Applying heuristic search strategies to plan with reconfigurable multi-robot systems

by

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Abstract

This thesis investigates heuristic search strategies that can be applied to planning with reconfigurable multi-robot systems.

In the Vehicle Routing Problem (VRP), an optimal route is searched for a set of vehicles to deliver a set of items to a set of customers. Temporal Planning for Reconfigurable Multi-Robot Systems (TemPl) is a constrained-based mission planner which introduces a mission description as a generalisation of the Vehicle Routing Problem (VRP). This use of generalisation means that heuristic search strategies used to find solutions in VRP could also possibly be used on TemPl. TemPl contains multiple constraints (spatial, temporal, load, inter-route) that aren't considered by the classical VRP or its variants. Hence, heuristics used to solve VRP require to be adapted before applying to TemPl.

For this reason, this thesis intends to evaluate existing literature and find heuristic search strategies that can be applied to robot planning with TemPl. An implementation of the Very Large Neighbourhood Search algorithm serves as proof of concept for the applicability of heuristic search strategies for robot planning.

Contents

1 Introduction and Motivation of Research

Heuristic search strategies are used in combinatorial optimization problems to find solutions in large problem spaces. Finding exact solutions could be computationally expensive, so heuristics are employed to find approximate solutions by optimising for speed rather than accuracy.

The Vehicle Routing Problem (VRP) [9] is a widely studied combinatorial optimization problem. In VRP, a set of vehicles need to deliver items to a set of customers. The challenge is to do it in the lowest cost possible, which is dependent on total distance travelled, total energy consumed or total time spent delivering. Several variants of VRP exist depending on the constraints and characteristics of vehicles and customers. Some popular variants include Capicatated VRP(CVRP) [15], VRP with Time Windows (VRPTWW) [8] and VRP with Pickup and Delivery (VRPDD) [10].

Reconfigurable robots can physically merge to create dynamic robotic systems, leading to additional degrees of freedom. To operate such systems autonomously, mission planning is required to deal with the flexibility of composite agents. For this purpose, Roehr(2019) [25] introduced Temporal Planning for Reconfigurable Multi-Robot Systems (TemPl), a constrained-based mission planner. This planner introduces a mission description as a generalisation of the Vehicle Routing Problem (VRP). TemPl uses a combination of knowledge-based reasoning, constraint-based programming and linear programming [24] to convert a mission specification into a mission solution. TemPl translates a mission description into a multicommodity min-cost flow problem [3] to identify a locally optimal plan. This optimization is solved as a linear integer problem (LP) which can be solved using existing linear integer program solvers. The size of the multicommodity min-cost flow problem as a linear program depends on the characteristics of the underlying solution representation, as well as the number of active mobile and immobile agents that need to be routed. This optimal planning approach and the used LP solvers limits the scalability of this planning approach.

As the mission description is a generalisation of the VRP, heuristics used for VRP could also be adapted and applied to TemPl. It is important to note that TemPl contains additional constraints (temporal, spatial and inter-route) than the classical VRPs, so heuristics applied to variants of VRP with multiple constraints could be useful. Additionally, most heuristic search strategies for classical VRPs assume routes to be mutually independent and don't consider time windows, capacities, vehicle synchrnoisation and heteregenous agents [24]. Drexl(2013) [11] noted how research on VRP under multiple synchronisation constraints is scarce, and the use of heuristics to solve it is even scarcer.

Therefore, this thesis aims to explore and evaluate the use of heuristic search strategies such as Simulated Annealing [1], Tabu Search [28] or Very Large Neighbourhood Search (VLNS) [7] which could possibly optimise the planner.

This thesis is structured in the following way. Section 2 describes the technical background necessary to understand concepts used in this thesis. Section 3 investigates the state-of-the-art in heuristic search strategies used and explains the Very Large Neighbourhood Search heuristic to be implemented. Section 4 describes the setup of the experiment and discusses the obtained results. Section 5 summarizes the results obtained and Section 6 suggests possible further investigation ideas.

2 Technical background

In this section, we will be going through the necessary technical concepts required to understand parts of this thesis.

2.1 Reconfigurable multi-robot systems

Reconfigurable multi-robots can physically merge to form composite systems, offering additional capabilities as compared to the previously individual systems. Its modularity helps adapt to challenges in robotic missions. Each heterogeneous agent used to form a reconfigurable multi-robot system contains individual capabilities, functionalities and limitations. A reconfigurable robot contains a standardised interface which allows new hardware to be attached and removed, so resources can be shared as required.

