current_day"] == self.number_of_areas
+ 1:
            while not node_to_explore[1].parent.is_fully_expanded():
                # self.logger.info(
                #    "Node to explore is last day but all siblings have
not been visited yet"
                # )
                node_to_explore = self.select(self.root)
                self.logger.info(f"Node to explore:
{node_to_explore[1].state}")
                result = node_to_explore[1].state["total_cost"]
                self.backpropagate(node_to_explore[1], result)

            node_to_explore[1].state["visited_zones"].append(
                self.associated_area_to_airport(
                    airport=node_to_explore[1].state["path"][-1]
                )
            )
            return

        if not node_to_explore[0]:
            expanded_node = self.expand_node(node=node_to_explore[1])
            if not expanded_node:
                self.logger.info("Not unexpandable so deleted")
                node_to_explore[1].delete_node()
                # self.logger.info(f"Nodes in tree:
{len(self.collect_all_nodes())}")
                if len(self.collect_all_nodes()) == 1:
                    self.logger.info("Everything has been deleted to the
root node")
                    self.end_time_data_preprocessing = 0
                    self.end_search_time = 0
                    self.print_characteristics_simulation()
                    self.print_execution_times()
                    break
                continue
            else:
                self.logger.info(
                    f"{node_to_explore[1].state} has been successfully
expanded"
```

```
                )
                continue

        else:
            simulation = self.simulate(node_to_explore[1])

            if simulation[0]:
                self.logger.info(f"Result from simulation:
{simulation[0]}")

                key = str(node_to_explore[1].state["current_day"])
                value_to_add = simulation[0]
                if key in self.simulations_dict:
                    self.simulations_dict[key].append(value_to_add)
                else:
                    self.simulations_dict[key] = [value_to_add]

                self.backpropagate(node_to_explore[1], simulation[0])

            else:
                self.logger.info(
                    "Simulation failed to reach a valuable state - node
deleted"
                )
                self.delete_node(node_to_explore[1])
                if len(self.collect_all_nodes()) == 1:
                    self.logger.info("Everything has been deleted to the
root node")
                    self.end_time_data_preprocessing = 0
                    self.end_search_time = 0
                    self.print_characteristics_simulation()
                    self.print_execution_times()
                    break

def simulate(self, node):
    self.logger.info("\n\nSIMULATION")
    simulation_policy = self.get_simulation_policy()
    current_simulation_state = deepcopy(node.state)
    self.logger.info(f"Selected node for simulation
{current_simulation_state}")
```

```
    while current_simulation_state["current_day"] != self.number_of_areas:
        actions =
self.possible_flights_from_an_airport_at_a_specific_day_with_previous_areas(
            day=current_simulation_state["current_day"],
            from_airport=current_simulation_state["current_airport"],
            visited_areas=current_simulation_state["visited_zones"],
        )

        action = simulation_policy(actions=actions)
        # self.logger.info(f"Action: {action}")
        if action is None:
            self.logger.info("Action is None")
            return False, False

        current_simulation_state = self.transition_function(
            current_simulation_state, action
        )
        # self.logger.info(f"Current simulation state
{current_simulation_state}")

    if current_simulation_state["current_day"] == self.number_of_areas:
        current_simulation_state["visited_zones"] =
current_simulation_state[
            "visited_zones"
        ][1:]
        current_simulation_state["remaining_zones"].append(
            self.associated_area_to_airport(self.starting_airport)
        )

        actions =
self.possible_flights_from_an_airport_at_a_specific_day_with_previous_areas(
            day=current_simulation_state["current_day"],
            from_airport=current_simulation_state["current_airport"],
            visited_areas=current_simulation_state["visited_zones"],
        )

        if not actions:
            self.logger.info("No flight available to go back to the
initial area")
            return False, False
        else:
```

```
            action = simulation_policy(actions=actions)

            current_simulation_state = self.transition_function(
                current_simulation_state, action
            )
            self.logger.info(f"Current simulation state
{current_simulation_state}")