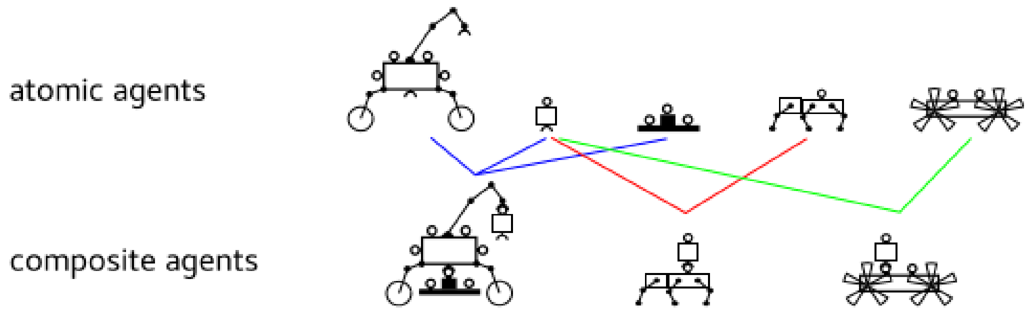

Figure 1: *Possible composite agents formed by combining atomic agents(Roehr 2019, Pg.29)* [25]

Composite agents may be required in certain scenarios of a mission. An immobile agent can be combined with mobile agent to transport it from one location to another. Some functionality in composite agents appears through the "super-additive effect" [24], when two or more atomic agents combine. Composite agents increase "functional redundancy". If one agent in a composite system fails, it can be replaced by another redundant agent. Adding relevant resources increases the redundancy and safety of an operation.

2.2 Reconfigurable system properties

Roehr (2019) [25] uses the flexibility of reconfiguration in planning and characterises solutions based on three system properties: efficacy, efficiency and safety.

The efficacy of a reconfigurable system is its ability to produce a desired result. If a mission consists of performing N tasks, then efficacy describes the fraction of completed tasks. If all tasks are completed, the efficacy is 1.

The efficiency of a reconfigurable system is determined by its execution time and energy consumption. The lower the execution time and resources used, the higher the efficiency. Similarly to how carpooling in cities [18] helps reduce energy usage, a reconfigurable system can increase its efficiency by making full use of the capabilities of a single robotic system.

The safety of a reconfigurable system, as designed by Roehr (2019) [25], is dependent on the redundancy of resources. A higher number of available resources means the whole system has a lower probability of failing, as the single resource is replaceable. Safety is highly prioritised as robotic systems are deployed and operated remotely. Losing even a single robotic system is expensive.

Efficiency, efficacy and safety are dependent on each other. A system could increase its efficiency and efficacy by increasing its safety i.e. its rate of survival. Conversely, increasing safety could decrease efficiency as higher the redundancy of resources leads to higher energy usage. Therefore, it is important to find a balance between all three properties to achieve optimal results.

2.3 Vehicle Routing problem

In the Vehicle Routing Problem (VRP) [9], a set of vehicles and a set of items to be delivered are set. The objective is to find the optimal route used by the group of vehicles to deliver the items at a minimum cost. This is similar to deciding which vehicle delivers which item in which sequence such that all vehicle routes can be feasibly executed. The total cost depends on the total distance travelled by the vehicles and the number of used vehicles.

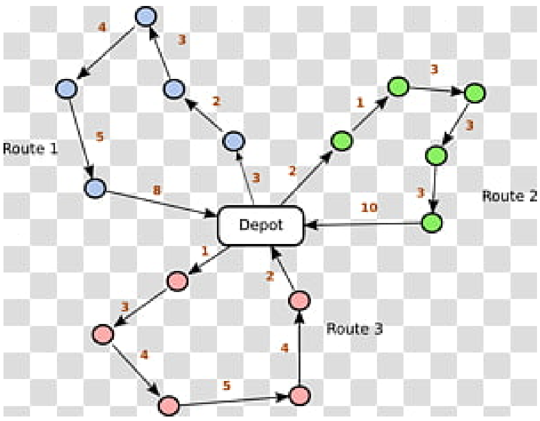

Figure 2: *Graphical representation of VRP, where each vehicle has its own route for delivering items* [21]

VRP and its variants has been extensively studied in the field of combinatorial optimization. Dantzig and Ramser(1959) [9] first described VRP as routing delivery trucks between stations and a terminal. Real world problems are more complex than the classical VRP. The need for additional constraints need to be considered created several variants of VRP. In Capacitated VRP (CVRP) [15], each vehicle has a limit of items it can carry. In VRP with Time Windows (VRPTWW) [8], each delivery needs to be made within a certain time interval. In VRP with Pickup and Delivery (VRPDD) [10], vehicles need to pick up and deliver items from one location to another.

VRP is a NP hard combinatorial optimization problem, so solving large problems is not always feasible in CPU time. Heuristics are employed to find acceptable solutions in a short time.

2.4 Vehicle Routing problem with Trailers and Transshipments

A more relevant VRP variant to planning with reconfigurable multi-robot system problem. is the VRP with trailers and transshipments (VRPTT) [11]. VRPTT is representative of the class of vehicle routing problems with multiple synchronization constraints (VRPMSs). VRPMSs is similar to the mission description introduced by TemPl. VRPMSs contain temporal, spatial and load constraints. A change in one vehicle's route affects other vehicles' routes due to synchronization constraints, which is not the case in classical VRP. Most heuristic algorithms used to solve vehicle routing problems assume the routes to be mutually independent, which can't be used to solve VRPMSs. Changing a route could render the whole solution useless.

VRP with trailers and transshipments (VRPTT) was used to model a real world problem of collecting milk from farmyards [12]. The problem description is as follows. Vehicles are split into two categories: lorries (autonomous vehicles that can move on their own) and trailers (non-autonomous vehicles that require an autonomous vehicle to be moved). Additionally, there are "task vehicles", which visit customers and collect milk, and "support vehicles", which are used as mobile depots for task vehicles to transfer their load. Transfers occur in "transshipment locations". Selecting transshipment locations could also create additional costs per each transshipment.

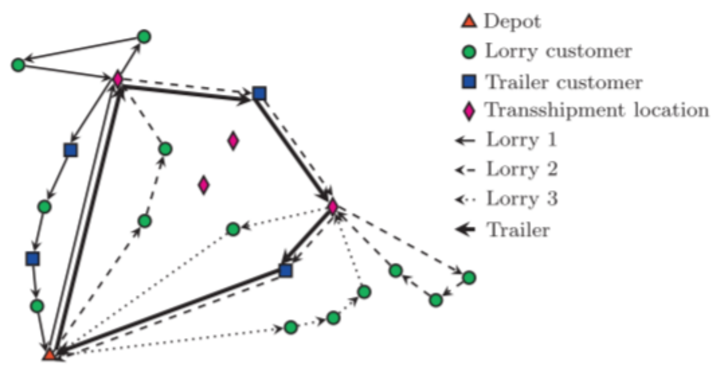

Figure 3: *Route plan of VRP with trailers and transshipments* [11]

As VRPTT is a subproblem of VRPMSs, multiple constraints exist. In addition to spatial, temporal and load constraints, vehicles may have accessibility constraints. Not every vehicle may be able to visit every location. The number of vehicles that can use a certain transshipment location and the number of transshipment operations that can occur in a transshipment locations is also limited. A time window for allowing transshipments can also exist.

Each customer has their own requirements. Customers that can be visited by lorries without a trailer are called "lorry customers". Customers that can be visited by lorries with or without a trailer are called "trailer customers".

The problem is to determine a route for the lorries and trailers such that the entire supply of customers is collected and dropped to a depot at the lowest possible cost. The final solution must respect all synchronization, temporal, spatial and load constraints.

2.5 Temporal Planning for Reconfigurable Multi-Robot systems (TemPl)

Roehr (2019) [25] introduced TemPl, a constraint-based mission planner for reconfigurable multi-robot systems. The planner uses a mission description as a generalisation of the Vehicle Routing Problem. TemPl converts planning with reconfigurable multi-robot systems into a multicommodity min-cost flow problem.

The mission planning problem is similar to the vehicle routing problem. "Mobile agents" are vehicles and "immobile agents" are items to be delivered. "Reconfiguration" is a transshipment between two vehicles. A key difference remains, however, that reconfigurable multi-robot systems can change their functional properties depending on the requirements of the mission. Reframing the mission planning problem as a vehicle routing problem allows it to be formalized as a multicommodity min-cost flow optimization problem so that locally optimal search can be applied. This is solved using linear programming in TemPl.

2.6 Mission planning with TemPl

The mission planner TemPl (Temporal Planning for Reconfigurable Multi-Robot Systems) introduces a mission description as a generalisation of VRP. In this section, we will be going through how missions are represented and planned in TemPl.

Space exploration missions require robots to perform tasks such as collecting and analysing soil samples. Different robots have different functionalities, and some tasks may require multiple robots to be present. Tasks are assigned dynamically depending on the available robots. TemPl is based on this requirement of encoding tasks and inter-dependencies of each robot into a mission specification.

The mission can be seen as a task assignment for multi-robot systems, with the additional capability of atomic agents (single-robot systems) to combine and form composite agents.

2.6.1 Mission specification

The mission specification[24] of a reconfigurable multi-robot system defines the states of an agent in different stages of a mission.

A mission specification contains a spatial-temporal requirement, which states the functional and agent instance requirements at a certain space-timepoint. This specifies the time and location where an agent should be present.

Fig 4 shows a typical mission. Each agent needs to be in a specific space and time window. The required functionality is displayed on top of the timeline.

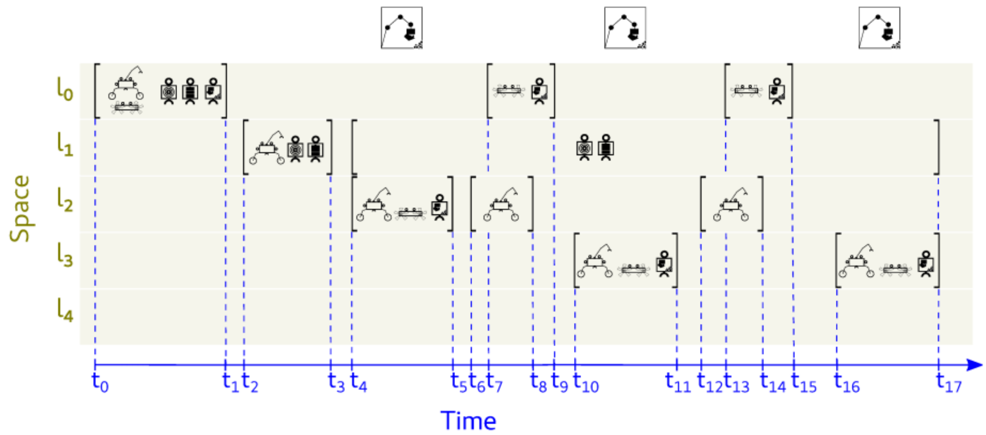

Figure 4: *Example of mission specification* [25]