            return current_simulation_state["total_cost"],
current_simulation_state
```

Appendix B

Test Instances

The instances can be found on the following website: https://code.kiwi.com/articles/travelling-salesman-challenge-2-0-wrap-up/

Appendix C

Simulations results

C.1 Instance 1

C.1.1 Solution found

Selec policy	Exp policy	Simu policy	N° childrens	Ratio	Cp	Best cost	Mean	Std	T(s)
UCB	ratio k	greedy	5	.3	2.8	1396	1396.00		.084
UCB	top k	greedy	5	.5	1.4	1396	1396.00		.085
UCB	top k	greedy	5	.3	1.4	1396	1396.00		.085
UCB	top k	greedy	10	.8	1.4	1396	1396.00		.096
UCB	top k	greedy	10	.3	1.4	1396	1396.00		.097
UCB	top k	greedy	5	.3	2.8	1396	1396.00		.097
UCB	top k	greedy	5	1	1.4	1396	1396.00		.097
UCB	top k	greedy	5	.8	2.8	1396	1396.00		.098
UCB	ratio k	greedy	10	1	2.8	1396	1396.00		.098
UCB	top k	greedy	5	0	2.8	1396	1396.00		.099
UCB	ratio k	greedy	5	0	2.8	1396	1396.00		.100
UCB	ratio k	greedy	5	1	1.4	1396	1396.00		.101
UCB	top k	greedy	5	.5	2.8	1396	1396.00		.101
UCB	ratio k	greedy	10	.3	2.8	1396	1396.00		.102
UCB	top k	greedy	10	0	1.4	1396	1396.00		.103
UCB	top k	greedy	15	.3	1.4	1396	1396.00		.107
UCB	top k	greedy	5	0	1.4	1396	1396.00		.107
UCB	ratio k	greedy	10	.5	2.8	1396	1396.00		.112
UCB	ratio k	greedy	15	.8	1.4	1396	1396.00		.112

UCB	top k	greedy	15	.8	1.4	1396	1396.00		.115
UCB	top k	greedy	15	1	1.4	1396	1396.00		.115
UCB	ratio k	greedy	10	0	2.8	1396	1396.00		.116
UCB	top k	greedy	10	1	1.4	1396	1396.00		.116
UCB	ratio k	greedy	10	.3	1.4	1396	1396.00		.117
UCB	top k	greedy	5	1	2.8	1396	1396.00		.117
UCB	top k	greedy	15	.3	2.8	1396	1396.00		.118
UCB	top k	greedy	10	.5	1.4	1396	1396.00		.118
UCB	top k	greedy	5	.8	1.4	1396	1396.00		.118
UCB	ratio k	greedy	15	.3	2.8	1396	1396.00		.119
UCB	ratio k	greedy	15	.8	2.8	1396	1396.00		.119
UCB	top k	greedy	15	.8	2.8	1396	1396.00		.120
UCB	ratio k	greedy	10	.5	1.4	1396	1396.00		.120
UCB	ratio k	tolerance	10	0	2.8	1396	1396.00	0.00	.120
UCB	ratio k	greedy	10	.8	2.8	1396	1396.00		.122
UCB	top k	greedy	15	0	2.8	1396	1396.00		.122
UCB	top k	tolerance	5	0	2.8	1396	1396.00	0.00	.126
UCB	top k	greedy	15	.5	1.4	1396	1396.00		.126
UCB	ratio k	greedy	10	0	1.4	1396	1396.00		.126
UCB	top k	greedy	10	.8	2.8	1396	1396.00		.127
UCB	ratio k	tolerance	15	0	2.8	1396	1396.00	0.00	.128
UCB	ratio k	greedy	15	1	2.8	1396	1396.00		.129
UCB	top k	greedy	10	.3	2.8	1396	1396.00		.131
UCB	ratio k	greedy	5	1	2.8	1396	1396.00		.131
UCB	ratio k	greedy	15	0	2.8	1396	1396.00		.132
UCB	top k	greedy	10	0	2.8	1396	1396.00		.132
UCB	ratio k	greedy	15	.3	1.4	1396	1396.00		.133
UCB	ratio k	greedy	15	.5	1.4	1396	1396.00		.133
UCB	top k	greedy	15	.5	2.8	1396	1396.00		.134
UCB	ratio k	greedy	10	1	1.4	1396	1396.00		.136
UCB	ratio k	greedy	15	1	1.4	1396	1396.00		.137
UCB	ratio k	tolerance	5	0	1.4	1396	1518.60	99.08	.139
UCB	top k	greedy	15	1	2.8	1396	1396.00		.142
UCB	top k	greedy	10	1	2.8	1396	1396.00		.143
UCB	ratio k	tolerance	15	0	1.4	1396	1396.00	0.00	.143
UCB	top k	greedy	15	0	1.4	1396	1396.00		.143
UCB	ratio k	greedy	15	.5	2.8	1396	1396.00		.147
UCB	ratio k	greedy	15	0	1.4	1396	1396.00		.148
UCB	ratio k	tolerance	10	0	1.4	1396	1396.00	0.00	.152
UCB	top k	tolerance	15	0	1.4	1396	1396.00	0.00	.153
UCB	top k	tolerance	10	0	1.4	1396	1396.00	0.00	.155

UCB	top k	greedy	10	.5	2.8	1396	1396.00		.157
UCB	top k	tolerance	15	.3	2.8	1396	1524.20	72.14	.157
UCB	top k	tolerance	5	0	1.4	1396	1396.00	0.00	.158
UCB	top k	tolerance	15	.8	1.4	1396	1654.70	185.65	.161
UCB	top k	tolerance	10	0	2.8	1396	1396.00	0.00	.174
UCB	top k	tolerance	15	0	2.8	1396	1396.00	0.00	.177
UCB	ratio k	greedy	10	.8	1.4	1396	1396.00		.178
UCB	ratio k	tolerance	15	.5	1.4	1396	1599.20	89.85	.385
UCB	top k	tolerance	5	.5	2.8	1396	1588.50	109.62	.394
UCB	ratio k	tolerance	10	1	1.4	1396	1572.20	148.00	.488
UCB	top k	tolerance	15	.8	2.8	1396	1647.80	209.03	.645
UCB	ratio k	tolerance	5	0	2.8	1396	1509.00	81.71	.659
UCB	top k	tolerance	10	1	1.4	1396	1617.70	183.61	.794
UCB	top k	tolerance	15	1	2.8	1396	1589.50	130.85	.809
UCB	top k	tolerance	15	.5	2.8	1396	1528.40	109.46	.837
UCB	ratio k	tolerance	15	1	1.4	1396	1606.10	125.35	.864
UCB	top k	tolerance	5	.3	2.8	1396	1528.60	76.94	.961
UCB	top k	tolerance	10	.3	1.4	1396	1528.90	109.87	1.060
UCB	ratio k	tolerance	5	.8	1.4	1396	1574.70	123.89	1.208
UCB	top k	tolerance	15	1	1.4	1396	1592.50	143.08	1.613
UCB	ratio k	random	10	.8	0	1407	3549.90	1959.51	2.745
UCB	top k	tolerance	5	.3	1.4	1431	1532.50	112.31	.514
UCB	top k	tolerance	5	.8	1.4	1431	1618.70	97.18	.806
UCB	ratio k	tolerance	10	.8	1.4	1431	1583.10	123.40	.830
UCB	ratio k	tolerance	10	.5	2.8	1431	1549.10	96.27	1.021
UCB	ratio k	tolerance	15	1	2.8	1431	1615.40	179.82	1.432
UCB	ratio k	tolerance	10	.3	2.8	1457	1508.70	40.06	.138
UCB	top k	tolerance	5	1	1.4	1457	1543.60	84.48	1.857
UCB	ratio k	greedy	5	.5	2.8	1458	1458.00		.113
UCB	ratio k	greedy	5	0	1.4	1458	1458.00		.115
UCB	top k	tolerance	5	1	2.8	1458	1563.00	88.51	.126
UCB	top k	tolerance	10	.8	2.8	1458	1640.50	101.40	.348
UCB	ratio k	tolerance	15	.8	2.8	1458	1575.60	102.64	.381
UCB	top k	tolerance	10	.8	1.4	1458	1571.40	123.30	.382
UCB	ratio k	random	15	.8	2.8	1458	4879.30	2587.48	.591
UCB	ratio k	tolerance	5	.8	2.8	1458	1586.00	106.15	.806
UCB	top k	tolerance	5	.5	1.4	1458	1541.30	45.20	.901
UCB	ratio k	tolerance	15	.3	2.8	1458	1502.60	63.95	1.081
UCB	ratio k	tolerance	10	.5	1.4	1458	1523.70	46.63	1.161
UCB	ratio k	random	10	1	1.4	1458	5975.30	4237.38	1.756
UCB1T	ratio k	greedy	10	.5	1.4	1472	1472.00		.893

UCB	top k	tolerance	10	.8	0	1472	1903.50	169.28	1.057
UCB	ratio k	tolerance	10	1	2.8	1472	1661.30	160.90	1.267
UCB	ratio k	greedy	5	1	0	1472	1472.00		1.801
UCB1T	ratio k	tolerance	15	.3	1.4	1472	1818.00	150.91	5.009
UCB	top k	tolerance	15	.5	0	1472	1808.00	146.75	5.484
UCB1T	top k	tolerance	5	0	2.8	1472	1803.50	208.94	6.320
UCB	ratio k	tolerance	5	1	0	1472	1799.70	161.43	6.925
UCB1T	ratio k	tolerance	15	1	0	1472	1870.00	220.25	19.040
UCB1T	ratio k	tolerance	5	1	2.8	1472	1895.10	211.12	28.132
UCB	top k	tolerance	10	.3	2.8	1479	1520.70	70.89	.160
UCB	ratio k	tolerance	5	.3	2.8	1479	1523.20	81.22	.216
UCB	ratio k	tolerance	5	.3	1.4	1479	1550.20	92.04	.440
UCB	top k	tolerance	5	.8	2.8	1479	1643.70	125.43	.500
UCB	ratio k	tolerance	10	.3	1.4	1479	1560.20	65.68	.870
UCB	top k	tolerance	15	.3	1.4	1479	1561.00	73.15	1.526
UCB	ratio k	greedy	5	.3	1.4	1481	1481.00		.095
UCB	ratio k	greedy	5	.8	2.8	1481	1481.00		.104
UCB	ratio k	greedy	5	.8	1.4	1481	1481.00		.115
UCB	ratio k	greedy	5	.5	1.4	1481	1481.00		.117
UCB	top k	tolerance	15	.5	1.4	1481	1566.80	83.76	.738
UCB	ratio k	tolerance	15	.3	1.4	1481	1607.00	95.21	1.236
UCB1T	ratio k	tolerance	5	.8	0	1481	1847.50	208.87	13.143
UCB	ratio k	tolerance	5	.5	2.8	1485	1559.70	90.12	.644
UCB	ratio k	tolerance	5	1	1.4	1489	1649.10	60.98	.126
UCB	ratio k	tolerance	5	.5	1.4	1490	1555.70	56.12	.106
UCB1T	top k	tolerance	15	.8	0	1490	1865.60	158.48	5.096
UCB1T	top k	random	5	.5	1.4	1493	2407.10	1045.81	3.136
UCB	ratio k	tolerance	15	.5	2.8	1495	1551.60	37.38	.316
UCB	top k	tolerance	10	.5	2.8	1495	1608.60	78.12	1.129
UCB	ratio k	random	5	1	1.4	1506	3187.40	1785.08	.179
UCB	ratio k	random	5	1	2.8	1506	4330.10	2775.69	.492
UCB	ratio k	tolerance	15	.3	0	1506	1745.30	193.93	1.829
UCB1T	top k	random	15	.3	0	1506	2634.80	1495.29	2.654
UCB	ratio k	tolerance	15	.8	1.4	1521	1664.60	140.50	.160
UCB	top k	random	5	0	1.4	1522	3817.40	2271.90	1.650
UCB1T	top k	tolerance	5	.3	1.4	1522	1803.10	135.11	44.419
UCB	ratio k	tolerance	5	1	2.8	1526	1636.10	95.27	.322
UCB	ratio k	tolerance	10	.8	2.8	1526	1658.90	95.49	.654
UCB1T	ratio k	greedy	5	0	1.4	1529	1529.00		.512
UCB1T	ratio k	random	5	.5	1.4	1529	2613.00	1381.25	.883
UCB	top k	tolerance	15	.3	0	1529	1816.10	204.92	1.285

UCB1T	ratio k	tolerance	5	0	0	1529	1889.20	191.58	2.025
UCB1T	ratio k	random	10	.3	1.4	1529	2922.40	1754.56	2.695
UCB1T	top k	tolerance	15	0	0	1529	1884.20	166.62	2.890
UCB1T	ratio k	tolerance	10	1	0	1529	1827.00	215.19	3.312
UCB1T	top k	tolerance	15	.3	2.8	1529	1890.20	168.87	4.693
UCB1T	ratio k	random	15	.8	1.4	1529	3993.00	2298.81	5.162
UCB1T	top k	tolerance	10	.5	0	1529	1823.10	211.45	6.695
UCB1T	ratio k	tolerance	10	.5	1.4	1529	1850.50	224.25	8.508
UCB1T	ratio k	tolerance	10	.3	1.4	1529	1796.60	167.63	9.516
UCB1T	top k	tolerance	15	1	0	1529	1831.70	133.56	11.001
UCB1T	ratio k	tolerance	5	.8	1.4	1529	1798.40	216.53	16.114
UCB	top k	tolerance	10	.5	1.4	1530	1609.90	76.29	.924
UCB1T	ratio k	random	5	0	2.8	1533	3012.00	1836.74	3.879
UCB1T	top k	tolerance	5	1	0	1533	1882.40	178.26	8.601
UCB1T	ratio k	tolerance	5	1	1.4	1533	1809.70	202.15	9.562
UCB1T	ratio k	tolerance	10	.8	0	1533	1838.20	145.60	9.573
UCB1T	top k	tolerance	10	1	0	1533	1834.90	172.42	17.707
UCB1T	ratio k	greedy	10	.8	0	1540	1540.00		.666
UCB1T	ratio k	greedy	10	1	0	1540	1540.00		.879
UCB1T	top k	random	15	.5	2.8	1540	3122.70	1753.55	1.088
UCB1T	top k	greedy	15	.5	2.8	1540	1540.00		1.181
UCB1T	ratio k	tolerance	5	.3	0	1540	1864.60	175.12	1.319
UCB1T	top k	greedy	15	.8	2.8	1540	1540.00		1.664
UCB	top k	greedy	5	.5	0	1540	1540.00		1.694
UCB	top k	greedy	5	0	0	1540	1540.00		1.702
UCB1T	ratio k	tolerance	10	.8	1.4	1540	1845.80	162.15	2.461
UCB1T	top k	greedy	5	.3	1.4	1540	1540.00		2.500
UCB	top k	tolerance	5	.5	0	1540	1800.30	156.39	2.706
UCB1T	ratio k	tolerance	10	.3	0	1540	1831.40	174.19	2.958
UCB1T	top k	tolerance	15	.3	0	1540	1896.80	214.92	3.424
UCB	ratio k	tolerance	10	0	0	1540	1850.20	183.61	4.229
UCB1T	ratio k	tolerance	5	.3	2.8	1540	1919.00	194.58	5.013
UCB1T	top k	tolerance	15	0	2.8	1540	1865.30	202.86	5.138
UCB1T	top k	tolerance	10	.5	2.8	1540	1776.30	180.87	6.638
UCB	ratio k	tolerance	15	0	0	1540	1913.30	207.39	7.511
UCB1T	top k	tolerance	10	.5	1.4	1540	1885.00	235.90	7.624
UCB	top k	tolerance	15	.8	0	1540	1810.70	162.48	7.951
UCB	top k	tolerance	10	0	0	1540	1882.00	169.58	8.397
UCB1T	ratio k	tolerance	10	.3	2.8	1540	1786.20	149.51	9.080
UCB1T	ratio k	tolerance	15	.8	2.8	1540	1758.30	183.71	9.664
UCB1T	top k	tolerance	15	1	2.8	1540	1814.90	116.59	9.710

UCB1T	ratio k	tolerance	15	1	2.8	1540	1862.50	184.05	9.835
UCB1T	ratio k	tolerance	15	.3	0	1540	1809.80	164.19	10.175
UCB1T	ratio k	tolerance	10	1	2.8	1540	1897.00	281.85	10.565
UCB1T	ratio k	tolerance	15	.8	1.4	1540	1908.50	196.92	13.413
UCB1T	ratio k	tolerance	15	.5	1.4	1540	1868.40	160.08	15.130
UCB1T	top k	tolerance	5	.8	0	1540	1824.20	165.59	16.175
UCB1T	top k	tolerance	5	0	1.4	1540	1806.50	198.51	17.011
UCB1T	top k	tolerance	5	.3	0	1540	1870.70	196.15	22.181
UCB1T	top k	tolerance	5	0	0	1540	1732.90	156.80	35.029
UCB1T	top k	tolerance	5	.5	2.8	1540	1828.10	128.77	53.816
UCB	ratio k	random	15	.8	0	1544	3538.60	1864.08	1.304
UCB1T	top k	random	5	0	2.8	1544	2510.60	969.95	1.983
UCB1T	top k	tolerance	15	.3	1.4	1546	1832.00	184.84	3.920
UCB	top k	tolerance	10	1	2.8	1547	1639.00	101.50	.350
UCB	top k	random	15	.3	2.8	1548	7304.10	5361.45	1.066
UCB1T	top k	tolerance	15	.5	0	1548	1838.50	129.02	5.476
UCB1T	top k	tolerance	10	.3	0	1548	1959.70	210.51	20.794
UCB1T	ratio k	random	15	0	0	1551	2592.00	1259.81	2.241
UCB1T	top k	tolerance	15	.8	2.8	1551	1862.00	139.22	12.043
UCB1T	ratio k	tolerance	5	1	0	1551	1884.40	202.74	22.815
UCB	ratio k	tolerance	5	.5	0	1552	1861.00	177.52	1.938
UCB	ratio k	tolerance	5	.8	0	1552	1818.80	158.49	2.109
UCB1T	top k	tolerance	10	1	2.8	1552	1826.90	170.80	7.951
UCB1T	ratio k	tolerance	5	.5	0	1553	1842.90	145.37	1.425
UCB1T	ratio k	tolerance	5	.5	2.8	1553	1820.10	155.51	3.897
UCB1T	top k	random	10	0	2.8	1553	3300.10	1765.23	3.970
UCB	ratio k	tolerance	10	.8	0	1553	1865.80	179.46	5.543
UCB1T	ratio k	tolerance	15	0	2.8	1553	1842.80	230.98	5.783
UCB1T	ratio k	tolerance	10	.5	0	1553	1832.90	113.14	9.797
UCB1T	ratio k	tolerance	15	.5	0	1553	1853.50	165.94	12.827
UCB1T	top k	random	5	.5	0	1555	2709.90	1386.28	.908
UCB1T	top k	random	15	.3	1.4	1555	2758.60	1549.45	5.773
UCB1T	top k	tolerance	10	.8	0	1561	1842.40	185.52	4.651
UCB1T	ratio k	tolerance	15	.5	2.8	1561	1886.10	209.51	8.565
UCB	ratio k	tolerance	10	1	0	1564	1792.40	163.67	.729
UCB	top k	greedy	10	.5	0	1564	1564.00		.746
UCB1T	ratio k	greedy	10	1	1.4	1564	1564.00		.967
UCB1T	ratio k	greedy	15	.3	1.4	1564	1564.00		1.123
UCB1T	top k	tolerance	10	.3	2.8	1564	1848.00	154.42	1.583
UCB1T	top k	tolerance	10	0	2.8	1564	1876.20	146.84	2.413
UCB	ratio k	tolerance	10	.3	0	1564	1894.60	168.37	3.180

UCB1T	ratio k	tolerance	15	0	1.4	1564	1926.10	169.41	3.914
UCB1T	ratio k	tolerance	10	0	0	1564	1894.10	209.84	5.046
UCB	top k	tolerance	5	.3	0	1564	1802.20	110.06	5.248
UCB1T	ratio k	tolerance	10	.5	2.8	1564	1903.40	202.94	5.620
UCB	top k	tolerance	15	0	0	1564	1996.80	188.44	7.431
UCB1T	top k	tolerance	15	.5	1.4	1564	1801.10	181.31	8.398
UCB	top k	tolerance	5	.8	0	1564	1821.10	171.24	8.987
UCB1T	top k	tolerance	15	1	1.4	1564	1857.30	200.71	10.041
UCB1T	ratio k	tolerance	15	1	1.4	1564	1931.50	183.48	12.772
UCB1T	top k	tolerance	5	.5	1.4	1564	1891.70	149.04	31.446
UCB	ratio k	random	10	.3	2.8	1565	5063.80	4094.92	.375
UCB1T	top k	random	10	.3	0	1565	3329.80	2124.79	2.699
UCB1T	top k	random	15	1	0	1565	3236.20	2047.21	5.953
UCB1T	top k	random	10	1	2.8	1569	2779.10	1889.48	1.492