2.6.2 Solution representation

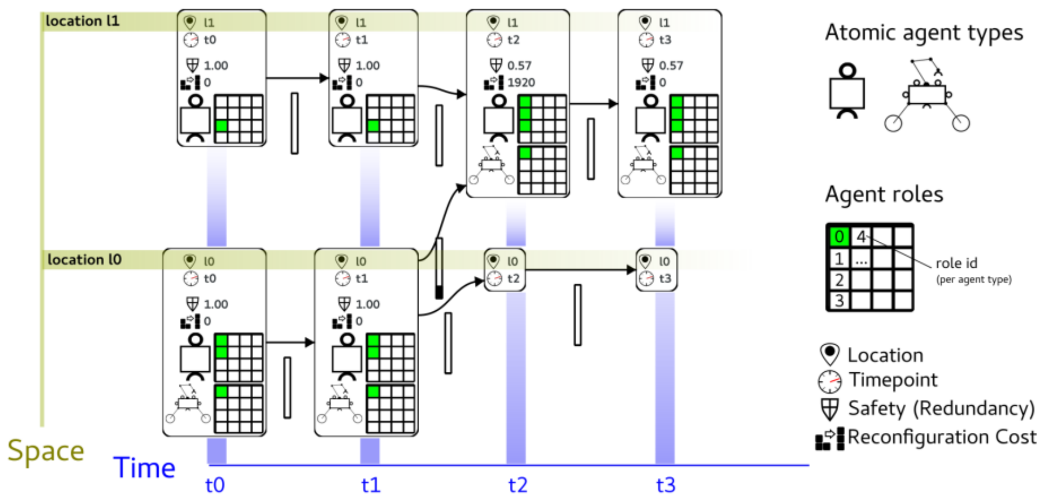

Figure 5: *Example solution (Roehr 2019, Pg.95)* [25]

Fig 5 is a visual representation of the mission solution generated by TemPl. A vertex corresponds to one spacetime tuple. The fillbars in the middle of tuples, represented by an upright rectangle, indicates the consumed capacity of the transitioning edge.

For example, the bottom-left tuple is in time t0 and location l0. It contains two atomic agent types. The first atomic agent type contains two green squares, which means there are two agents of that type. The second atomic agent type contains one green square, which means there is one agent of that type. The color green stands for the fulfilled requirement of each role agent. The color grey (not displayed in Fig 2.5) represents an agent role present without a requirement. The color red represents an unfulfilled requirement of a role agent.

2.6.3 Mission constraints in TemPl

Mission constraints in TemPl consist of:

(i) *Temporal*: Agent roles have lower and upper bound time intervals.

(ii) *Model*: Model constraints set the requirement of agent type and roles.

(iii) *Functionality and Property*: Functionality constraints state the number of required agents. To provide functionality, a minimum of one agent is always needed. Property constraints are for constraining the property of a functionality, e.g., an agent with a certain transport capacity may be demanded.

We refer the reader to Roehr (2019), pg. 96 [25] for details about how each constraint is modelled.

3 Description of the Investigation

In this section, we will be going through different types of heuristic search strategies that are employed to solve vehicle routing problems. Then we will explain why metaheuristics such as Very Large Neighbourhood Search are more promising than others.

3.1 State of the art research

An evaluation of the state of the art in heuristic search strategies was performed from which the most promising ones are listed below.

3.1.1 Constructive heuristics

Constructive heuristics are used to create a starting solution for other improvement heuristics to use. They aren't used anymore as most metaheuristics can now be initialized from an existing feasible or infeasible solution.

Afshar-Nadjafi (2019)[2] used a constructive heuristic to solve the time-dependent multi-depot vehicle routing problem. The heuristic minimized the total heterogeneous fleet cost by assuming travel time between two different locations depends on the departure time of the vehicle. It managed to outperform Lingo [16], a software tool for solving optimization models, on 180 test problems.

A classical example is the Clarke and Wright savings heuristic [6]. It creates multiple routes back and forth before gradually merging them to reduce the total cost.

Classical heuristics are rather too simple. This has been largely replaced by the more robust metaheuristics. This heuristic isn't relevant to our problem as we're already starting with a solution i.e the one generated by TemPl.

3.1.2 Classical improvement heuristics

Classical improvement heuristics split and combine routes to achieve optimal results.

The best performing classical improvement heuristic was found [13] to be the Lin and Kernighan 2-opt algorithm. Thhis algorithm swaps edges to make the final route shorter. A modified version of the Lin and Kernighan algorithm by Helsgaun [14] managed a running time of $O(n^{2.2})$. Unfortunately, it was considered impractical for large problems containing more than 100,000 vertices.

Classical improvement heuristics are older, less robust and don't scale well with the problem size. Hence, we will not be using this for our investigation.

3.1.3 Metaheuristics

Baugh (1998) [5] used metaheuristics to improve suboptimal results of dynamic programming for pickup and delivery problems. Toth and Vigo stated [29] most metaheuristics tend to be similar to each other and are hybrids of several metaheuristics. The more distinct ones are detailed below:

Local Search Algorithms Local search algorithms improve an initial solution by moving to the neighbourhood of another solution in each iteration. “Cycling” occurs in local search algorithms when the algorithm keeps iterating within the same neighbourhoods. Local Search Algorithms do not require the cost of the next solution to be lower than the cost of the current solution, which could lead to an endless loop.