UCB	ratio k	random	15	.3	2.8	1577	6779.70	3457.07	1.545
UCB1T	top k	tolerance	10	0	0	1577	1873.80	178.43	2.373
UCB1T	ratio k	random	15	1	0	1577	3337.20	1588.71	5.721
UCB1T	ratio k	random	10	1	0	1577	2901.20	1262.22	5.992
UCB1T	top k	tolerance	5	.3	2.8	1578	1838.70	131.18	30.039
UCB1T	top k	tolerance	10	.8	2.8	1580	1939.40	235.60	4.992
UCB	top k	random	15	.8	2.8	1583	3255.00	1757.31	.794
UCB	top k	random	5	.3	0	1583	3648.60	2136.03	1.634
UCB	top k	random	10	1	0	1583	3451.60	2094.03	3.372
UCB	ratio k	random	5	.5	2.8	1588	5819.70	3215.99	.441
UCB1T	ratio k	random	10	.8	1.4	1591	3953.30	2378.61	2.344
UCB	ratio k	random	5	.8	1.4	1602	3413.60	1617.10	.687
UCB1T	top k	random	15	.8	0	1606	3215.40	1457.51	2.597
UCB1T	ratio k	random	10	.5	0	1615	2917.70	1738.06	1.223
UCB1T	top k	random	5	0	1.4	1615	2243.60	798.90	2.994
UCB1T	top k	random	15	.8	1.4	1615	3428.80	2035.35	3.857
UCB1T	top k	random	10	0	0	1623	4175.70	2223.66	3.049
UCB1T	ratio k	greedy	5	.3	0	1624	1624.00		.749
UCB	top k	random	5	1	1.4	1627	3999.30	2670.48	.513
UCB	top k	random	5	0	0	1629	2414.10	1280.07	.261
UCB1T	top k	random	5	1	2.8	1633	2838.30	1236.17	3.507
UCB1T	ratio k	random	5	1	2.8	1644	3006.80	1803.40	.479
UCB	top k	random	15	1	0	1647	2351.30	1096.41	1.609
UCB	top k	random	15	.3	1.4	1651	3986.00	2543.37	1.927
UCB1T	ratio k	random	5	.8	1.4	1651	2863.80	1129.95	3.658
UCB	top k	random	10	0	0	1658	2117.20	621.46	3.543
UCB1T	ratio k	random	5	.5	0	1659	4723.70	1707.27	3.918

UCB	top k	random	10	1	2.8	1660	4102.50	2659.39	.610
UCB1T	top k	tolerance	5	.8	1.4	1660	1874.60	188.31	47.533
UCB1T	ratio k	random	10	.8	0	1661	3054.30	1542.70	1.292
UCB	top k	random	10	.8	2.8	1661	4508.90	3139.63	1.591
UCB1T	ratio k	random	5	.8	0	1662	1940.40	231.25	4.169
UCB1T	ratio k	tolerance	5	.8	2.8	1662	1837.90	117.26	6.998
UCB1T	ratio k	greedy	5	.3	1.4	1663	1663.00		.480
UCB	ratio k	tolerance	5	.3	0	1663	1865.90	178.68	1.407
UCB	ratio k	random	10	1	2.8	1663	4552.30	3487.52	1.795
UCB1T	ratio k	tolerance	5	0	2.8	1663	1927.80	140.83	3.367
UCB1T	top k	tolerance	15	.5	2.8	1663	1829.20	105.51	4.329
UCB1T	ratio k	random	10	.3	2.8	1663	3892.50	2094.32	4.499
UCB	top k	tolerance	5	0	0	1663	1838.30	154.11	9.751
UCB1T	ratio k	random	10	0	0	1666	2367.30	814.70	1.318
UCB	ratio k	random	5	.3	2.8	1666	5948.00	4768.95	1.669
UCB1T	ratio k	tolerance	5	.3	1.4	1666	1941.90	195.48	7.231
UCB1T	top k	tolerance	15	0	1.4	1666	1904.90	142.41	9.858
UCB1T	top k	random	15	.8	2.8	1668	2303.00	1087.21	4.729
UCB1T	ratio k	random	10	.3	0	1673	3451.40	2083.35	4.420
UCB	top k	tolerance	10	1	0	1674	1853.70	131.34	2.065
UCB1T	top k	tolerance	10	1	1.4	1674	1878.20	129.77	5.518
UCB	top k	random	5	1	0	1678	2416.90	959.20	1.502
UCB1T	ratio k	tolerance	10	0	1.4	1678	1914.00	147.42	3.342
UCB	top k	tolerance	5	1	0	1678	1867.30	151.01	3.844
UCB	ratio k	random	5	.5	1.4	1681	5446.30	3691.78	.327
UCB	ratio k	tolerance	10	.5	0	1689	1904.90	154.68	2.938
UCB1T	top k	random	10	.5	1.4	1689	2506.30	1778.12	4.497
UCB1T	ratio k	greedy	15	.3	0	1690	1690.00		1.255
UCB	top k	random	15	.5	2.8	1691	7503.60	5126.19	1.821
UCB	top k	random	5	.3	1.4	1695	4332.60	2620.35	.510
UCB	ratio k	tolerance	5	0	0	1695	1905.40	153.02	3.821
UCB	ratio k	tolerance	15	1	0	1695	1890.90	135.28	6.258
UCB1T	ratio k	tolerance	10	1	1.4	1695	1859.40	127.66	6.288
UCB1T	ratio k	random	5	.5	2.8	1696	2727.90	1650.15	2.736
UCB1T	ratio k	random	15	0	2.8	1698	3103.20	2377.88	1.629
UCB1T	top k	greedy	5	.8	2.8	1698	1698.00		3.695
UCB1T	top k	random	10	.8	0	1698	2707.90	1578.17	4.028
UCB1T	top k	tolerance	5	1	2.8	1698	1864.90	122.14	35.399
UCB	ratio k	random	10	.5	1.4	1703	3470.90	2151.66	.579
UCB	ratio k	random	10	.3	1.4	1704	4665.60	2019.66	.354
UCB	top k	random	10	.5	1.4	1704	5167.30	2683.04	.807

UCB	top k	random	5	.8	1.4	1706	3614.60	1951.29	.381
UCB	top k	random	5	.5	1.4	1706	4569.00	2297.57	1.213
UCB1T	top k	tolerance	10	.8	1.4	1708	1906.30	132.86	2.060
UCB	top k	random	5	.5	0	1709	2336.70	1046.92	1.765
UCB1T	top k	random	5	.3	0	1709	3106.80	1567.96	2.854
UCB1T	ratio k	tolerance	15	.8	0	1710	1881.00	143.86	15.660
UCB	top k	greedy	10	.3	0	1711	1711.00		.738
UCB	ratio k	random	5	.5	0	1715	3376.90	2127.71	1.448
UCB1T	ratio k	random	15	.5	1.4	1717	3660.50	2148.20	4.281
UCB1T	top k	random	5	1	0	1718	3008.10	1546.53	1.967
UCB1T	top k	greedy	5	.5	2.8	1720	1720.00		3.694
UCB1T	top k	tolerance	5	.5	0	1720	1858.30	108.43	5.149
UCB1T	ratio k	random	15	.8	0	1720	3732.40	1699.79	6.089
UCB1T	top k	random	10	.3	2.8	1724	2674.40	1285.84	3.201
UCB1T	top k	random	5	.8	2.8	1726	2636.60	1126.54	1.093
UCB	ratio k	random	5	0	1.4	1728	4667.50	2998.11	.755
UCB	ratio k	random	10	0	2.8	1729	5947.60	3119.40	1.541
UCB1T	top k	tolerance	5	1	1.4	1729	1885.90	169.41	34.003
UCB1T	top k	random	10	1	0	1730	3578.90	2090.43	.633
UCB	ratio k	random	15	1	0	1730	2956.50	1754.33	2.322
UCB1T	ratio k	greedy	15	1	0	1734	1734.00		1.119
UCB	top k	random	10	.3	1.4	1734	6041.60	3811.51	1.387
UCB	ratio k	tolerance	15	.8	0	1734	1937.30	160.39	2.265
UCB1T	top k	tolerance	10	.3	1.4	1740	1937.60	141.06	5.471
UCB1T	top k	greedy	10	.8	0	1741	1741.00		.881
UCB1T	ratio k	random	10	.5	2.8	1741	3925.10	2795.34	5.267
UCB	top k	tolerance	10	.5	0	1741	1849.90	89.06	6.946
UCB1T	ratio k	tolerance	15	.3	2.8	1741	1966.30	171.06	15.788
UCB	top k	random	5	.3	2.8	1742	5442.90	2963.68	.342
UCB	top k	greedy	5	.3	0	1742	1742.00		1.340
UCB1T	ratio k	random	15	0	1.4	1743	3496.30	1585.15	2.786
UCB1T	top k	random	10	.3	1.4	1744	2799.80	1512.75	3.386
UCB1T	ratio k	tolerance	10	.8	2.8	1744	1942.20	114.58	7.479
UCB	top k	tolerance	15	1	0	1745	1888.90	110.64	2.671
UCB1T	top k	random	15	.3	2.8	1746	3621.40	1663.32	.667
UCB1T	top k	random	15	.5	0	1746	3835.00	1661.25	5.242
UCB1T	top k	random	5	.3	1.4	1748	2388.70	1026.37	.811
UCB	ratio k	random	5	.8	0	1752	3143.70	1727.99	.330
UCB	top k	random	10	0	1.4	1752	6513.10	2763.61	.388
UCB1T	ratio k	greedy	15	.3	2.8	1752	1752.00		.822
UCB	top k	random	15	.3	0	1752	2640.80	1776.83	.905

UCB1T	ratio k	random	5	.8	2.8	1752	2631.00	1651.86	1.930
UCB1T	top k	random	15	0	0	1754	3047.90	1422.93	4.130
UCB1T	top k	random	15	0	1.4	1755	3598.20	1915.88	.549
UCB1T	ratio k	random	10	.8	2.8	1755	3665.50	1700.67	4.641
UCB	ratio k	greedy	5	.3	0	1757	1757.00		.308
UCB1T	ratio k	random	15	.3	0	1758	3812.60	1938.27	1.372
UCB1T	top k	greedy	15	1	1.4	1759	1759.00		1.236
UCB1T	top k	random	10	.5	0	1767	3736.40	2107.52	3.212
UCB	ratio k	random	15	.5	0	1771	2491.90	1254.11	.934
UCB1T	ratio k	random	15	.5	2.8	1771	3457.70	1985.88	5.624
UCB	ratio k	greedy	15	0	0	1773	1773.00		.384
UCB1T	ratio k	random	15	.3	1.4	1773	3853.40	2207.96	.599
UCB1T	top k	greedy	15	.3	0	1773	1773.00		1.033
UCB1T	top k	greedy	15	1	2.8	1774	1774.00		.618
UCB	ratio k	greedy	15	.5	0	1778	1778.00		.669
UCB1T	ratio k	greedy	15	.8	0	1778	1778.00		.732
UCB1T	top k	greedy	10	.5	2.8	1778	1778.00		.835
UCB	ratio k	greedy	10	.8	0	1778	1778.00		.852
UCB1T	ratio k	tolerance	15	0	0	1778	1959.60	159.75	1.432
UCB1T	top k	greedy	5	0	0	1778	1778.00		2.859
UCB1T	ratio k	greedy	5	.8	1.4	1778	1778.00		3.065
UCB1T	top k	tolerance	10	0	1.4	1778	1907.20	101.60	8.331
UCB1T	ratio k	random	15	.8	2.8	1779	3335.30	2191.39	5.037
UCB1T	top k	tolerance	15	.8	1.4	1780	1896.70	105.56	6.394
UCB	top k	random	10	.8	1.4	1782	6276.60	2458.38	.204
UCB1T	ratio k	random	15	1	2.8	1782	3349.50	1615.37	.677
UCB	ratio k	random	15	.3	0	1782	3142.90	2500.95	2.405
UCB1T	top k	greedy	10	.3	2.8	1783	1783.00		1.084
UCB	ratio k	random	10	.5	2.8	1783	6292.70	2661.63	1.304
UCB	top k	random	10	1	1.4	1783	5389.80	2177.70	1.721
UCB	top k	greedy	5	.8	0	1783	1783.00		2.146
UCB1T	top k	random	5	.3	2.8	1783	3757.60	1922.41	2.584
UCB1T	top k	greedy	5	.8	1.4	1783	1783.00		2.623
UCB1T	ratio k	tolerance	10	0	2.8	1783	1951.40	99.87	5.562
UCB	top k	random	5	1	2.8	1791	4959.50	2252.57	.836
UCB1T	top k	random	5	.8	1.4	1792	3362.30	1680.69	1.490
UCB	top k	random	15	0	2.8	1793	6246.20	3845.94	1.006
UCB1T	top k	random	10	.5	2.8	1795	2935.90	1756.79	.671
UCB1T	ratio k	random	10	0	1.4	1796	3402.30	1591.21	4.567
UCB1T	ratio k	random	15	.5	0	1796	2785.10	1424.75	5.271
UCB	ratio k	random	15	0	2.8	1797	4958.80	3035.26	.991

UCB1T	ratio k	tolerance	5	.5	1.4	1797	1952.50	142.06	6.487
UCB1T	top k	tolerance	5	.8	2.8	1797	1906.40	90.79	11.151
UCB	top k	random	10	.8	0	1798	3569.70	2296.99	.390
UCB	top k	greedy	10	.8	0	1798	1798.00		.466
UCB1T	ratio k	greedy	10	.3	0	1798	1798.00		.909
UCB1T	ratio k	greedy	10	.8	1.4	1798	1798.00		1.255
UCB1T	ratio k	tolerance	5	0	1.4	1798	1927.00	109.64	2.407
UCB1T	top k	greedy	5	1	0	1798	1798.00		2.471
UCB1T	top k	greedy	5	0	1.4	1798	1798.00		2.742
UCB	top k	random	15	0	0	1800	3375.00	1522.78	1.985
UCB1T	top k	random	15	.5	1.4	1801	3564.00	2310.60	1.718
UCB	top k	random	5	0	2.8	1802	5150.30	3980.89	.696
UCB1T	top k	random	10	.8	2.8	1804	3337.90	1579.14	3.917
UCB1T	ratio k	greedy	15	.5	0	1805	1805.00		1.020
UCB1T	top k	greedy	10	1	1.4	1805	1805.00		1.252
UCB	ratio k	random	15	1	2.8	1805	3020.50	1454.09	1.851
UCB	top k	random	15	.5	0	1810	2685.60	1291.87	2.002
UCB	ratio k	random	5	0	2.8	1811	5222.20	2594.44	1.431
UCB1T	ratio k	random	5	.3	0	1811	3121.80	1195.49	2.154
UCB1T	top k	random	15	1	1.4	1811	2746.10	1029.79	4.165
UCB	top k	random	15	1	1.4	1812	3813.70	2108.22	1.580
UCB	ratio k	tolerance	15	.5	0	1815	1933.60	109.14	7.289
UCB1T	top k	random	5	.8	0	1817	2863.50	1598.52	4.821
UCB	top k	greedy	15	.8	0	1819	1819.00		.819
UCB	top k	random	5	.8	0	1819	2653.10	1378.29	2.417
UCB	top k	random	15	.8	0	1821	2959.50	1379.33	.548
UCB	top k	greedy	5	1	0	1822	1822.00		1.778
UCB1T	top k	greedy	5	.3	0	1822	1822.00		3.199
UCB1T	ratio k	greedy	5	.5	1.4	1833	1833.00		.770
UCB1T	ratio k	greedy	10	.3	2.8	1833	1833.00		.850
UCB	ratio k	greedy	10	.5	0	1833	1833.00		.896
UCB1T	ratio k	greedy	5	.8	2.8	1833	1833.00		1.920
UCB1T	top k	greedy	5	.5	0	1833	1833.00		2.552
UCB1T	top k	greedy	5	.8	0	1833	1833.00		3.735
UCB	top k	random	10	.3	0	1837	2984.40	1548.27	.343
UCB1T	ratio k	random	5	1	0	1839	2988.30	987.59	1.384
UCB	ratio k	random	10	.3	0	1839	2936.70	1766.59	3.191
UCB	ratio k	random	10	1	0	1840	2954.60	1488.65	1.376
UCB	ratio k	random	10	0	0	1844	3452.30	1914.01	2.469
UCB1T	top k	random	5	.5	2.8	1845	3487.20	1871.64	1.131
UCB1T	top k	random	10	.8	1.4	1845	2470.80	1026.68	6.022

UCB	top k	greedy	10	0	0	1846	1846.00		.531
UCB1T	ratio k	greedy	5	.8	0	1846	1846.00		2.147
UCB1T	top k	greedy	15	.5	0	1847	1847.00		1.365
UCB1T	top k	greedy	5	1	2.8	1847	1847.00		2.332
UCB1T	top k	random	15	1	2.8	1847	3483.10	1585.60	5.841
UCB	ratio k	random	10	.8	1.4	1849	6728.60	2720.00	.551
UCB1T	top k	random	5	0	0	1849	2920.70	1313.92	3.279
UCB1T	top k	greedy	5	.3	2.8	1850	1850.00		2.709
UCB1T	ratio k	greedy	5	.5	0	1851	1851.00		.718
UCB1T	top k	random	10	0	1.4	1851	2614.40	1646.27	.728
UCB1T	ratio k	greedy	5	1	1.4	1851	1851.00		2.352
UCB	top k	random	5	.5	2.8	1855	5007.10	2533.14	1.484
UCB1T	ratio k	random	5	.3	1.4	1855	3247.80	1139.79	1.912
UCB1T	ratio k	random	10	1	2.8	1855	4480.10	2346.39	6.490
UCB1T	top k	greedy	10	.5	0	1856	1856.00		.920
UCB1T	top k	greedy	10	.3	1.4	1856	1856.00		1.010
UCB1T	top k	greedy	5	0	2.8	1856	1856.00		1.684
UCB1T	top k	random	10	1	1.4	1856	3578.30	2326.86	5.097
UCB	top k	greedy	15	.5	0	1861	1861.00		.648
UCB1T	ratio k	greedy	5	.3	2.8	1861	1861.00		.896
UCB1T	top k	greedy	10	.5	1.4	1861	1861.00		.970
UCB1T	ratio k	greedy	10	0	2.8	1861	1861.00		1.369
UCB	top k	tolerance	10	.3	0	1861	1980.50	93.92	10.326
UCB	top k	greedy	15	.3	0	1862	1862.00		.438
UCB1T	ratio k	random	15	.3	2.8	1863	3343.90	2736.34	2.367
UCB1T	ratio k	random	5	0	1.4	1864	4090.10	2412.61	1.531
UCB1T	top k	random	5	1	1.4	1865	2448.10	971.91	2.612
UCB	ratio k	random	15	1	1.4	1866	6731.90	3376.22	1.466
UCB	ratio k	random	5	.3	0	1871	3780.50	1986.19	.225
UCB	ratio k	random	15	0	0	1871	3548.20	2364.24	1.076
UCB	top k	random	10	.5	2.8	1871	7492.80	3399.24	1.248
UCB1T	ratio k	greedy	10	0	0	1880	1880.00		1.468
UCB1T	ratio k	random	5	.3	2.8	1881	3384.70	1996.79	3.608
UCB	top k	random	10	.5	0	1886	2432.70	1384.12	.622
UCB	ratio k	random	15	.8	1.4	1888	5276.10	3156.41	.173
UCB1T	ratio k	random	5	0	0	1889	4056.40	1786.38	.491
UCB1T	ratio k	random	5	1	1.4	1891	2279.90	630.36	3.158
UCB	top k	random	15	.8	1.4	1894	6800.10	3085.13	1.668
UCB1T	top k	random	15	0	2.8	1894	3414.70	2159.40	5.490
UCB	ratio k	random	10	.5	0	1899	3775.90	1612.17	2.071
UCB1T	ratio k	random	10	1	1.4	1900	3640.40	1458.18	3.926

UCB	top k	random	5	.8	2.8	1901	4658.20	2594.64	.823
UCB	top k	random	15	.5	1.4	1902	7399.70	2650.98	.834
UCB1T	ratio k	random	15	1	1.4	1904	3899.60	2062.78	5.620
UCB1T	top k	greedy	15	0	2.8	1905	1905.00		.984
UCB	ratio k	greedy	5	.5	0	1910	1910.00		.476
UCB	ratio k	greedy	5	.8	0	1910	1910.00		1.994
UCB	ratio k	random	5	.8	2.8	1915	5654.40	3277.84	.157
UCB1T	ratio k	greedy	5	.5	2.8	1916	1916.00		.606
UCB1T	top k	greedy	10	1	0	1917	1917.00		1.081
UCB	top k	random	10	0	2.8	1917	4964.00	2954.44	1.358
UCB1T	ratio k	greedy	15	1	1.4	1937	1937.00		.818
UCB	ratio k	random	15	.5	1.4	1941	7036.40	3592.63	1.856
UCB1T	ratio k	greedy	5	1	0	1941	1941.00		1.996
UCB1T	ratio k	greedy	5	0	0	1943	1943.00		.723
UCB	ratio k	random	10	0	1.4	1945	4955.90	2402.73	1.456
UCB	ratio k	greedy	15	1	0	1951	1951.00		.764
UCB1T	top k	greedy	5	1	1.4	1951	1951.00		2.631
UCB1T	ratio k	random	10	.5	1.4	1957	3272.20	1591.64	2.647
UCB1T	top k	greedy	15	0	0	1959	1959.00		1.223
UCB1T	ratio k	greedy	10	0	1.4	1960	1960.00		1.371
UCB1T	top k	greedy	10	.3	0	1961	1961.00		1.035
UCB1T	top k	greedy	15	.8	0	1962	1962.00		.757
UCB	ratio k	greedy	10	1	0	1969	1969.00		.610
UCB	top k	greedy	15	1	0	1971	1971.00		1.004
UCB	ratio k	greedy	5	0	0	1972	1972.00		.390
UCB1T	top k	greedy	10	1	2.8	1972	1972.00		.880
UCB1T	ratio k	greedy	15	.8	2.8	1972	1972.00		1.064
UCB1T	ratio k	greedy	10	.8	2.8	1972	1972.00		1.067
UCB	top k	greedy	10	1	0	1972	1972.00		1.072
UCB1T	ratio k	greedy	15	0	1.4	1972	1972.00		1.131
UCB1T	ratio k	greedy	15	0	0	1972	1972.00		1.301
UCB	ratio k	random	5	0	0	1972	4122.00	2790.15	2.345
UCB1T	top k	greedy	5	.5	1.4	1972	1972.00		2.618
UCB	top k	greedy	15	0	0	1977	1977.00		.635
UCB1T	top k	greedy	15	.8	1.4	1979	1979.00		2.432
UCB1T	ratio k	greedy	15	.5	1.4	1992	1992.00		.746
UCB1T	ratio k	greedy	15	1	2.8	1992	1992.00		1.310
UCB1T	top k	greedy	10	.8	1.4	1994	1994.00		1.255
UCB1T	top k	greedy	15	.3	2.8	1995	1995.00		1.126
UCB	top k	random	10	.3	2.8	1999	5307.10	1971.19	1.000
UCB	top k	random	15	1	2.8	2001	6131.90	2126.47	1.596

UCB	ratio k	random	5	1	0	2010	4339.90	1942.49	1.911
UCB	ratio k	greedy	10	0	0	2029	2029.00		.802
UCB1T	top k	greedy	15	1	0	2029	2029.00		1.061
UCB1T	ratio k	greedy	15	.5	2.8	2035	2035.00		1.150
UCB	ratio k	random	15	0	1.4	2040	5329.50	2769.75	1.122
UCB	ratio k	greedy	10	.3	0	2044	2044.00		.755
UCB1T	ratio k	greedy	5	1	2.8	2053	2053.00		2.321
UCB1T	top k	greedy	10	.8	2.8	2068	2068.00		.915
UCB1T	ratio k	greedy	10	.5	0	2074	2074.00		1.003
UCB	top k	random	15	0	1.4	2100	6246.40	3562.81	.221
UCB1T	ratio k	random	10	0	2.8	2105	3032.10	980.16	5.624
UCB1T	ratio k	greedy	15	0	2.8	2108	2108.00		1.132
UCB	ratio k	greedy	15	.3	0	2116	2116.00		.962
UCB1T	top k	greedy	10	0	0	2116	2116.00		1.385
UCB1T	ratio k	greedy	10	.5	2.8	2128	2128.00		.988
UCB1T	top k	greedy	10	0	2.8	2128	2128.00		1.014
UCB1T	top k	greedy	15	0	1.4	2165	2165.00		1.313
UCB1T	top k	greedy	10	0	1.4	2175	2175.00		1.272
UCB	ratio k	greedy	15	.8	0	2188	2188.00		.955
UCB1T	ratio k	greedy	15	.8	1.4	2188	2188.00		1.447
UCB	ratio k	random	15	.5	2.8	2189	4892.40	1736.65	1.437
UCB1T	top k	greedy	15	.5	1.4	2211	2211.00		2.119
UCB	ratio k	random	10	.8	2.8	2229	8014.20	3618.47	.742
UCB1T	ratio k	greedy	10	1	2.8	2258	2258.00		1.518
UCB1T	top k	greedy	15	.3	1.4	2261	2261.00		1.174
UCB1T	ratio k	greedy	10	.3	1.4	2273	2273.00		1.990
UCB	ratio k	random	15	.3	1.4	2437	5466.50	1930.17	1.931
UCB	ratio k	random	5	.3	1.4	2564	5817.90	3017.59	.167
UCB1T	ratio k	greedy	5	0	2.8	2945	2945.00		.469

C.1.2 Solution not found

Selec policy	Exp policy	Simu policy	N° childrens	Ratio	Cp	Best cost	Mean	Std	T(s)
-	-	-	-	-	-	-	-	-	-

C.2 Instance 2

C.2.1 Solution found

Selec policy	Exp policy	Simu policy	N° childrens	Ratio	Cp	Best cost	Mean	Std	T(s)
UCB	ratio k	greedy	5	.8	0	1498	1498.00		.082
UCB	ratio k	greedy	5	.3	1.4	1498	1498.00		.083
UCB1T	ratio k	greedy	10	1	1.4	1498	1498.00		.084
UCB1T	ratio k	greedy	15	.5	0	1498	1498.00		.087
UCB	ratio k	greedy	5	.8	1.4	1498	1498.00		.087
UCB	ratio k	greedy	15	.3	2.8	1498	1498.00		.087
UCB	ratio k	greedy	15	0	2.8	1498	1498.00		.088
UCB1T	ratio k	greedy	15	0	1.4	1498	1498.00		.088
UCB	top k	tolerance	10	0	2.8	1498	1498.00	0.00	.089
UCB1T	ratio k	greedy	10	1	2.8	1498	1498.00		.089
UCB	ratio k	greedy	10	.5	2.8	1498	1498.00		.089
UCB	top k	tolerance	15	.5	2.8	1498	1498.00	0.00	.090
UCB1T	ratio k	tolerance	15	1	1.4	1498	1498.00	0.00	.091
UCB1T	ratio k	tolerance	15	.3	1.4	1498	1498.00	0.00	.092
UCB	ratio k	greedy	10	0	2.8	1498	1498.00		.092
UCB	ratio k	greedy	5	.5	0	1498	1498.00		.092
UCB	top k	tolerance	10	0	1.4	1498	1498.00	0.00	.093
UCB	top k	greedy	15	.5	1.4	1498	1498.00		.093
UCB	top k	tolerance	10	.8	2.8	1498	1498.00	0.00	.093
UCB	ratio k	greedy	10	.3	2.8	1498	1498.00		.093
UCB	ratio k	tolerance	15	1	0	1498	1498.00	0.00	.094
UCB	top k	greedy	15	1	2.8	1498	1498.00		.094
UCB	top k	tolerance	15	.8	2.8	1498	1498.00	0.00	.095
UCB	ratio k	greedy	15	1	0	1498	1498.00		.095
UCB1T	ratio k	greedy	15	.3	0	1498	1498.00		.095
UCB	top k	greedy	15	0	0	1498	1498.00		.095
UCB1T	ratio k	greedy	10	0	1.4	1498	1498.00		.096
UCB1T	ratio k	greedy	10	.8	2.8	1498	1498.00		.096
UCB1T	ratio k	greedy	10	.8	1.4	1498	1498.00		.096
UCB	ratio k	greedy	15	0	1.4	1498	1498.00		.096
UCB1T	top k	greedy	15	1	1.4	1498	1498.00		.097
UCB	ratio k	greedy	5	.3	0	1498	1498.00		.097
UCB	top k	greedy	15	.3	1.4	1498	1498.00		.097
UCB1T	ratio k	tolerance	15	1	0	1498	1498.00	0.00	.098

UCB1T	ratio k	greedy	15	.8	2.8	1498	1498.00		.098
UCB	ratio k	tolerance	5	.5	0	1498	1498.00	0.00	.099
UCB1T	ratio k	greedy	15	.3	1.4	1498	1498.00		.099
UCB	top k	greedy	10	0	2.8	1498	1498.00		.099
UCB	ratio k	greedy	15	1	2.8	1498	1498.00		.099
UCB	ratio k	greedy	10	0	1.4	1498	1498.00		.100
UCB1T	ratio k	greedy	15	.5	1.4	1498	1498.00		.100
UCB	top k	greedy	10	.5	1.4	1498	1498.00		.100
UCB1T	top k	greedy	15	0	1.4	1498	1498.00		.100
UCB1T	ratio k	greedy	10	.5	0	1498	1498.00		.100
UCB1T	top k	greedy	10	0	2.8	1498	1498.00		.100
UCB1T	ratio k	tolerance	5	.5	2.8	1498	1498.00	0.00	.101
UCB1T	ratio k	greedy	10	.8	0	1498	1498.00		.101
UCB1T	ratio k	tolerance	10	0	2.8	1498	1498.00	0.00	.101
UCB	ratio k	greedy	15	1	1.4	1498	1498.00		.101
UCB1T	ratio k	tolerance	15	.3	2.8	1498	1498.00	0.00	.101
UCB1T	ratio k	tolerance	15	.5	1.4	1498	1498.00	0.00	.102
UCB	ratio k	greedy	15	0	0	1498	1498.00		.102
UCB1T	ratio k	greedy	10	.5	1.4	1498	1498.00		.102
UCB	top k	greedy	10	.3	1.4	1498	1498.00		.103
UCB1T	top k	greedy	15	.8	2.8	1498	1498.00		.103
UCB	ratio k	tolerance	15	1	2.8	1498	1498.00	0.00	.103
UCB1T	ratio k	tolerance	15	0	0	1498	1498.00	0.00	.104
UCB	top k	greedy	15	.8	2.8	1498	1498.00		.104
UCB	ratio k	greedy	15	.8	1.4	1498	1498.00		.104
UCB	top k	greedy	10	0	1.4	1498	1498.00		.104
UCB	ratio k	greedy	10	.8	2.8	1498	1498.00		.104
UCB	ratio k	greedy	10	1	1.4	1498	1498.00		.105
UCB	ratio k	greedy	15	.8	0	1498	1498.00		.105
UCB	ratio k	greedy	10	.3	0	1498	1498.00		.105
UCB	top k	tolerance	10	1	1.4	1498	1498.00	0.00	.106
UCB	top k	greedy	10	.8	1.4	1498	1498.00		.106
UCB	ratio k	tolerance	15	.5	1.4	1498	1498.00	0.00	.106
UCB	top k	tolerance	15	.3	1.4	1498	1498.00	0.00	.106
UCB	ratio k	greedy	15	.5	2.8	1498	1498.00		.107
UCB1T	ratio k	tolerance	15	0	2.8	1498	1498.00	0.00	.107
UCB	top k	greedy	10	.8	0	1498	1498.00		.108
UCB	ratio k	greedy	5	0	0	1498	1498.00		.108
UCB	top k	greedy	15	0	1.4	1498	1498.00		.108
UCB	ratio k	greedy	15	.3	1.4	1498	1498.00		.109
UCB	top k	tolerance	15	.3	0	1498	1498.00	0.00	.109

UCB	ratio k	greedy	10	.5	1.4	1498	1498.00		.109
UCB	ratio k	greedy	10	.3	1.4	1498	1498.00		.109
UCB	ratio k	greedy	10	.8	1.4	1498	1498.00		.109
UCB	top k	tolerance	10	.8	1.4	1498	1498.00	0.00	.110
UCB1T	ratio k	greedy	15	0	0	1498	1498.00		.110
UCB1T	top k	tolerance	10	1	2.8	1498	1498.00	0.00	.110
UCB1T	ratio k	greedy	10	.3	0	1498	1498.00		.110
UCB1T	top k	greedy	10	.3	2.8	1498	1498.00		.110
UCB	top k	tolerance	10	.5	1.4	1498	1498.00	0.00	.110
UCB1T	top k	greedy	10	.3	0	1498	1498.00		.110
UCB	ratio k	greedy	10	.8	0	1498	1498.00		.110
UCB1T	ratio k	greedy	10	.3	1.4	1498	1498.00		.110
UCB1T	top k	tolerance	10	.5	0	1498	1498.00	0.00	.110
UCB	ratio k	tolerance	15	.5	2.8	1498	1498.00	0.00	.111
UCB1T	top k	greedy	15	.3	0	1498	1498.00		.111
UCB	top k	greedy	10	.8	2.8	1498	1498.00		.111
UCB	ratio k	greedy	10	1	2.8	1498	1498.00		.111
UCB	ratio k	tolerance	15	.3	1.4	1498	1498.00	0.00	.111
UCB1T	top k	greedy	10	1	1.4	1498	1498.00		.111
UCB	top k	tolerance	15	1	1.4	1498	1498.00	0.00	.112
UCB	top k	greedy	15	.3	0	1498	1498.00		.112
UCB1T	top k	greedy	15	.5	1.4	1498	1498.00		.112
UCB	top k	tolerance	15	.8	1.4	1498	1498.00	0.00	.112
UCB1T	ratio k	tolerance	5	0	2.8	1498	1498.00	0.00	.112
UCB1T	ratio k	greedy	15	.5	2.8	1498	1498.00		.112
UCB1T	top k	greedy	15	.8	1.4	1498	1498.00		.112
UCB	top k	greedy	15	.8	1.4	1498	1498.00		.112
UCB1T	top k	tolerance	15	.5	2.8	1498	1498.00	0.00	.112
UCB1T	ratio k	greedy	5	.5	2.8	1498	1498.00		.113
UCB	top k	tolerance	10	1	2.8	1498	1498.00	0.00	.113
UCB	ratio k	tolerance	10	.3	1.4	1498	1498.00	0.00	.113
UCB1T	ratio k	tolerance	10	.5	0	1498	1498.00	0.00	.113
UCB	ratio k	tolerance	15	.8	2.8	1498	1498.00	0.00	.114
UCB1T	ratio k	tolerance	15	.5	0	1498	1498.00	0.00	.114
UCB1T	top k	greedy	10	.5	2.8	1498	1498.00		.114
UCB	ratio k	greedy	15	.8	2.8	1498	1498.00		.114
UCB	top k	greedy	15	0	2.8	1498	1498.00		.114
UCB	top k	greedy	10	.5	2.8	1498	1498.00		.114
UCB	top k	tolerance	15	1	2.8	1498	1498.00	0.00	.115
UCB	top k	greedy	10	.3	0	1498	1498.00		.115
UCB1T	ratio k	greedy	10	.3	2.8	1498	1498.00		.115

UCB1T	top k	greedy	10	.3	1.4	1498	1498.00		.115
UCB1T	top k	greedy	10	.8	2.8	1498	1498.00		.116
UCB1T	ratio k	tolerance	15	.8	0	1498	1498.00	0.00	.116
UCB	ratio k	greedy	15	.5	1.4	1498	1498.00		.116
UCB1T	top k	greedy	15	.3	1.4	1498	1498.00		.116
UCB1T	top k	greedy	15	1	0	1498	1498.00		.116
UCB	ratio k	tolerance	5	0	0	1498	1498.00	0.00	.117
UCB	top k	greedy	10	1	0	1498	1498.00		.117
UCB	ratio k	tolerance	5	.8	1.4	1498	1498.00	0.00	.117
UCB1T	top k	tolerance	10	.5	2.8	1498	1498.00	0.00	.117
UCB1T	top k	tolerance	10	.3	1.4	1498	1498.00	0.00	.117
UCB	top k	greedy	10	.3	2.8	1498	1498.00		.118
UCB1T	top k	tolerance	10	0	1.4	1498	1498.00	0.00	.118
UCB	ratio k	greedy	15	.3	0	1498	1498.00		.118
UCB	top k	greedy	15	.5	2.8	1498	1498.00		.118
UCB	top k	greedy	15	1	0	1498	1498.00		.118
UCB	top k	tolerance	10	.3	2.8	1498	1498.00	0.00	.119
UCB1T	top k	greedy	10	.5	0	1498	1498.00		.119
UCB	ratio k	greedy	5	.5	2.8	1498	1498.00		.119
UCB1T	top k	greedy	10	0	0	1498	1498.00		.119
UCB1T	ratio k	tolerance	5	.3	1.4	1498	1498.00	0.00	.120
UCB	ratio k	tolerance	10	1	0	1498	1498.00	0.00	.120
UCB	top k	greedy	10	1	1.4	1498	1498.00		.120
UCB1T	ratio k	greedy	15	.8	1.4	1498	1498.00		.120
UCB1T	top k	greedy	10	1	0	1498	1498.00		.120
UCB1T	ratio k	greedy	10	1	0	1498	1498.00		.120
UCB	ratio k	greedy	10	0	0	1498	1498.00		.121
UCB1T	top k	greedy	15	.5	2.8	1498	1498.00		.121
UCB1T	top k	greedy	15	.3	2.8	1498	1498.00		.121
UCB	ratio k	tolerance	10	0	0	1498	1498.00	0.00	.121
UCB	ratio k	greedy	10	.5	0	1498	1498.00		.121
UCB	ratio k	tolerance	15	.3	2.8	1498	1498.00	0.00	.121
UCB1T	ratio k	greedy	15	.3	2.8	1498	1498.00		.122
UCB1T	top k	greedy	15	.5	0	1498	1498.00		.122
UCB1T	top k	tolerance	10	.3	0	1498	1498.00	0.00	.122
UCB1T	ratio k	tolerance	15	.3	0	1498	1498.00	0.00	.122
UCB1T	ratio k	tolerance	15	0	1.4	1498	1498.00	0.00	.123
UCB1T	ratio k	greedy	15	1	2.8	1498	1498.00		.123
UCB1T	top k	tolerance	15	.8	0	1498	1498.00	0.00	.123
UCB	ratio k	tolerance	10	0	1.4	1498	1498.00	0.00	.123
UCB	top k	greedy	10	.5	0	1498	1498.00		.124

UCB1T	top k	tolerance	15	.5	1.4	1498	1498.00	0.00	.124
UCB	top k	greedy	15	1	1.4	1498	1498.00		.124
UCB	top k	greedy	10	1	2.8	1498	1498.00		.124
UCB1T	ratio k	greedy	15	0	2.8	1498	1498.00		.125
UCB1T	top k	tolerance	10	.8	0	1498	1498.00	0.00	.125
UCB1T	top k	tolerance	15	0	1.4	1498	1498.00	0.00	.125
UCB1T	ratio k	greedy	15	1	0	1498	1498.00		.125
UCB1T	top k	tolerance	10	.8	2.8	1498	1498.00	0.00	.125
UCB	ratio k	tolerance	5	.8	0	1498	1498.00	0.00	.125
UCB	ratio k	greedy	15	.5	0	1498	1498.00		.126
UCB1T	top k	tolerance	10	.8	1.4	1498	1498.00	0.00	.126
UCB1T	ratio k	tolerance	5	0	0	1498	1498.00	0.00	.126
UCB1T	top k	tolerance	10	1	1.4	1498	1498.00	0.00	.126
UCB	ratio k	greedy	10	1	0	1498	1498.00		.126
UCB1T	top k	tolerance	10	.5	1.4	1498	1498.00	0.00	.126
UCB1T	top k	tolerance	15	.8	1.4	1498	1498.00	0.00	.126
UCB	top k	tolerance	15	1	0	1498	1498.00	0.00	.127
UCB	top k	tolerance	15	0	0	1498	1498.00	0.00	.127
UCB	ratio k	tolerance	5	.3	1.4	1498	1498.00	0.00	.127
UCB1T	top k	tolerance	15	0	2.8	1498	1498.00	0.00	.127
UCB1T	top k	greedy	10	.8	1.4	1498	1498.00		.128
UCB1T	ratio k	greedy	10	.5	2.8	1498	1498.00		.128
UCB	top k	tolerance	15	.5	1.4	1498	1498.00	0.00	.129
UCB1T	top k	greedy	15	.8	0	1498	1498.00		.129
UCB1T	top k	greedy	10	1	2.8	1498	1498.00		.130
UCB1T	top k	tolerance	15	.3	0	1498	1498.00	0.00	.130
UCB1T	top k	greedy	15	0	2.8	1498	1498.00		.130
UCB	ratio k	tolerance	10	.5	1.4	1498	1498.00	0.00	.131
UCB	ratio k	tolerance	10	.5	0	1498	1498.00	0.00	.131
UCB1T	ratio k	tolerance	15	.8	1.4	1498	1498.00	0.00	.132
UCB1T	ratio k	greedy	15	1	1.4	1498	1498.00		.133
UCB1T	ratio k	tolerance	15	.5	2.8	1498	1498.00	0.00	.133
UCB1T	top k	greedy	10	.5	1.4	1498	1498.00		.134
UCB1T	top k	greedy	10	.8	0	1498	1498.00		.134
UCB	top k	greedy	15	.3	2.8	1498	1498.00		.134
UCB1T	top k	tolerance	15	1	0	1498	1498.00	0.00	.135
UCB1T	top k	tolerance	15	0	0	1498	1498.00	0.00	.135
UCB1T	ratio k	tolerance	5	.8	1.4	1498	1498.00	0.00	.136
UCB	top k	tolerance	15	0	1.4	1498	1498.00	0.00	.136
UCB1T	ratio k	tolerance	5	.5	1.4	1498	1498.00	0.00	.137
UCB1T	ratio k	tolerance	10	0	0	1498	1498.00	0.00	.137

UCB	ratio k	tolerance	10	.8	0	1498	1498.00	0.00	.139
UCB1T	top k	greedy	10	0	1.4	1498	1498.00		.140
UCB1T	top k	tolerance	10	0	2.8	1498	1498.00	0.00	.140
UCB	top k	tolerance	10	.5	2.8	1498	1498.00	0.00	.140