Simulated Annealing In the classical version of simulated annealing by Osman (1993) [20], degraded solutions are occasionally accepted in the hopes of escaping the local optimum. The algorithm uses randomized search, acceptance and stopping criteria on a local search algorithm to prevent cycling. Osman observed new best solutions for upto 163 vehicles but a large variance still existed in terms of computation time and solution quality. This algorithm was also implemented on the classical version of VRP, which has no constraints.

Afifi, Dang, Moukrim (2013) [1] used simulated annealing for VRP with Time Windows and Synchronization Constraints (VRPTWSyn). In this variant of VRP, each customer has a time window for receiving items. If a vehicle arrives before the time window, it must wait. If a vehicle arrives later than the time window, it is rejected. Customers requiring two visits from two vehicles also exist. For cases like these, visits must be synchronized i.e. both vehicles must have the same starting time.

This was one of the few papers where simulated annealing was applied to VRPTWSyn. This algorithm was able to find all known optimal solutions in short computational times. The algorithm can be divided into three parts: construction heuristic, diversification process and local search procedure.

In the construction heuristic, a solution is built from scratch. In each iteration of the heuristic, visits with lower insertion costs are picked to be inserted in the associated route. More routes will only be added after it is impossible to insert any remaining visits to existing routes. The algorithm terminates after all visits are routed. As it’s necessary to adhere to synchronization constraints, an update is sent to different routes after every insertion.

In the diversification process, a random number of visits are removed. The solution is built again using the construction heuristic. This “destroy and repair” operation helps obtain a new solution without losing much quality compared to the older solution. Each visit is recorded with a priority number of 0. For every insertion of a visit that creates an extra route, the priority number is increased by 1. This way, visits that cause lots of extra routes are identified as ”critical”. Critical visits are prioritized during insertion with the construction heuristic. The algorithm can always move back to a feasible solution when it reaches an infeasible one.

In the local search procedure, a random neighbourhood w is selected from a set W and initialized to 2-opt* or or-opt in every iteration. The picked neighbourhood is removed from W and applied to the current solution multiple times. If an improvement occurs with the random neighbourhood w, the other neighbourhood will be reinserted into W (if it was removed). This process recurs until there are no more neighbourhoods left in W.

The local search procedure uses two types of operations: 2-opt and or-opt.

2-opt* (exchange of path between routes): In this operator, two edges are swapped with two others in the same route and checked if it improved the solution. This version of 2-opt is different from the classical one as it wouldn’t have been possible to find an improvement due to the preset order of visits from time windows. In this version of 2-opt, a subset of visits is selected. For each pair of visits (v^i, v^j), the pairs v^i, v^{i+1} and v^j, v^{j+1} are considered (v^i denotes the visit v at position i; v^i and v^j are in two different routes). If an exchange is feasible, the new cost is computed and recorded. After multiple random selections, the lowest cost is selected and the corresponding visits are swapped.

Or-opt (exchange of visits in the same route): In this operator, consecutive visits are moved to another location in the same route. A random selection is followed by a feasibility check, which is partially similar to 2-opt*.

Deterministic Annealing As compared to simulated annealing where a solution is picked randomly, deterministic annealing uses deterministic methods to pick a solution. In the search process, some directions have a higher chance of finding an optimal solution. The stochastic search process used by the algorithm is guided towards these directions to save time and computational cost.

Baranwal et al. (2016) [4] implemented, to our knowledge, the first ever deterministic-annealing based approach to VRP with Time Windows (VRPTW). This paper gave a high-level explanation of its algorithm.

Tabu Search Tabu search starts with a solution and moves to the best non-tabu solution in every iteration. Several variants of tabu search exist. Potvin et.al. (1996) [22] implemented the tabu search heuristic based on 2-opt* and or-opt exchanges. Rochat and Taillard (1995) [23] used a tabu search heuristic which exploits a neighbourhood by exchanging customers between routes. An "adaptive memory" records the best routes found from each search. This memory is used to create new starting solutions for tabu search.

Edge-exchange heuristics: This is similar to 2-opt* and or-opt exchanges. A staring solution is picked. All solutions in its neighbourhood are generated using one of several heuristics. The best solution is picked and defined to be the starting solution. This repeats for a number of times. Increasing the graph size increases the total number of iterations taken to reach a local optimum.

Gendrau et. al.(1997) [28] uses a modified version of this edge-exchange heuristic to find neighbourhoods for its solution. Moves are evaluated by calculating the difference in cost (measured by distance travelled) between the neighbouring and current solution. The size of the neighbourhood is decreased by getting rid of moves that do not improve the solution. Initially, this tabu search heuristic creates a solution from the routes found in the adaptive memory. The solution is broken down into subset of routes. Tabu search is applied on each subset. The new routes formed by tabu search are merged to create a new solution. The new routes are stored in the adaptive memory, and the entire process is repeated.

The algorithm has the following components:

Initialization: A randomized insertion heuristic combines routes from the adaptive memory. The set of routes is broken down into subsets, which will be fed to the tabu serch heuristic.