UCB	ratio k	tolerance	10	0	2.8	1498	1498.00	0.00	.141
UCB	ratio k	tolerance	10	.5	2.8	1498	1498.00	0.00	.141
UCB1T	ratio k	tolerance	5	.5	0	1498	1498.00	0.00	.141
UCB1T	ratio k	tolerance	10	0	1.4	1498	1498.00	0.00	.142
UCB	ratio k	tolerance	15	.8	0	1498	1498.00	0.00	.142
UCB	ratio k	tolerance	15	1	1.4	1498	1498.00	0.00	.142
UCB	ratio k	tolerance	15	0	0	1498	1498.00	0.00	.142
UCB1T	ratio k	greedy	5	.5	0	1498	1498.00		.142
UCB1T	ratio k	tolerance	10	.3	2.8	1498	1498.00	0.00	.143
UCB1T	ratio k	tolerance	10	.5	1.4	1498	1498.00	0.00	.143
UCB1T	top k	greedy	15	1	2.8	1498	1498.00		.143
UCB	top k	greedy	10	0	0	1498	1498.00		.145
UCB1T	ratio k	tolerance	10	.5	2.8	1498	1498.00	0.00	.145
UCB	ratio k	tolerance	15	.3	0	1498	1498.00	0.00	.145
UCB1T	ratio k	tolerance	15	1	2.8	1498	1498.00	0.00	.146
UCB	ratio k	tolerance	15	0	2.8	1498	1498.00	0.00	.146
UCB	ratio k	tolerance	15	.5	0	1498	1498.00	0.00	.146
UCB	ratio k	tolerance	5	.5	1.4	1498	1498.00	0.00	.147
UCB1T	ratio k	tolerance	10	.3	0	1498	1498.00	0.00	.148
UCB	top k	tolerance	15	0	2.8	1498	1498.00	0.00	.148
UCB	ratio k	tolerance	10	.3	2.8	1498	1498.00	0.00	.149
UCB	top k	tolerance	15	.5	0	1498	1498.00	0.00	.149
UCB1T	top k	tolerance	10	.3	2.8	1498	1498.00	0.00	.149
UCB1T	ratio k	tolerance	10	.8	2.8	1498	1498.00	0.00	.150
UCB1T	top k	greedy	15	0	0	1498	1498.00		.151
UCB	ratio k	tolerance	10	.3	0	1498	1498.00	0.00	.152
UCB	ratio k	tolerance	5	.3	2.8	1498	1498.00	0.00	.152
UCB	ratio k	tolerance	15	0	1.4	1498	1498.00	0.00	.152
UCB1T	top k	tolerance	15	1	2.8	1498	1498.00	0.00	.152
UCB	ratio k	tolerance	5	.5	2.8	1498	1498.00	0.00	.153
UCB	ratio k	tolerance	10	1	1.4	1498	1498.00	0.00	.153
UCB1T	top k	tolerance	15	.3	2.8	1498	1498.00	0.00	.153
UCB1T	top k	tolerance	10	0	0	1498	1498.00	0.00	.154
UCB1T	top k	tolerance	15	.5	0	1498	1498.00	0.00	.154
UCB1T	ratio k	greedy	10	0	0	1498	1498.00		.155
UCB	top k	greedy	15	.5	0	1498	1498.00		.155
UCB	top k	tolerance	10	1	0	1498	1498.00	0.00	.156

UCB	ratio k	tolerance	5	.3	0	1498	1498.00	0.00	.156
UCB1T	top k	tolerance	15	.3	1.4	1498	1498.00	0.00	.156
UCB1T	ratio k	tolerance	10	.8	0	1498	1498.00	0.00	.157
UCB1T	ratio k	greedy	10	0	2.8	1498	1498.00		.157
UCB	top k	tolerance	10	0	0	1498	1498.00	0.00	.160
UCB	top k	tolerance	15	.8	0	1498	1498.00	0.00	.161
UCB1T	ratio k	tolerance	10	1	0	1498	1498.00	0.00	.163
UCB	top k	tolerance	10	.5	0	1498	1498.00	0.00	.163
UCB	top k	tolerance	15	.3	2.8	1498	1498.00	0.00	.164
UCB1T	top k	tolerance	15	1	1.4	1498	1498.00	0.00	.164
UCB	ratio k	tolerance	10	1	2.8	1498	1498.00	0.00	.164
UCB1T	top k	tolerance	10	1	0	1498	1498.00	0.00	.165
UCB1T	ratio k	greedy	15	.8	0	1498	1498.00		.167
UCB1T	ratio k	tolerance	5	.8	0	1498	1498.00	0.00	.168
UCB1T	ratio k	tolerance	10	1	2.8	1498	1498.00	0.00	.171
UCB	ratio k	tolerance	10	.8	1.4	1498	1498.00	0.00	.174
UCB	ratio k	tolerance	15	.8	1.4	1498	1498.00	0.00	.174
UCB	top k	tolerance	10	.8	0	1498	1498.00	0.00	.175
UCB	ratio k	tolerance	10	.8	2.8	1498	1498.00	0.00	.175
UCB	ratio k	tolerance	5	.8	2.8	1498	1498.00	0.00	.176
UCB	ratio k	tolerance	5	0	1.4	1498	1498.00		.177
UCB1T	ratio k	tolerance	10	.8	1.4	1498	1498.00	0.00	.179
UCB	top k	tolerance	10	.3	1.4	1498	1498.00	0.00	.183
UCB1T	ratio k	tolerance	10	1	1.4	1498	1498.00	0.00	.186
UCB1T	ratio k	tolerance	5	.3	0	1498	1498.00	0.00	.186
UCB1T	ratio k	tolerance	15	.8	2.8	1498	1498.00	0.00	.189
UCB	top k	greedy	15	.8	0	1498	1498.00		.191
UCB1T	ratio k	tolerance	5	.3	2.8	1498	1498.00	0.00	.192
UCB1T	top k	tolerance	15	.8	2.8	1498	1498.00	0.00	.200
UCB1T	ratio k	tolerance	10	.3	1.4	1498	1498.00	0.00	.219
UCB	top k	tolerance	10	.3	0	1498	1498.00	0.00	.231
UCB1T	ratio k	tolerance	5	.8	2.8	1498	1498.00	0.00	.241
UCB	ratio k	tolerance	5	0	2.8	1498	1498.00	0.00	.258
UCB1T	ratio k	tolerance	5	0	1.4	1498	1498.00		.362

C.2.2 Solution not found

Selec policy	Exp policy	Simu policy	N° childrens	Ratio	Cp	Best cost	Mean	Std	T(s)
UCB	ratio k	greedy	5	0	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	greedy	5	0	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	greedy	5	.3	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	greedy	5	.5	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	greedy	5	.8	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	greedy	5	1	0	NaN	NaN	NaN	NaN
UCB	ratio k	greedy	5	1	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	greedy	5	1	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	0	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	0	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	0	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	.3	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	.3	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	.3	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	.5	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	.8	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	.8	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	.8	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	1	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	1	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	greedy	5	1	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	0	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	0	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	0	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	.3	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	.3	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	.3	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	.5	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	.5	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	.5	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	.8	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	.8	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	.8	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	1	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	1	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	5	1	2.8	NaN	NaN	NaN	NaN

UCB	ratio k	random	10	0	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	0	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	0	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	.3	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	.3	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	.3	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	.5	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	.5	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	.5	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	.8	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	.8	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	.8	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	1	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	1	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	10	1	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	0	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	0	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	0	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	.3	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	.3	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	.3	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	.5	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	.5	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	.5	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	.8	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	.8	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	.8	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	1	0	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	1	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	random	15	1	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	0	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	0	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	0	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	.3	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	.3	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	.3	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	.5	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	.5	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	.5	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	.8	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	.8	1.4	NaN	NaN	NaN	NaN

UCB1T	ratio k	random	5	.8	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	1	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	1	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	5	1	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	0	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	0	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	0	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	.3	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	.3	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	.3	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	.5	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	.5	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	.5	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	.8	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	.8	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	.8	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	1	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	1	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	10	1	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	0	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	0	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	0	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	.3	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	.3	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	.3	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	.5	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	.5	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	.5	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	.8	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	.8	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	.8	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	1	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	1	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	random	15	1	2.8	NaN	NaN	NaN	NaN
UCB	ratio k	tolerance	5	1	0	NaN	NaN	NaN	NaN
UCB	ratio k	tolerance	5	1	1.4	NaN	NaN	NaN	NaN
UCB	ratio k	tolerance	5	1	2.8	NaN	NaN	NaN	NaN
UCB1T	ratio k	tolerance	5	1	0	NaN	NaN	NaN	NaN
UCB1T	ratio k	tolerance	5	1	1.4	NaN	NaN	NaN	NaN
UCB1T	ratio k	tolerance	5	1	2.8	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	0	0	NaN	NaN	NaN	NaN

UCB	top k	greedy	5	0	1.4	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	0	2.8	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	.3	0	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	.3	1.4	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	.3	2.8	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	.5	0	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	.5	1.4	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	.5	2.8	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	.8	0	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	.8	1.4	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	.8	2.8	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	1	0	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	1	1.4	NaN	NaN	NaN	NaN
UCB	top k	greedy	5	1	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	0	0	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	0	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	0	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	.3	0	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	.3	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	.3	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	.5	0	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	.5	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	.5	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	.8	0	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	.8	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	.8	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	1	0	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	1	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	greedy	5	1	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	5	0	0	NaN	NaN	NaN	NaN
UCB	top k	random	5	0	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	5	0	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	5	.3	0	NaN	NaN	NaN	NaN
UCB	top k	random	5	.3	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	5	.3	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	5	.5	0	NaN	NaN	NaN	NaN
UCB	top k	random	5	.5	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	5	.5	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	5	.8	0	NaN	NaN	NaN	NaN
UCB	top k	random	5	.8	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	5	.8	2.8	NaN	NaN	NaN	NaN

UCB	top k	random	5	1	0	NaN	NaN	NaN	NaN
UCB	top k	random	5	1	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	5	1	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	10	0	0	NaN	NaN	NaN	NaN
UCB	top k	random	10	0	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	10	0	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	10	.3	0	NaN	NaN	NaN	NaN
UCB	top k	random	10	.3	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	10	.3	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	10	.5	0	NaN	NaN	NaN	NaN
UCB	top k	random	10	.5	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	10	.5	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	10	.8	0	NaN	NaN	NaN	NaN
UCB	top k	random	10	.8	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	10	.8	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	10	1	0	NaN	NaN	NaN	NaN
UCB	top k	random	10	1	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	10	1	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	15	0	0	NaN	NaN	NaN	NaN
UCB	top k	random	15	0	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	15	0	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	15	.3	0	NaN	NaN	NaN	NaN
UCB	top k	random	15	.3	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	15	.3	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	15	.5	0	NaN	NaN	NaN	NaN
UCB	top k	random	15	.5	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	15	.5	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	15	.8	0	NaN	NaN	NaN	NaN
UCB	top k	random	15	.8	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	15	.8	2.8	NaN	NaN	NaN	NaN
UCB	top k	random	15	1	0	NaN	NaN	NaN	NaN
UCB	top k	random	15	1	1.4	NaN	NaN	NaN	NaN
UCB	top k	random	15	1	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	0	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	0	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	0	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	.3	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	.3	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	.3	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	.5	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	.5	1.4	NaN	NaN	NaN	NaN

UCB1T	top k	random	5	.5	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	.8	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	.8	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	.8	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	1	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	1	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	5	1	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	0	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	0	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	0	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	.3	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	.3	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	.3	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	.5	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	.5	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	.5	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	.8	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	.8	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	.8	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	1	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	1	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	10	1	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	0	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	0	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	0	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	.3	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	.3	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	.3	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	.5	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	.5	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	.5	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	.8	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	.8	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	.8	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	1	0	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	1	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	random	15	1	2.8	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	0	0	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	0	1.4	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	0	2.8	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	.3	0	NaN	NaN	NaN	NaN

UCB	top k	tolerance	5	.3	1.4	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	.3	2.8	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	.5	0	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	.5	1.4	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	.5	2.8	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	.8	0	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	.8	1.4	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	.8	2.8	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	1	0	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	1	1.4	NaN	NaN	NaN	NaN
UCB	top k	tolerance	5	1	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	0	0	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	0	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	0	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	.3	0	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	.3	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	.3	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	.5	0	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	.5	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	.5	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	.8	0	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	.8	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	.8	2.8	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	1	0	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	1	1.4	NaN	NaN	NaN	NaN
UCB1T	top k	tolerance	5	1	2.8	NaN	NaN	NaN	NaN

C.3 Instance 3

C.3.1 Solution found

Selec policy	Exp policy	Simu policy	N° childrens	Ratio	Cp	Best cost	Mean	Std	T(s)
UCB	top k	greedy	5	.3	1.4	7672	7672.00		.200
UCB	top k	greedy	5	0	2.8	7672	7672.00		.207
UCB	top k	greedy	5	.8	1.4	7672	7672.00		.208
UCB	top k	greedy	5	0	1.4	7672	7672.00		.213
UCB	top k	greedy	5	1	1.4	7672	7672.00		.214
UCB	top k	greedy	5	.8	2.8	7672	7672.00		.238
UCB	top k	greedy	5	1	2.8	7672	7672.00		.240
UCB	top k	greedy	5	.3	2.8	7672	7672.00		.284
UCB	top k	tolerance	5	0	1.4	7672	7672.00	0.00	.290
UCB	top k	greedy	5	.5	2.8	7672	7672.00		.294
UCB	top k	greedy	5	.5	1.4	7672	7672.00		.312
UCB	top k	tolerance	5	0	2.8	7672	7672.00	0.00	.352
UCB	top k	greedy	10	.3	2.8	7672	7672.00		.352
UCB	top k	greedy	10	.8	1.4	7672	7672.00		.355
UCB	top k	greedy	10	1	1.4	7672	7672.00		.363
UCB	top k	greedy	10	.5	2.8	7672	7672.00		.380
UCB	top k	greedy	10	1	2.8	7672	7672.00		.391
UCB	top k	greedy	10	.8	2.8	7672	7672.00		.401
UCB	top k	tolerance	10	0	2.8	7672	7672.00	0.00	.418
UCB	top k	greedy	10	0	2.8	7672	7672.00		.426
UCB	ratio k	greedy	5	.8	1.4	7672	7672.00		.446
UCB	ratio k	greedy	5	1	1.4	7672	7672.00		.450
UCB	top k	greedy	15	.3	2.8	7672	7672.00		.467
UCB	top k	greedy	15	0	2.8	7672	7672.00		.478
UCB	ratio k	greedy	5	.8	2.8	7672	7672.00		.479
UCB	top k	greedy	10	.5	1.4	7672	7672.00		.492
UCB	top k	greedy	15	1	2.8	7672	7672.00		.496
UCB	top k	greedy	15	.8	2.8	7672	7672.00		.503
UCB	top k	greedy	15	1	1.4	7672	7672.00		.514
UCB	top k	greedy	10	0	1.4	7672	7672.00		.516
UCB	top k	greedy	15	.8	1.4	7672	7672.00		.541
UCB	top k	tolerance	10	0	1.4	7672	7672.00	0.00	.548
UCB	top k	greedy	15	.5	2.8	7672	7672.00		.557
UCB	top k	greedy	10	.3	1.4	7672	7672.00		.603

UCB	top k	greedy	15	0	1.4	7672	7672.00		.625
UCB	top k	greedy	15	.3	1.4	7672	7672.00		.633
UCB	ratio k	greedy	5	1	2.8	7672	7672.00		.652
UCB	top k	tolerance	15	0	1.4	7672	7672.00	0.00	.652
UCB	ratio k	greedy	10	.8	2.8	7672	7672.00		.679
UCB	top k	tolerance	15	0	2.8	7672	7672.00	0.00	.681
UCB	ratio k	greedy	10	.5	2.8	7672	7672.00		.689
UCB	ratio k	greedy	10	.5	1.4	7672	7672.00		.695
UCB	ratio k	greedy	10	1	1.4	7672	7672.00		.701
UCB	ratio k	greedy	10	.8	1.4	7672	7672.00		.715
UCB	ratio k	greedy	10	1	2.8	7672	7672.00		.738
UCB	ratio k	greedy	15	.8	2.8	7672	7672.00		.749
UCB	ratio k	greedy	15	1	2.8	7672	7672.00		.757
UCB	top k	greedy	15	.5	1.4	7672	7672.00		.759
UCB	ratio k	greedy	15	1	1.4	7672	7672.00		.770
UCB	ratio k	greedy	15	.8	1.4	7672	7672.00		.815
UCB	ratio k	greedy	15	0	2.8	7672	7672.00		.827
UCB	ratio k	greedy	15	.5	2.8	7672	7672.00		.831
UCB	ratio k	greedy	15	.5	1.4	7672	7672.00		.850
UCB	ratio k	greedy	15	.3	2.8	7672	7672.00		.912
UCB	ratio k	greedy	15	.3	1.4	7672	7672.00		1.005
UCB	ratio k	tolerance	15	0	2.8	7672	8573.10	559.93	6.983
UCB	ratio k	tolerance	15	0	1.4	7672	8263.90	430.30	10.542
UCB	top k	tolerance	10	.3	1.4	7698	8780.00	948.02	1.719
UCB	ratio k	tolerance	15	.3	2.8	7698	8641.60	813.79	3.949
UCB	top k	tolerance	5	.3	0	7698	8008.40	218.67	5.022
UCB1T	top k	tolerance	5	.3	1.4	7698	8107.90	305.55	9.659
UCB1T	top k	tolerance	15	0	0	7698	7882.80	164.42	182.043
UCB1T	ratio k	tolerance	15	.5	0	7721	8718.20	579.66	79.793
UCB	top k	tolerance	10	.5	0	7768	8236.70	380.98	8.330
UCB1T	top k	tolerance	15	.3	1.4	7768	8325.50	292.49	56.962
UCB1T	ratio k	tolerance	15	.5	1.4	7773	8597.90	631.44	13.476
UCB	top k	tolerance	10	0	0	7773	7852.30	98.81	51.039
UCB1T	top k	tolerance	10	.5	1.4	7783	8461.40	397.30	63.413
UCB1T	top k	greedy	10	.5	2.8	7787	7787.00		10.736
UCB1T	top k	greedy	10	.8	2.8	7787	7787.00		11.403
UCB1T	ratio k	tolerance	10	.3	2.8	7787	8348.60	501.73	37.585
UCB1T	top k	tolerance	10	0	0	7787	7997.70	422.18	87.021
UCB1T	top k	tolerance	10	.3	0	7787	8123.80	235.47	98.578
UCB1T	top k	tolerance	10	0	1.4	7787	7896.40	200.02	158.137
UCB1T	top k	tolerance	15	0	1.4	7787	7862.90	139.25	187.179

UCB	ratio k	greedy	5	1	0	7790	7790.00		3.224
UCB1T	top k	tolerance	5	.5	2.8	7790	8377.50	392.26	3.328
UCB	top k	tolerance	5	.5	0	7790	8355.00	794.39	4.352
UCB1T	top k	tolerance	5	0	2.8	7790	7885.80	154.45	17.335
UCB1T	top k	tolerance	5	0	1.4	7790	7985.60	196.55	22.795
UCB	top k	tolerance	10	.3	0	7792	8075.70	248.59	6.283
UCB	top k	tolerance	15	.3	0	7792	7989.20	191.06	7.784
UCB	top k	greedy	15	1	0	7792	7792.00		19.714
UCB1T	top k	greedy	15	.3	2.8	7792	7792.00		34.543
UCB	top k	tolerance	15	0	0	7792	7923.10	116.70	44.285
UCB	ratio k	tolerance	5	.5	0	7795	8732.50	498.67	.680
UCB1T	ratio k	greedy	5	.5	2.8	7795	7795.00		1.596
UCB1T	ratio k	greedy	5	.5	1.4	7795	7795.00		1.963
UCB1T	ratio k	greedy	5	.8	1.4	7795	7795.00		2.338
UCB	ratio k	tolerance	10	.3	1.4	7795	8538.30	656.25	2.588
UCB	top k	tolerance	5	0	0	7795	7945.60	322.05	3.805
UCB1T	top k	tolerance	5	.3	0	7795	8095.20	299.20	3.992
UCB1T	top k	tolerance	5	0	0	7795	7946.30	221.23	9.568
UCB1T	top k	tolerance	5	.3	2.8	7795	8071.10	198.78	19.558
UCB1T	top k	tolerance	15	0	2.8	7795	7895.00	134.49	369.106
UCB1T	ratio k	tolerance	5	.5	1.4	7802	8618.30	399.09	4.321
UCB1T	ratio k	tolerance	10	.5	0	7802	8550.70	428.13	6.740
UCB1T	ratio k	tolerance	10	.3	1.4	7802	8344.10	250.39	197.703
UCB1T	top k	greedy	15	.8	0	7806	7806.00		35.496
UCB1T	top k	greedy	10	.3	0	7807	7807.00		31.799
UCB	ratio k	greedy	10	.3	1.4	7809	7809.00		.651
UCB1T	top k	greedy	5	1	0	7809	7809.00		1.781
UCB1T	ratio k	greedy	5	1	1.4	7809	7809.00		2.251
UCB	top k	random	10	.5	0	7809	10125.50	1205.49	4.779
UCB	top k	greedy	10	.3	0	7809	7809.00		6.929
UCB1T	top k	greedy	10	1	0	7809	7809.00		8.337
UCB1T	top k	tolerance	10	0	2.8	7809	7879.10	105.36	10.799
UCB	top k	greedy	15	0	0	7809	7809.00		12.782
UCB	top k	greedy	10	0	0	7809	7809.00		13.295
UCB1T	top k	greedy	15	.3	1.4	7809	7809.00		30.037
UCB1T	ratio k	tolerance	15	.3	0	7809	8415.30	423.02	369.372
UCB1T	top k	greedy	10	0	2.8	7811	7811.00		9.875
UCB1T	top k	greedy	10	.8	1.4	7811	7811.00		19.065
UCB1T	top k	greedy	15	.5	0	7811	7811.00		28.979
UCB1T	top k	tolerance	10	.3	2.8	7811	8303.50	318.45	90.492
UCB1T	top k	tolerance	15	.5	2.8	7813	8462.00	476.51	82.497

UCB	top k	greedy	5	.3	0	7814	7814.00		1.086
UCB1T	top k	greedy	5	.5	0	7814	7814.00		1.234
UCB1T	top k	greedy	5	.3	1.4	7814	7814.00		1.586
UCB	ratio k	greedy	5	.8	0	7814	7814.00		1.910
UCB1T	top k	greedy	5	.3	2.8	7814	7814.00		2.181
UCB1T	top k	greedy	5	1	1.4	7814	7814.00		2.553
UCB	top k	greedy	10	.8	0	7814	7814.00		6.149
UCB	top k	greedy	15	.3	0	7814	7814.00		8.584
UCB1T	top k	greedy	10	1	2.8	7814	7814.00		8.961
UCB1T	top k	greedy	10	.3	2.8	7814	7814.00		12.062
UCB1T	top k	greedy	10	.5	1.4	7814	7814.00		12.569
UCB1T	top k	greedy	10	1	1.4	7814	7814.00		13.856
UCB1T	top k	greedy	10	.3	1.4	7814	7814.00		15.910
UCB1T	top k	greedy	15	1	0	7814	7814.00		32.989
UCB1T	ratio k	greedy	15	1	1.4	7814	7814.00		39.298
UCB1T	top k	greedy	15	0	0	7814	7814.00		39.814
UCB1T	ratio k	greedy	10	1	1.4	7814	7814.00		40.871
UCB1T	ratio k	greedy	10	1	0	7814	7814.00		51.606
UCB1T	ratio k	tolerance	10	.5	2.8	7814	8410.30	332.19	68.062
UCB	top k	greedy	15	.5	0	7828	7828.00		14.617
UCB	ratio k	greedy	15	1	0	7828	7828.00		17.028
UCB1T	top k	tolerance	10	.3	1.4	7828	8253.40	244.19	66.938
UCB1T	ratio k	tolerance	15	.3	2.8	7828	8600.70	462.84	328.377
UCB	top k	tolerance	5	.3	1.4	7829	8559.60	552.55	2.099
UCB1T	ratio k	tolerance	10	.3	0	7829	8319.00	328.00	137.821
UCB1T	top k	greedy	5	0	1.4	7833	7833.00		1.325