Stopping criterion: The tabu search stops after a number of iterations, depending on the decomposition/reconstruction cycle. Nodes are removed and reinserted into the solution in this cycle. The entire solution improves incrementally after every cycle, so a higher number of iterations creates a better solution. Gendrau et. al. [28] uses the following formula to calculate the stopping criterion. $A \times (1 + \frac{DR-1}{B})$

where, A and B are parameters and DR is the current iteration of the decomposition and reconstruction cycle.

Tabu list: The tabu list is an array where each element is associated with a solution. A solution is assigned into the list by this formula:(cost of the solution MODULO length of tabu list). An element of the list stores the number of iteration at which the solution will lose its "tabu" status. The (cost of the solution) modulo (length of tabu list) is calculated after every solution generation. The number of iterations of this new solution is compared with the one in tabu list. If the value is greater, then the current move is accepted, else, it is considered as "tabu".

Diversification: Diversification occurs by preventing exchanges that are frequently performed. An equation is used to penalize exchanges:

$p_e = x\times\ \Delta max.iter\times\ \frac{fr_e}{fr_{max}}$

where, x is a random value between 0 and 0.5. $\Delta max.iter$ is the maximum difference in cost between two consecutive solutions upto the iteration $iter$. fr_e is the frequency of an exchange e, fr_{max} is the maximal frequency obtained. fr_{max} normalizes frequencies as it is lower for larger neighbourhoods.

Reordering of routes: Each vehicle needs to deliver items to customers in a route. When a best solution is found, the customers within each individual route may be reordered. Gendrau et. al. uses Solomon's I1 insertion heuristic [27]. This heuristic works on a given route the following way. The customers in a single route are unrouted. The customer that is farthest from the depot is selected as a "seed customer" i.e a vehicle starts at the depot, delivers to the seed customer, and then goes back to the depot. The customers that were unrouted are then reinserted in succession into the new route. The customer which maximizes a generalized savings measure is picked first to be reinserted. The picked customer is reinserted in a location which minimizes a weighted sum of detour in space and time. Solomon's I1 insertion heuristic is applied N times, and the best solution is picked. If the new route generated by the heuristic is worse in terms of cost or if the new route doesn't cover all the customers that were unrouted, then the original route is restored.

3.2 Selected heuristic: Very Large Neighbourhood Search

Cotlin, Veloso (2014) [7] introduced the Very Large Neighbourhood Search with Transfers (VLNS-T) algorithm which improved the previously known benchmark of pickup and delivery problem solutions. This is similar to the Adaptive VLNS algorithm for PDP without transfers by Ropke and Pisinger (2006) [26]. It is a variant of the Simulated Annealing algorithm from Section 3.1.3. Items are removed and reinserted with different heuristics to find "neighbors".

This algorithm introduces transfers to reduce cost of solutions. Masson (2013) et al. [17] showed the effectiveness of introducing transfers to improve solutions. Through transfers, routes of vehicles are split and shared with other vehicles. Transfers with different metrics minimizes delivery time of vehicles.

Algorithm 1: vlns(S): Use VLNS to form a new schedule from previous schedule S

1 $S_{best} \leftarrow S$
2 $T \leftarrow \frac{w}{-ln0.5} cost(S, \gamma = 0)$
3 **for** $i \in 1, ..., N$ **do**
4     $q \leftarrow$ random integer in $[min(4, |P|), min(100, \xi|P|)]$
5     $R \leftarrow$ random-items(S, q)
6     $S' \leftarrow$ remove-items(S, R)
7     $S' \leftarrow$ insert-items(S', UND(S))
8   **if** $cost(S') < cost(S_{best})$ **then**
9         $S_{best} \leftarrow S'$
10   **end**
11   **if** $random() < exp - (cost(S') - cost(S))/T$ **then**
12         $S \leftarrow S'$
13   **end**
14     $T \leftarrow cT$
15 **end**
16 **return** S_{best}

The explanation of the algorithm is as follows.

- (Line 5): A random number of items are picked from the existing schedule.
- (Line 6): The picked items are removed from the schedule using one of several heuristics.
- (Line 7): Items that are not part of the schedule are reinserted.
- (Line 8, 9): If the cost of the new solution is lesser than that of the best known solution, the new solution becomes the best solution.
- (Line 11, 12): The likelihood of the new schedule being accepted decreases with time.

Removal heuristics : The remove-items function uses three different heuristics. The *Shaw* removal heuristic picks items that are similar in distance, time and demand. The *Random* removal heuristic picks selects *q* items randomly to remove. The *Worst* removal heuristic picks items by calculating the cost before and after its removal from the solution. Items that are the most ”expensive” have a higher probability of being removed from the solution.

Insertion heuristics : The insert-items function uses two different heuristics to insert items into the schedule. Both use transfers. The *Split Routes* insertion heuristic takes a vehicle’s existing route and splits it with another vehicle. The *Insert item with transfer* heuristic searches the solution for a possible insertion but with max one transfer.

3.3 Very Large Neighbourhood Search with TemPl

Cotlin and Veloso's [7] VLNS-T algorithm was adapted to work with TemPl. Since TemPl deals with inter-route constraints, there are limits to the removal and insertion heuristics we can apply to the solution.