UCB	top k	greedy	5	.8	0	7833	7833.00		1.378
UCB1T	top k	greedy	5	.5	2.8	7833	7833.00		1.459
UCB1T	top k	greedy	5	.8	0	7833	7833.00		1.529
UCB1T	ratio k	greedy	5	1	0	7833	7833.00		1.630
UCB1T	top k	greedy	5	.8	1.4	7833	7833.00		1.725
UCB1T	ratio k	greedy	5	1	2.8	7833	7833.00		2.233
UCB1T	top k	greedy	5	.8	2.8	7833	7833.00		3.351
UCB	top k	greedy	10	.5	0	7833	7833.00		5.611
UCB1T	top k	greedy	10	0	0	7833	7833.00		11.729
UCB1T	top k	random	10	.8	2.8	7833	9409.90	1209.94	15.743
UCB	ratio k	greedy	15	.8	0	7833	7833.00		16.700
UCB	ratio k	greedy	15	.3	0	7833	7833.00		20.392
UCB1T	top k	greedy	15	1	1.4	7833	7833.00		27.002
UCB1T	top k	greedy	15	.8	2.8	7833	7833.00		27.553
UCB1T	top k	greedy	15	.8	1.4	7833	7833.00		29.471

UCB1T	ratio k	greedy	15	.5	1.4	7833	7833.00		30.957
UCB1T	top k	greedy	15	0	1.4	7833	7833.00		32.556
UCB1T	top k	greedy	15	1	2.8	7833	7833.00		38.422
UCB	ratio k	tolerance	10	.3	0	7834	8166.00	260.49	21.151
UCB	top k	tolerance	5	1	0	7840	8817.90	648.65	3.709
UCB	ratio k	greedy	5	.3	2.8	7849	7849.00		.419
UCB1T	top k	tolerance	5	.5	1.4	7851	8145.70	292.95	16.814
UCB1T	ratio k	tolerance	15	0	1.4	7878	8618.00	473.76	257.548
UCB	top k	tolerance	15	.5	0	7885	8597.80	461.89	30.058
UCB	ratio k	tolerance	5	.5	1.4	7896	9104.50	931.77	1.318
UCB1T	top k	tolerance	10	.5	0	7907	8305.80	267.70	76.671
UCB	ratio k	tolerance	10	.8	0	7911	8953.70	529.05	10.214
UCB1T	ratio k	random	10	.3	0	7919	9796.40	1214.36	26.393
UCB	ratio k	greedy	15	0	1.4	7939	7939.00		.973
UCB1T	ratio k	random	5	1	2.8	7944	10010.40	1102.87	4.052
UCB1T	top k	tolerance	15	.5	0	7946	8635.60	345.10	405.457
UCB1T	top k	tolerance	15	.3	0	7957	8358.50	304.53	368.495
UCB	ratio k	tolerance	15	.5	1.4	7961	8971.50	516.62	1.731
UCB	ratio k	tolerance	15	.3	0	7962	8320.90	318.62	47.525
UCB1T	top k	tolerance	15	.8	0	7971	8819.10	631.76	54.065
UCB	top k	random	5	0	2.8	7974	10241.80	1172.42	1.553
UCB	ratio k	tolerance	15	.5	0	7975	8621.60	440.34	87.850
UCB	top k	greedy	15	.8	0	7976	7976.00		9.543
UCB1T	ratio k	tolerance	15	.5	2.8	7980	8883.40	488.35	133.902
UCB	top k	tolerance	15	.3	2.8	7981	9028.60	1081.07	.807
UCB	ratio k	greedy	10	1	0	7981	7981.00		10.701
UCB1T	ratio k	tolerance	5	.3	2.8	7983	8657.50	353.87	8.798
UCB	ratio k	tolerance	10	.5	0	7986	8631.00	351.74	6.338
UCB1T	ratio k	tolerance	10	.8	0	7990	9101.20	521.70	11.200
UCB1T	ratio k	greedy	15	1	0	7995	7995.00		29.512
UCB1T	top k	tolerance	15	.3	2.8	7996	8268.10	260.53	1260.729
UCB1T	top k	random	5	.5	0	7998	9842.80	1380.99	1.316
UCB1T	top k	greedy	15	0	2.8	8000	8000.00		38.365
UCB	top k	tolerance	5	.3	2.8	8003	8665.60	439.19	1.062
UCB1T	top k	tolerance	5	.5	0	8003	8305.70	186.60	2.132
UCB	top k	tolerance	10	.5	1.4	8004	9464.70	949.85	2.829
UCB1T	ratio k	tolerance	15	0	0	8009	8658.70	473.49	10.147
UCB1T	ratio k	tolerance	15	0	2.8	8009	8609.70	409.15	396.987
UCB1T	top k	greedy	10	.8	0	8017	8017.00		11.994
UCB	ratio k	greedy	10	.8	0	8017	8017.00		22.371
UCB1T	ratio k	greedy	15	.8	0	8017	8017.00		63.606

UCB1T	top k	greedy	10	0	1.4	8022	8022.00		16.905
UCB1T	top k	greedy	15	.5	1.4	8022	8022.00		34.601
UCB1T	ratio k	greedy	15	.5	2.8	8022	8022.00		51.124
UCB1T	ratio k	tolerance	5	.5	0	8025	8650.40	496.57	9.937
UCB	top k	tolerance	10	.3	2.8	8038	8894.40	849.42	3.260
UCB	ratio k	tolerance	15	.3	1.4	8039	9082.10	901.81	6.121
UCB	top k	random	5	1	0	8043	9731.70	861.09	1.126
UCB1T	ratio k	tolerance	10	1	0	8045	9381.20	601.54	70.665
UCB	ratio k	greedy	5	.3	1.4	8048	8048.00		.524
UCB	ratio k	tolerance	15	0	0	8050	8687.90	500.88	23.757
UCB1T	ratio k	greedy	10	.3	2.8	8056	8056.00		30.338
UCB1T	top k	greedy	15	.3	0	8059	8059.00		34.218
UCB	top k	tolerance	5	.8	0	8061	8779.10	671.24	4.696
UCB1T	top k	tolerance	10	1	0	8064	9386.90	653.21	7.406
UCB	top k	greedy	5	0	0	8068	8068.00		1.281
UCB1T	top k	greedy	5	0	2.8	8068	8068.00		1.691
UCB	ratio k	tolerance	5	.8	0	8068	8858.80	679.55	2.576
UCB1T	top k	tolerance	5	.8	0	8069	8838.70	746.66	8.677
UCB1T	ratio k	greedy	15	.5	0	8069	8069.00		25.091
UCB1T	top k	greedy	10	.5	0	8069	8069.00		30.133
UCB1T	top k	tolerance	5	.8	1.4	8073	8861.00	429.72	16.872
UCB1T	ratio k	random	15	.3	0	8073	9772.90	1530.73	26.867
UCB1T	top k	tolerance	15	.8	1.4	8075	8964.00	495.24	18.058
UCB1T	ratio k	tolerance	5	1	0	8078	8915.70	498.59	2.441
UCB1T	top k	greedy	5	1	2.8	8082	8082.00		1.796
UCB	top k	tolerance	10	.8	0	8083	8919.10	495.18	20.294
UCB1T	ratio k	tolerance	15	1	1.4	8083	9196.90	621.43	27.608
UCB	ratio k	greedy	5	.3	0	8084	8084.00		3.395
UCB	ratio k	tolerance	5	.5	2.8	8085	9525.60	1055.85	.200
UCB1T	top k	greedy	5	.5	1.4	8087	8087.00		1.718
UCB1T	ratio k	tolerance	15	.3	1.4	8087	8345.30	237.76	58.238
UCB	ratio k	tolerance	10	0	2.8	8092	9589.90	1011.62	3.384
UCB1T	ratio k	tolerance	5	.3	1.4	8093	8867.30	505.76	4.550
UCB	ratio k	tolerance	10	.5	1.4	8100	9223.90	1261.94	.365
UCB1T	top k	tolerance	5	1	1.4	8103	9074.30	648.40	8.864
UCB1T	ratio k	tolerance	15	.8	0	8103	9155.30	666.90	12.096
UCB1T	ratio k	greedy	15	1	2.8	8110	8110.00		28.532
UCB	ratio k	greedy	5	.5	0	8111	8111.00		3.036
UCB1T	top k	tolerance	10	.8	2.8	8118	9219.50	459.51	24.346
UCB1T	top k	random	15	0	2.8	8123	9885.10	847.05	9.942
UCB1T	top k	tolerance	10	1	2.8	8123	9450.50	724.56	39.373

UCB1T	top k	random	5	0	0	8125	10056.70	960.58	1.005
UCB	ratio k	greedy	5	.5	1.4	8129	8129.00		.511
UCB	ratio k	tolerance	15	.5	2.8	8130	9410.10	1009.94	2.712
UCB1T	ratio k	tolerance	5	1	2.8	8130	8966.70	557.68	8.944
UCB1T	ratio k	random	5	.5	1.4	8136	10097.00	1475.50	5.917
UCB1T	ratio k	greedy	10	.5	2.8	8141	8141.00		15.360
UCB1T	ratio k	greedy	15	.8	2.8	8141	8141.00		31.803
UCB	top k	random	10	1	0	8157	9539.20	903.83	4.431
UCB	top k	tolerance	15	.3	1.4	8160	9360.00	883.92	2.817
UCB1T	ratio k	tolerance	10	.5	1.4	8162	8535.70	300.63	43.973
UCB1T	ratio k	greedy	10	.5	1.4	8163	8163.00		15.327
UCB	ratio k	greedy	10	.5	0	8168	8168.00		11.645
UCB1T	top k	tolerance	10	.5	2.8	8172	8521.70	246.51	46.757
UCB1T	top k	tolerance	5	.8	2.8	8178	9084.50	563.33	7.335
UCB	ratio k	random	15	.5	0	8180	9814.60	1167.34	2.408
UCB1T	ratio k	tolerance	5	.8	0	8180	8991.60	537.80	6.765
UCB1T	top k	random	10	.3	2.8	8184	9948.30	1004.16	3.127
UCB	ratio k	tolerance	5	.3	0	8185	8850.50	419.40	3.335
UCB1T	ratio k	tolerance	5	.8	1.4	8189	8916.60	393.87	5.939
UCB1T	ratio k	random	5	.8	0	8191	10115.70	1215.77	3.216
UCB1T	top k	tolerance	5	1	0	8192	9327.90	637.77	5.854
UCB	top k	greedy	10	1	0	8195	8195.00		15.594
UCB1T	ratio k	greedy	10	1	2.8	8198	8198.00		35.089
UCB1T	ratio k	greedy	15	0	2.8	8200	8200.00		37.129
UCB	top k	tolerance	15	.8	0	8203	9139.40	420.08	2.137
UCB	ratio k	random	5	.5	1.4	8210	11675.80	1713.66	.202
UCB1T	ratio k	tolerance	5	.8	2.8	8218	8970.30	555.19	5.347
UCB	ratio k	tolerance	10	.3	2.8	8221	8899.60	584.85	3.138
UCB1T	ratio k	greedy	10	.8	0	8224	8224.00		54.102
UCB1T	top k	random	5	1	2.8	8239	9560.20	754.88	9.633
UCB	ratio k	tolerance	5	.8	2.8	8242	9778.50	946.33	.764
UCB	ratio k	random	5	.5	0	8246	9715.30	1095.07	1.182
UCB1T	top k	tolerance	5	1	2.8	8246	9170.00	484.50	10.171
UCB	ratio k	random	5	.8	1.4	8247	11005.20	1213.92	.608
UCB1T	ratio k	tolerance	5	1	1.4	8252	9205.10	587.24	6.970
UCB	ratio k	greedy	10	.3	2.8	8253	8253.00		.745
UCB1T	top k	random	5	.3	2.8	8259	9659.80	789.11	6.112
UCB1T	top k	greedy	5	.3	0	8266	8266.00		3.156
UCB1T	ratio k	greedy	5	.3	1.4	8266	8266.00		3.805
UCB1T	ratio k	random	5	.5	0	8271	9804.30	1176.58	1.272
UCB	top k	random	10	.8	0	8274	9857.30	1043.54	5.183

UCB1T	top k	random	5	0	2.8	8274	9647.80	1138.28	6.541
UCB1T	ratio k	random	5	1	1.4	8275	9774.10	1232.98	6.764
UCB1T	ratio k	random	10	.8	1.4	8275	9432.30	975.80	10.835
UCB	top k	tolerance	10	.5	2.8	8277	9295.00	816.74	.438
UCB1T	ratio k	greedy	10	.3	1.4	8280	8280.00		27.394
UCB1T	top k	greedy	15	.5	2.8	8285	8285.00		34.157
UCB	top k	tolerance	5	.5	1.4	8287	9565.40	1286.61	2.055
UCB	top k	tolerance	10	1	0	8294	9337.10	602.46	1.299
UCB1T	top k	random	5	.8	0	8295	9729.60	1285.81	3.525
UCB	ratio k	tolerance	10	0	0	8295	9181.00	613.36	38.392
UCB1T	top k	random	10	.8	1.4	8296	9389.10	850.03	4.800
UCB1T	ratio k	random	10	.8	0	8301	9616.90	971.91	11.543
UCB	ratio k	greedy	15	.5	0	8302	8302.00		17.546
UCB1T	top k	tolerance	15	.8	2.8	8306	9080.30	457.49	37.139
UCB1T	ratio k	greedy	15	.3	0	8307	8307.00		13.662
UCB1T	top k	random	15	.5	2.8	8311	9689.70	735.83	22.661
UCB1T	top k	random	15	0	0	8313	9675.60	1308.85	16.277
UCB1T	top k	random	5	1	0	8319	9730.10	685.51	3.527
UCB1T	top k	tolerance	10	.8	1.4	8321	9174.30	432.76	33.553
UCB1T	ratio k	greedy	10	.8	2.8	8326	8326.00		13.992
UCB	ratio k	greedy	5	.5	2.8	8329	8329.00		.401
UCB	top k	random	10	.3	0	8332	9932.50	1132.52	2.071
UCB	ratio k	tolerance	5	1	2.8	8339	10169.00	1052.35	1.394
UCB1T	top k	random	10	.5	0	8340	9304.40	765.56	9.770
UCB	top k	greedy	5	1	0	8343	8343.00		.809
UCB1T	top k	random	5	.3	1.4	8344	9758.80	1178.58	4.042
UCB	ratio k	tolerance	10	.5	2.8	8353	9650.50	1330.35	.387
UCB	top k	tolerance	5	.8	2.8	8359	10031.10	1008.64	1.082
UCB1T	ratio k	random	10	.5	0	8366	10154.30	887.00	6.281
UCB1T	ratio k	tolerance	10	.8	1.4	8367	8972.20	430.26	9.005
UCB1T	ratio k	tolerance	15	.8	1.4	8370	9103.60	452.21	76.763
UCB1T	ratio k	tolerance	10	0	2.8	8373	9240.50	639.43	32.656
UCB1T	ratio k	tolerance	5	.3	0	8375	8712.00	266.31	8.578
UCB	top k	random	10	1	1.4	8381	11519.30	1876.57	2.428
UCB	ratio k	tolerance	15	1	0	8389	9526.10	753.11	14.259
UCB	top k	random	5	0	0	8391	10252.70	1074.89	.871
UCB1T	top k	random	15	1	0	8392	9874.00	1034.57	14.920
UCB	ratio k	tolerance	5	1	0	8393	9231.00	460.12	1.608
UCB	top k	random	15	.5	0	8396	9875.00	1034.04	6.305
UCB1T	ratio k	greedy	15	.3	1.4	8405	8405.00		20.983
UCB1T	ratio k	tolerance	5	.5	2.8	8406	8801.90	257.14	5.285

UCB1T	top k	tolerance	15	.5	1.4	8408	8883.70	414.39	333.005
UCB1T	ratio k	random	10	.3	1.4	8415	9791.20	687.92	9.297
UCB1T	ratio k	greedy	10	.3	0	8415	8415.00		20.757
UCB1T	ratio k	greedy	10	.8	1.4	8422	8422.00		30.414
UCB	top k	random	15	0	0	8428	9929.90	800.26	3.837
UCB1T	ratio k	tolerance	15	.8	2.8	8428	9300.30	639.72	26.370
UCB	ratio k	random	10	.5	0	8435	9228.00	653.42	2.834
UCB	ratio k	tolerance	10	1	1.4	8441	10842.80	1399.49	1.710
UCB1T	ratio k	tolerance	15	1	0	8449	9507.40	573.94	10.174
UCB1T	top k	random	10	0	0	8450	9858.70	999.06	5.554
UCB1T	ratio k	random	15	.5	0	8453	9841.10	805.36	46.671
UCB1T	top k	random	15	0	1.4	8458	9899.60	795.31	14.235
UCB1T	ratio k	greedy	5	.5	0	8459	8459.00		1.098
UCB	top k	tolerance	10	.8	1.4	8460	10902.00	1586.89	2.978
UCB1T	ratio k	random	15	.3	2.8	8464	9790.20	1119.14	20.588
UCB1T	top k	tolerance	10	1	1.4	8467	9269.70	594.51	1.677
UCB	ratio k	greedy	10	.3	0	8474	8474.00		16.423
UCB	top k	tolerance	5	.5	2.8	8485	9515.20	784.52	2.105
UCB1T	top k	random	5	1	1.4	8485	10118.20	900.48	6.552
UCB1T	ratio k	random	15	1	2.8	8486	9634.20	858.60	2.026
UCB1T	ratio k	tolerance	10	0	1.4	8486	9185.30	503.12	104.836
UCB1T	top k	random	10	.5	1.4	8487	9884.70	1256.65	8.563
UCB1T	top k	random	10	1	2.8	8489	9568.30	977.22	4.257
UCB1T	ratio k	random	10	.3	2.8	8489	9729.10	1036.01	15.118
UCB1T	ratio k	random	5	.8	2.8	8494	10247.80	852.53	9.194
UCB1T	ratio k	greedy	15	.3	2.8	8494	8494.00		12.394
UCB1T	ratio k	greedy	15	.8	1.4	8494	8494.00		46.277
UCB	ratio k	tolerance	5	.8	1.4	8496	9784.70	1324.18	.536
UCB1T	ratio k	tolerance	10	.8	2.8	8505	9242.10	490.97	43.849
UCB	ratio k	random	10	.3	0	8506	9614.60	778.59	5.658
UCB	ratio k	random	15	.8	0	8509	10132.20	1140.25	10.332
UCB1T	top k	greedy	5	0	0	8512	8512.00		3.636
UCB	top k	random	5	.5	2.8	8515	10877.50	1366.32	1.499
UCB1T	top k	tolerance	15	1	2.8	8525	9035.10	467.54	46.063
UCB	ratio k	greedy	15	0	0	8527	8527.00		13.473
UCB	ratio k	greedy	10	0	0	8531	8531.00		4.461
UCB1T	top k	random	15	.3	1.4	8533	9991.90	743.93	8.888
UCB	top k	tolerance	15	.5	1.4	8535	9880.60	956.57	5.774
UCB1T	top k	tolerance	10	.8	0	8540	9218.80	427.85	37.228
UCB1T	ratio k	greedy	5	.8	0	8542	8542.00		7.271
UCB	ratio k	tolerance	5	.3	2.8	8568	9682.40	1293.25	.972

UCB1T	ratio k	random	5	.3	1.4	8570	10137.00	1315.70	4.292
UCB1T	top k	random	10	0	1.4	8574	10342.80	876.85	5.309
UCB1T	ratio k	tolerance	10	0	0	8577	9068.40	523.64	141.461
UCB	ratio k	tolerance	5	.3	1.4	8582	9580.90	1102.93	1.623
UCB1T	top k	random	5	.8	2.8	8582	10236.90	1213.91	6.184
UCB1T	top k	random	5	.3	0	8586	9805.40	896.01	1.966
UCB1T	top k	random	15	.8	2.8	8599	9659.30	628.53	18.657
UCB	ratio k	tolerance	15	.8	0	8602	9379.80	393.34	31.087
UCB	ratio k	random	10	.8	0	8611	10166.20	933.93	3.300
UCB1T	ratio k	random	15	1	0	8613	9825.00	880.12	3.971
UCB	top k	random	5	.8	0	8620	10162.70	914.00	.254
UCB	top k	tolerance	15	.8	1.4	8630	11125.90	1556.90	5.328
UCB	top k	random	5	.3	0	8641	9874.50	750.15	1.659
UCB	top k	tolerance	5	1	2.8	8644	10458.20	1114.30	1.337
UCB1T	top k	random	15	1	2.8	8648	9836.20	1070.71	8.378
UCB1T	ratio k	random	5	1	0	8653	9447.60	553.73	1.589
UCB1T	ratio k	tolerance	10	1	2.8	8660	9439.30	459.55	5.174
UCB1T	ratio k	random	10	.8	2.8	8663	9834.10	958.80	3.752
UCB1T	ratio k	random	5	.3	0	8663	10722.80	1280.44	5.143
UCB1T	top k	random	15	.3	2.8	8671	10282.90	1224.17	12.681
UCB1T	ratio k	random	15	.3	1.4	8673	10338.40	1174.68	23.982
UCB1T	ratio k	tolerance	10	1	1.4	8678	9242.10	494.99	4.885
UCB	ratio k	random	10	1	0	8679	10233.60	999.64	1.649
UCB1T	top k	tolerance	15	1	0	8690	9750.30	858.54	40.761
UCB	top k	greedy	5	.5	0	8691	8691.00		3.630
UCB1T	ratio k	random	10	1	2.8	8692	9917.30	713.33	20.178
UCB	ratio k	random	10	.8	2.8	8697	11557.10	1772.50	1.090
UCB	ratio k	tolerance	10	0	1.4	8704	9582.50	738.12	.463
UCB1T	ratio k	random	10	1	0	8706	9831.10	797.46	11.980
UCB1T	ratio k	random	10	.5	1.4	8718	10027.70	975.79	18.639
UCB	top k	random	5	0	1.4	8723	10321.40	972.56	.231
UCB1T	top k	random	15	1	1.4	8725	9829.50	879.58	8.498
UCB1T	top k	random	5	.5	2.8	8734	9693.20	775.35	4.174
UCB	top k	tolerance	15	.5	2.8	8735	9514.70	667.92	4.540
UCB1T	top k	random	10	1	1.4	8736	9577.20	557.79	3.537
UCB	ratio k	tolerance	10	1	2.8	8737	10733.10	1155.87	.388
UCB	ratio k	tolerance	10	.8	1.4	8737	10035.50	881.08	.443
UCB1T	ratio k	random	5	.5	2.8	8743	10570.70	1045.53	.884
UCB1T	ratio k	random	15	0	2.8	8750	10007.10	1013.49	4.828
UCB	ratio k	random	5	.3	0	8759	9897.40	782.31	2.518
UCB1T	ratio k	greedy	10	.5	0	8761	8761.00		4.507

UCB1T	top k	tolerance	15	1	1.4	8764	9291.60	388.60	17.685
UCB	top k	random	5	1	1.4	8779	10827.50	1321.62	.313
UCB	ratio k	tolerance	10	1	0	8789	9429.50	361.75	9.397
UCB1T	ratio k	random	15	.8	0	8819	10242.10	668.10	33.414
UCB1T	ratio k	greedy	10	0	1.4	8820	8820.00		7.187
UCB1T	top k	random	15	.5	1.4	8827	10184.60	1149.31	4.737
UCB1T	top k	random	5	.8	1.4	8837	9740.20	553.46	3.305
UCB1T	ratio k	greedy	5	.8	2.8	8837	8837.00		9.090
UCB1T	ratio k	random	15	1	1.4	8847	9989.30	801.84	20.877
UCB	top k	random	15	1	0	8849	9661.70	717.77	1.115
UCB1T	top k	random	10	.5	2.8	8854	9946.10	601.69	20.386
UCB1T	top k	random	10	1	0	8861	10033.90	881.82	11.215
UCB1T	ratio k	random	15	.5	1.4	8868	10080.10	809.17	19.241
UCB1T	ratio k	tolerance	15	1	2.8	8871	9385.30	239.18	28.951
UCB1T	ratio k	greedy	15	0	1.4	8874	8874.00		49.978
UCB	ratio k	random	5	.3	1.4	8875	11848.70	1779.17	1.631
UCB1T	ratio k	random	10	0	0	8875	10395.70	1031.48	5.976
UCB1T	top k	random	10	.3	1.4	8891	9613.40	599.65	9.789
UCB1T	top k	random	10	.8	0	8892	9949.60	694.59	20.271
UCB	top k	random	5	.5	0	8893	10006.70	698.88	.859
UCB	ratio k	random	5	1	0	8905	10072.00	1036.20	1.856
UCB	ratio k	random	15	1	1.4	8917	12051.10	1674.08	3.544
UCB1T	ratio k	random	10	.5	2.8	8924	9815.00	843.98	13.140
UCB1T	top k	random	5	0	1.4	8929	10574.50	838.55	1.432
UCB	ratio k	random	10	.3	2.8	8935	12146.70	1905.43	1.520
UCB1T	ratio k	greedy	5	.3	0	8942	8942.00		2.543
UCB	top k	tolerance	5	.8	1.4	8954	9766.30	541.30	1.850
UCB1T	ratio k	greedy	5	.3	2.8	8955	8955.00		2.579
UCB	ratio k	random	10	.3	1.4	8972	11315.20	1340.21	1.652
UCB1T	ratio k	random	15	.8	1.4	8972	9920.20	717.72	13.723
UCB	top k	random	10	0	0	8973	10319.20	864.44	2.265
UCB	top k	tolerance	15	.8	2.8	8989	10942.30	1326.75	2.039
UCB	top k	random	15	.3	0	9000	10229.20	902.06	4.202
UCB	ratio k	tolerance	10	.8	2.8	9017	10457.60	768.00	3.394
UCB1T	ratio k	random	10	0	1.4	9034	11226.80	1403.10	7.757
UCB1T	top k	random	15	.5	0	9035	10323.20	987.87	11.669
UCB1T	top k	random	15	.3	0	9045	10593.10	706.37	26.571
UCB	ratio k	random	5	1	1.4	9052	11163.80	1123.42	.477
UCB1T	top k	random	5	.5	1.4	9072	9900.20	704.11	4.683
UCB1T	ratio k	random	15	0	0	9083	10129.80	598.94	6.173
UCB1T	ratio k	tolerance	5	0	2.8	9087	9946.70	646.34	17.432

UCB	ratio k	random	5	1	2.8	9089	10182.60	921.88	.947
UCB	ratio k	random	15	.3	0	9113	10154.50	890.95	12.084
UCB	ratio k	tolerance	15	.8	2.8	9115	10800.50	1242.11	3.025
UCB	ratio k	greedy	5	0	0	9115	9115.00		3.474
UCB	ratio k	tolerance	15	.8	1.4	9119	10433.20	1442.39	3.964
UCB	top k	tolerance	5	1	1.4	9122	10203.40	960.35	1.855
UCB1T	ratio k	tolerance	5	0	0	9129	10220.00	570.58	15.087
UCB1T	top k	random	15	.8	1.4	9137	10317.70	610.53	30.007
UCB1T	ratio k	random	15	.8	2.8	9152	10352.00	746.14	14.252
UCB	ratio k	random	5	.8	2.8	9164	10712.80	973.79	.934
UCB1T	ratio k	greedy	10	0	0	9189	9189.00		6.152
UCB	top k	tolerance	15	1	0	9189	9364.90	196.14	12.684
UCB1T	ratio k	greedy	15	0	0	9189	9189.00		23.281
UCB1T	ratio k	random	10	1	1.4	9191	10322.50	640.37	21.799
UCB	top k	tolerance	10	.8	2.8	9196	10544.80	1021.02	3.781
UCB	ratio k	random	10	.8	1.4	9206	11498.40	1315.81	1.877
UCB	ratio k	random	5	.8	0	9216	10223.10	787.78	.700
UCB	top k	random	15	.8	0	9228	10110.20	506.08	5.200
UCB1T	top k	random	15	.8	0	9231	9765.10	598.81	5.897
UCB1T	ratio k	greedy	10	0	2.8	9232	9232.00		35.096
UCB1T	top k	random	10	0	2.8	9233	10300.60	803.69	16.070
UCB	ratio k	greedy	10	0	2.8	9236	9236.00		.659
UCB	top k	random	15	1	2.8	9239	12212.80	1406.29	3.511
UCB	ratio k	tolerance	15	1	1.4	9246	11366.30	1648.52	6.255
UCB	top k	random	5	.3	1.4	9251	11292.70	1502.66	1.159
UCB	top k	random	5	1	2.8	9257	11222.30	1151.01	.989
UCB1T	ratio k	random	5	.8	1.4	9266	10009.20	640.87	3.151
UCB	ratio k	random	15	0	0	9284	10521.00	783.56	8.310
UCB	ratio k	random	15	1	0	9334	10134.30	511.22	12.707
UCB	ratio k	random	10	0	0	9338	10853.20	1144.09	2.073
UCB1T	ratio k	random	15	.5	2.8	9384	10217.30	665.69	17.305
UCB	top k	tolerance	10	1	2.8	9391	10632.40	808.59	.807
UCB	ratio k	tolerance	5	1	1.4	9422	10579.60	1329.62	1.284
UCB1T	ratio k	greedy	5	0	0	9430	9430.00		2.293
UCB	top k	random	5	.8	1.4	9431	10993.20	1331.87	1.051
UCB	top k	tolerance	15	1	2.8	9485	12004.20	1256.16	3.696
UCB1T	top k	random	10	.3	0	9511	10481.10	650.31	2.531
UCB	ratio k	greedy	10	0	1.4	9536	9536.00		.643
UCB	ratio k	tolerance	5	0	2.8	9569	11463.30	1286.05	1.440
UCB1T	ratio k	tolerance	5	0	1.4	9581	10286.80	544.81	32.538
UCB	top k	random	5	.3	2.8	9613	10768.50	844.53	1.359

UCB1T	ratio k	random	15	0	1.4	9613	10153.20	449.14	11.352
UCB	top k	random	10	1	2.8	9633	11761.40	1489.27	1.137
UCB	ratio k	random	15	.3	1.4	9639	11901.60	1288.61	1.061
UCB	ratio k	tolerance	5	0	0	9695	10291.30	466.44	4.190
UCB	top k	random	10	.5	1.4	9698	12463.80	1366.28	2.842
UCB	top k	random	15	1	1.4	9698	12630.10	1429.18	3.732
UCB1T	ratio k	random	10	0	2.8	9703	10693.80	875.76	10.973
UCB	ratio k	random	15	0	2.8	9718	12662.00	1535.14	2.647
UCB	top k	random	5	.5	1.4	9731	10960.40	1244.33	.204
UCB	ratio k	random	10	1	1.4	9804	12267.30	1761.04	1.165
UCB	top k	random	5	.8	2.8	9827	10856.00	725.07	1.735
UCB1T	ratio k	random	5	.3	2.8	9842	10578.40	531.71	2.281
UCB	top k	random	10	.8	1.4	9936	12495.00	1408.75	.714
UCB	ratio k	tolerance	15	1	2.8	9997	11191.30	1014.87	4.340
UCB	ratio k	random	15	1	2.8	10141	12119.70	1338.30	2.413
UCB	top k	random	15	.5	2.8	10172	11972.90	1288.14	.961
UCB	ratio k	random	15	.5	2.8	10172	12561.20	1450.61	3.983
UCB	top k	tolerance	10	1	1.4	10240	11519.00	1085.64	.715
UCB	top k	random	10	.5	2.8	10240	11399.80	1240.29	.741
UCB	top k	random	10	0	2.8	10247	12594.30	1643.72	1.830
UCB	ratio k	random	10	1	2.8	10250	12025.30	1001.33	2.499
UCB	ratio k	random	15	.5	1.4	10252	12541.00	1897.10	5.190
UCB	top k	tolerance	15	1	1.4	10312	11632.90	692.63	3.092
UCB	ratio k	random	5	.5	2.8	10322	12311.00	1633.32	.329
UCB	ratio k	random	15	.8	1.4	10351	12264.70	1379.91	.843
UCB	top k	random	15	.8	1.4	10360	12904.00	1390.08	3.797
UCB	top k	random	15	0	2.8	10382	12060.70	1064.34	3.429
UCB	top k	random	15	.3	2.8	10386	12310.80	1304.34	3.967
UCB1T	ratio k	greedy	5	0	1.4	10418	10418.00		4.672
UCB1T	ratio k	random	5	0	2.8	10425	12340.90	992.99	5.120
UCB	ratio k	random	5	0	0	10456	12393.40	1459.53	2.280
UCB1T	ratio k	greedy	5	0	2.8	10617	10617.00		5.336
UCB	top k	random	10	0	1.4	10618	12624.50	1477.42	2.489
UCB	ratio k	random	10	0	1.4	10626	12982.00	1706.24	3.566
UCB1T	ratio k	random	5	0	0	10700	12418.30	1540.91	2.397
UCB	ratio k	random	10	0	2.8	10731	13376.80	1541.42	2.458
UCB	ratio k	random	15	0	1.4	10733	12938.40	1697.15	3.340
UCB	top k	random	10	.3	2.8	10759	11974.30	983.85	.408
UCB	top k	random	15	0	1.4	10875	13082.40	1137.34	2.177
UCB	ratio k	random	15	.3	2.8	10933	13835.70	1477.97	.987
UCB	top k	random	10	.3	1.4	11090	12812.50	1534.00	1.942

UCB	ratio k	tolerance	5	0	1.4	11120	12717.90	1112.21	.678
UCB	top k	random	15	.5	1.4	11183	12500.60	1155.49	4.472
UCB	ratio k	random	5	.3	2.8	11251	13089.10	1100.05	1.516
UCB	top k	random	15	.3	1.4	11262	12587.30	1086.89	2.102
UCB	ratio k	random	5	0	1.4	11338	14560.90	1639.92	1.635
UCB	ratio k	random	10	.5	1.4	11353	12593.80	999.04	3.786
UCB	top k	random	10	.8	2.8	11443	12957.10	1080.45	3.772
UCB	ratio k	random	10	.5	2.8	11466	12476.20	737.26	1.552
UCB	ratio k	random	15	.8	2.8	11498	12393.90	912.85	4.729
UCB1T	ratio k	random	5	0	1.4	11895	13167.60	872.16	2.528
UCB	top k	random	15	.8	2.8	12157	13707.20	731.47	1.514
UCB	ratio k	greedy	5	0	2.8	12249	12249.00		.438
UCB	ratio k	random	5	0	2.8	12661	14077.90	1063.20	1.268
UCB	ratio k	greedy	5	0	1.4	13021	13021.00		.481

C.3.2 Solution not found

Selec policy	Exp policy	Simu policy	N° childrens	Ratio	Cp	Best cost	Mean	Std	T(s)
-	-	-	-	-	-	-	-	-	-

C.4 Instance 4

Table C.7: Kolmogorov-Smirnov and Mann-Whitney U Test Results for 5 cores parralelisation vs no parralelisation

Key	KS p-value	MW p-value
2	0.1678	0.01133
3	0.05394	0.06774
4	6.09e-05	1.728e-05
5	1.28e-05	2.788e-06
6	3.822e-05	3.611e-05
7	1.752e-06	1.753e-06
8	1.448e-08	9.996e-08
9	1.498e-10	2.082e-08
10	7.503e-08	9.91e-07
11	2.147e-14	4.124e-10
12	4.417e-15	3.446e-11
13	1.612e-12	1.002e-08
14	1.635e-10	4.312e-08
15	6.337e-12	9.826e-09
16	1.354e-13	8.184e-09
17	4.858e-13	9.855e-09
18	6.246e-11	2.576e-08
19	2.39e-15	1.003e-10
20	2.088e-12	1.611e-09
21	1.491e-19	2.17e-12
22	1.829e-11	9.687e-09
23	0.02023	0.01578
24	3.065e-06	9.508e-06
25	0.1477	0.0325
26	0.01048	0.003051
27	0.0002042	0.003623
28	0.02166	0.01133
29	0.1402	0.1316
30	0.008867	0.0009358
31	2.717e-07	5.519e-07
32	4.007e-05	2.086e-05
33	0.000234	0.0001292
34	0.007192	0.003185
35	4.021e-05	0.0009069
36	0.02597	0.06494
37	0.08591	0.05994
38	0.1099	0.1264
39	0.9333	0.8
40	1	1

Table C.8: Kolmogorov-Smirnov and Mann-Whitney U Test Results for paralelisation 5 vs 10 cores

Key	**KS p-value**	**MW p-value**
2	0.7869	0.9097
3	0.4936	0.5597
4	0.559	0.9029
5	0.5726	0.8215
6	0.7308	0.5249
7	0.5362	0.2212
8	8.03e-05	0.000113
9	3.651e-06	1.492e-05
10	3.182e-05	1.874e-05
11	0.02005	0.001727
12	4.094e-05	0.0002752
13	0.009494	0.001714
14	0.005447	0.007363
15	0.4848	0.2415
16	0.006502	0.001958
17	5.38e-05	4.063e-06
18	0.001678	0.002008
19	1.131e-08	1.017e-06
20	0.446	0.7367
21	0.6276	0.6335
22	0.9451	0.6936
23	0.1712	0.04649
24	0.9095	0.8391
25	0.5248	0.3179
26	0.111	0.6057
27	0.6856	0.3729
28	0.09346	0.2532
29	0.000215	0.0001052
30	0.007774	0.05043
31	0.08092	0.09824
32	0.6077	0.3848
33	0.08476	0.04293
34	0.003479	0.002516
35	0.2366	0.1629
36	0.7839	0.662
37	0.4286	0.4127
38	0.1	0.1
39	1	1
40	1	1

Appendix D

Best solutions

Instance 1

- Starting airport:'ABO'
- Solution = ['AB0', 'AB7', 'AB4', 'AB9', 'AB1', 'AB6', 'AB2', 'AB8', 'AB3', 'AB5', 'AB0']
- Associated cost = 1396

Instance 2

- Starting airport:'EBJ'
- Solution = ['EBJ', 'NBP', 'OMG', 'NCA', 'NUJ', 'OHT', 'GSM', 'EFZ', 'QKK', 'SSC', 'TKT']
- Associated cost = 1498

Instance 3

- Starting airport:'GDN'
- Solution = ['GDN', 'SZY', 'WMI', 'LD3', 'LB1', 'PD1', 'KRK', 'SA1', 'WRO', 'IEG', 'POZ', 'BZG', 'OSZ', 'OSP']
- Associated cost = 7672

Instance 4

- Starting airport:
- Solution: ['GDN', 'SXF', 'CPH', 'OSL', 'BLE', 'TLL', 'HEL', 'LED', 'RIX', 'VNO', 'BQT', 'LWO', 'KIV', 'IAS', 'VAR', 'IST', 'AKT', 'PVK', 'SKP', 'TGD', 'TIA', 'MLA', 'DBV', 'SJJ', 'BEG', 'BUD', 'BTS', 'LJU', 'INN', 'VCE', 'GVA', 'LUX', 'BRU', 'AMS', 'LTN', 'ORK', 'OPO', 'MAD', 'MRS', 'PRG', 'POZ']
- Associated cost: 15101

Instance 5-6

Not found

Instance 7

Instance 8

- Starting airport: 'AEW'
- Solution: ['AEW', 'AUO', 'ZMT', 'TRH', 'IDB', 'LVN', 'FCJ', 'OAE', 'FMC', 'VCO', 'AOY', 'KCY', 'RIS', 'IHK', 'OTQ', 'JBS', 'SXJ', 'ILI', 'JQL', 'MZO', 'TGY', 'PCD', 'CJM', 'DVQ', 'EBC', 'JKB', 'ULO', 'BNL', 'OOM', 'CKW', 'JLS', 'CJT', 'OBE', 'PDI', 'ZZP', 'OVD', 'HRX', 'AZF', 'OLQ', 'WCD', 'XMD', 'IHD', 'FWA', 'NPF', 'FCP', 'RLT', 'NPT', 'BPY', 'YED', 'KIL', 'RGK', 'IYZ', 'ECS', 'CHK', 'IID', 'VRF', 'EBY', 'VDQ', 'ALA', 'CZJ', 'MYR', 'FKP', 'UYS', 'RAA', 'UPZ', 'VFT', 'JEL', 'AKF', 'URK', 'WCU', 'RWZ', 'MVV', 'FGF', 'XSF', 'PRO', 'FYA', 'ZCX', 'VXE', 'KFD', 'CQP', 'JSR', 'EBK', 'RZG', 'LII', 'KIW', 'UEW', 'IXO', 'GHI', 'USB', 'JZU', 'JRX', 'LKE', 'QHR', 'RHQ', 'XSY', 'ASF', 'HPZ', 'CIL', 'EOG', 'JQI', 'QBR', 'PUW', 'PFI', 'WUL', 'PNH', 'TBS', 'LTP', 'RAR', 'DDZ', 'FIG', 'EGV', 'SRY', 'NVV', 'NZN', 'UJW', 'JCY', 'ZNG', 'RWM', 'IUN', 'OPC', 'JRT', 'MHW', 'LTF', 'DRO', 'SVZ', 'QRL', 'BJG', 'BFZ', 'EXV', 'IVF', 'LRU', 'HMM', 'DCY', 'PUG', 'CGR', 'JBJ', 'PEP', 'GSC', 'EHZ', 'CUU', 'BMD', 'PJS', 'GPI', 'BLJ', 'QMS', 'FAO', 'JIM', 'CAA', 'MYZ', 'GRH', 'KBN', 'IPE', 'MMN', 'AUJ', 'LNC', 'ROM', 'JAH', 'DSR', 'HTD', 'EQV', 'NOR', 'RUP', 'OXH',

'BYB', 'BQL', 'EOW', 'PEU', 'JFU', 'MSW', 'DNZ', 'AME', 'JHO', 'HNP', 'LTI', 'PFU', 'QZU', 'RWO', 'LRL', 'KIC', 'MFT', 'EOB', 'QXU', 'QQT', 'BKB', 'AFH', 'MRE', 'MAE', 'BCU', 'PDY', 'ZXD', 'BIN', 'DWQ', 'NRS', 'JJY', 'DSN', 'HIX', 'BAB', 'DCB', 'OVC', 'HIN', 'AEW']

- Associated cost: 4037

Instance 9

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