For this VLNS algorithm, we've employed one removal heuristic and one insertion heuristic, both based on randomness.

Algorithm 2: vlns(S): Use VLNS to form a new solution from previous solution S

1 $S_{best} \leftarrow S$
2 $T \leftarrow \frac{w}{-ln0.5} cost(S, \gamma = 0)$
3 **for** $i \in 1, ..., N$ **do**
4     $q \leftarrow$ random agent from list of agents $[1......roles]$
5     $S' \leftarrow$ remove-items(S, q)
6     $S' \leftarrow$ insert-items(S, q)
7   **if** $cost(S') < cost(S_{best})$ **then**
8         $S_{best} \leftarrow S'$
9   **end**
10   **if** $random() < exp - (cost(S') - cost(S))/T$ **then**
11         $S \leftarrow S'$
12   **end**
13     $T \leftarrow cT$
14 **end**
15 **return** S_{best}

The explanation of the algorithm is as follows.

- (Line 3): The algorithm iterates N number of times.
- (Line 4): One random agent in a space-timepoint is picked from the list of agents in a solution.
- (Line 5 and 6): The picked agent is removed from the solution and reinserted in a different location.
- (Line 7, 8): If the cost of the new solution is lesser than that of the best known solution, the new solution becomes the best solution.
- (Line 11, 12): The likelihood of the new schedule being accepted decreases with time.

Removal heuristics : The remove-item function is a random removal heuristic to remove agents from a solution. An agent is picked in random from a list of available agents. An agent can exist in multiple space-timepoint tuples (Section 2.6) but it is only removed from one specific space-timepoint tuple. This is because each agent contains multiple dependencies in the mission solution and requiring every single one would make the problem complicated.

Insertion heuristics : The insert-item function reinserts the removed agent back into another tuple of the same timepoint but different location. Agents aren't allowed to exist in two different timepoints in the same location. In real life terms, it wouldn't make sense for a robot to be in two places at the same time.

After an agent is removed and reinserted, its cost is compared to that of the current solution. The new solution is accepted if the cost decreased.

4 Evaluation of the Investigation

4.1 Evaluation criteria

Mission solutions are evaluated based on a cost function to analyse the effectiveness of heuristics. Traditional VRP problems use “total distance travelled by all vehicles” as a cost function. Dealing with reconfigurable multi-robot systems is more complicated so additional variables need to be considered.

As stated in Section 2.1, Roehr (2019)[25] uses three system properties to analyze the flexibility of reconfigurable multi-robot systems: efficacy, efficiency and safety. Our cost function to analyse solutions is based on these three properties.

Efficiency: In VRP, efficiency is the highest when travelled distance is lowest. Reconfigurable mutli-robot systems are heterogenous. Each robot consumes energy differently. Moving robots with higher energy consumption will decrease efficiency as compared to moving robots with lower energy consumption. Therefore, efficiency can't be measured solely by the distance travelled. The total energy consumed by all robotic systems in a solution also needs to be considered.

Reconfigurable multi-robot systems also share energy when reconfigured into one composite agent. This reconfiguration affects the efficiency of the system.

Safety: A higher redundancy of resources in the same space-timepoint increases safety. If an agent fails, it can be replaced by another agent of the same type.

Efficacy: Efficacy is described as the ability of a reconfigurable multi-robot system to provide a particular functionality. Higher the number of fulfilled requirements of a mission, higher the efficacy of the solution.

The cost function we use combines the three system properties:

$$cost = \alpha \times efficiency + \beta \times efficacy + \epsilon \times safety \quad (1)$$

α, β and ϵ are used to balance the parameters: efficiency, efficacy and safety. Efficacy and safety is a value between [0,1] so α accounts for normalisation to [0,1] for the energy cost. Therefore, α is calculated with the use of E_{max}^{-1}, where E_{max} is the maximum energy cost allowed or observed in an existing mission solution [24].

4.2 Data setup

In order to evaluate the performance of the Very Large neighbourhood Search with TemPl, we've used missions of different sizes and complexity.

TemPl was intially used to search the solutions. Then, a the VLNS heuristics was applied. The application of heuristic is analyzed.

The tested mission consists of 14 timepoints and 10 locations. The coordinates of each location is given below. The distance between two coordinates is measured in metres.

We've used a value of 1 for α, β and ϵ in the cost function. We aren't concerned about balancing the parameters during our experiments as we want to observe the change in cost with respect to each system property. Varying α, β and ϵ could lead to invalid conclusions.

The coordinate of each location in our mission is as follows.

Location	**Latitude**	**Longitude**
lander	-83.82009	87.53932
base1	-84.1812	87.60494
base2	-83.58491	85.98319
b1	-84.1812	87.60494
b2	-83.96893	86.75471
b3	-83.66856	87.42557
b4	-83.54570	87.09851
b5	-83.82009	84.66000
b6	-83.77371	84.70960
b7	-83.34083	84.64467

The timepoints use relational values, unlike the coordinate of locations. The timepoints are ordered in the following way,

```
t1 < t2 < t3 < t4 < t5 < t6 < t7 < t8 < t9 < t10 < t11 < t12 < t13 < t14
```

The operator " $<$ " shows the temporal relationship between two different timepoints. When $t1 < t2$, $t1$ occurs before $t2$.

4.3 Results

The Very Large Neighbourhood Search (VLNS) algorithm from section 4.3 was implemented to mission solutions of different sizes for an iteration of N = 100. The cost was calculated three times, averaged and recorded in the table below.

In the first set of experiment, the VLNS algorithm with random insertion and removal heuristic was implemented. As described in Algorithm 2, the search strategy optimises for cost of the solution. This led to the efficacy of solutions to continuously decrease. This isn't optimal. An efficacy value of 0 will lead to high efficiency but could leads to missions with lots of unfulfilled requirements.

It is important to balance the three system properties of the cost function. To prevent efficacy from falling to 0, a stopping criterion was added to not accept solutions with efficacy lower than 0.33. The results of the experiment are displayed below.

Experiment no.	No. of mobile agents	Cost with TemPl	Cost after applying VLNS
1	5	2478.93	2474.04
2	7	7580.76	7575.91
3	5	4806.33	4804.27
4	7	6681.61	6676.97
5	5	3501.63	3502.63
6	6	6604.69	6603.89
7	7	8312.93	8306.86
8	7	8629.58	8626.47
9	5	5092.88	5088.76
10	7	6682.77	6676.83

Table 1: Analysis of VLNS with solutions of minimum efficacy ≥ 0.33

Optimising for cost lead to solutions with low efficacy. After each iteration, the efficacy of the solution would decrease, which meant requirements weren't being fulfilled. We implemented the VLNS again with a new condition in the heuristic. This time, solutions which lowered the efficacy wouldn't be accepted. This way, we hoped to maintain an efficacy of 1.0 even after the random removal/insertion.

Experiment no.	No. of mobile agents	Cost with TemPl	Cost after applying VLNS
1	5	2478.93	2477.41
2	7	7580.76	7578.17
3	5	4806.33	4807.09
4	7	6681.61	6678
5	5	3501.63	3503.73
6	6	6604.69	6607.9
7	7	8312.93	8314.09
8	7	8629.58	8628.79
9	5	5092.88	5092.88
10	7	6682.77	6674.1

Table 2: Analysis of VLNS with solutions of minimum efficacy ≥ 1.0

From our results, we can observe that applying a random insertion and removal insertion heuristic succeeded in lowering the solution cost. Decreasing efficacy seems to be the best way to reduce total cost of the entire solution. We purposely chose a number of 0.5 and 0.33 of minimum efficacy accepted for solutions. Lowering the efficacy even more for better solution could be possible, but, would harm the effectiveness of the solutions.

4.4 Summary

This section will summarize the experiment from the previous section.

The Very Large Neighbourhood Search algorithm from Section 4.3 was adapted for TemPl. To test its effectiveness, we applied the algorithm to a solution generated by TemPl. The cos before and after the application of the algorithm was compared. A positive improvement was noticed in the solutions in terms of total cost.

The most promising results came when the efficacy was the lowest. As efficacy stands for the proportion of fulfilled requirements, removing every single agent from the solution would lead to a minimum cost. But, this is not feasible in real life scenarios as we would want our mission requirements to be at least partially fulfilled. Therefore, we performed two different experiments with a minimum efficacy of 0.33 and 1.0 for accepted solutions.

We observed from our experiments that lowering the minimum efficacy created solutions of lower costs. It depends on the human generating mission solutions to decide the proportion of unfilled requirements they are willing to tolerate when applying this heuristic.

5 Conclusion

In this thesis, we evaluated existing state-of-the-art heuristics that has been applied to solve VRPs, picked a promising heuristic, implemented it in the context of TemPl. We picked Very Large Neighbourhood Search (VLNS) [7], and adapted it to deal with planning with reconfigurable multi-robot systems.

The VLNS algorithm was applied to a mission solution and its results were evaluated. We used TemPl to generate 10 solutions from 1 mission consisting of 14 timepoints and 10 locations. Each solution generated contained different number of mobile agents and different costs when analyzed. The VLNS with random insertion and removal heuristic was applied to the solutions. We observed a decrease in the cost of the solutions after applying VLNS, but we observed the efficacy decreasing after every iteration. So, we set a minimum efficacy of accepted solutions at 0.33 and 1.0. The VLNS algorithm was applied again. We observed a decrease in cost again. Setting the minimum accepted efficacy at 0.33 produced solutions with lower cost than at 1.0.

The satisfactory results observed by this thesis displayed the applicability of the VLNS metaheuristic (and heuristic search strategies in general) to planning with reconfigurable multi-robot systems.

6 Future Work and Possible Improvements

There are two further research areas that can be explored to continue the work introduced by this thesis.

Metaheuristics are the most robust and well-performing heuristic search strategies. The other metaheuristics could be implemented and its performance compared with the VLNS algorithm used in this thesis. Heuristics that had promising results in solving VRP wasthe Tabu heuristic [28] and Iterated Local Search [19].

Increasing the constraints, e.g. load and reconfiguration, can also be interesting to observe. Planning with reconfigurable multi-robot systems consists of temporal, model, functionality and property constraints. We didn't consider all of these constraints while applying VLNS. Further changes to the metaheuristic in this thesis is required to adapt for all constraints. Different results, as compared to solutions without constraints, can also be expected.

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