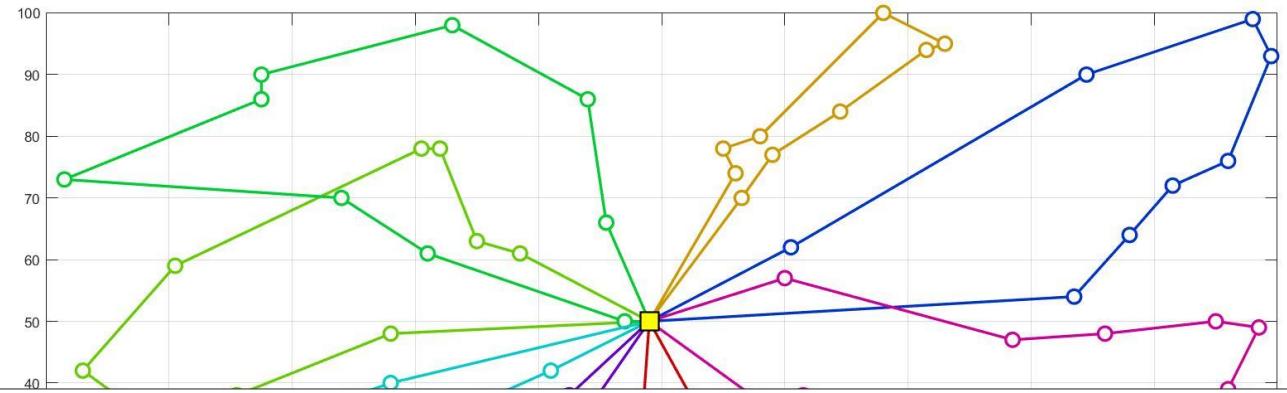
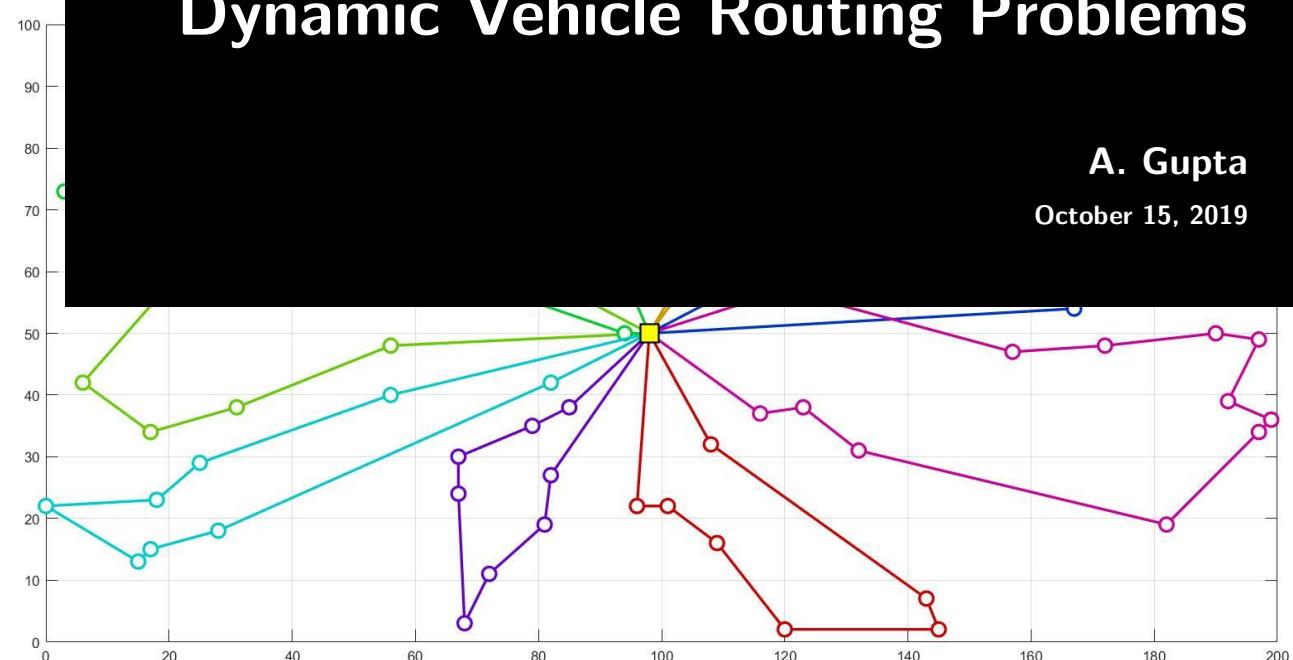


# Human Performance in Solving Multi-UAV Over-Constrained Dynamic Vehicle Routing Problems

A. Gupta

October 15, 2019





# **Human Performance in Solving Multi-UAV Over-Constrained Dynamic Vehicle Routing Problems**

MASTER OF SCIENCE THESIS

For obtaining the degree of Master of Science in Aerospace Engineering  
at Delft University of Technology

A. Gupta

October 15, 2019



**Delft University of Technology**

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DELFT UNIVERSITY OF TECHNOLOGY  
DEPARTMENT OF  
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Dated: October 15, 2019

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*Ankit*

*Delft, 13 October 2019*



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## Acronyms

**DCVRP** Distance-Constrained Capacitated Vehicle Routing Problem

**SA** Situation Awareness

**TSP** Traveling Salesman Problem

**UAV** Unmanned Areal Vehicle

**UAVs** Unmanned Areal Vehicles

**VRP** Vehicle Routing Problem



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# Chapter 1

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## Introduction

### 1-1 Background

Unmanned Areal Vehicles (UAVs) are pilotless aircraft which are commonly used for civil, military and commercial use. Some examples of its uses are monitoring crops, surveillance of animals/borders, search and rescue, communications or package delivery (Koldaev, 2007). There has been an increase in the use of these vehicles in the civilian areas as this technology is more available in the market. It was estimated that the global spending on UAVs in 2009 reached \$ 5.1 billion, and in the estimated span of 2010-2020, the cumulative Unmanned Areal Vehicle (UAV) market will nearly be worth \$ 71 billion (Brief, 2011).

The traditional package delivery methods are omnipresent and are an important aspect for the current commercial aspect; however, it is an outdated 20th-century system, wasteful, and is expensive. As a result, companies are working on different delivery technologies. Considering the "DHL", "Amazon prime air" and "Taco copter", there has been some development with the concepts of autonomously delivery drone systems (Milhouse, 2015)(Stolaroff, 2014). Using the UAVs as a "last-mile" package delivery hopes to change the outlook of the logistical industry. Using UAVs as package delivery (Goh et al., 2017):

- Improves time management: since it may consist of active locating programs, thus easily finding the target locations. The margin error would be lesser when finding the exact target spot.
- Conserves Energy: these drones aid the workers to save their energy while making deliveries. The risk of exhaustion is reduced, as the human involvement is replaced by the devices
- Accessible to difficult locations: drones can be used to transport commodities in locations which may be problematic to reach by humans.
- Promote safety: As the drones are physically delivering the package, it reduces the exposure of humans to possible hazardous situations when making deliveries.

These benefits allow the UAVs to be used in case of natural disasters to pass around supplies and commodities to the people in need. This will be a useful tool in case of search and rescue missions, where the people in need could be able to get essential supplies (such as medication, water and food) delivered to them by UAVs.

Previously, UAVs had to be flown manually by a controller from the ground, while, there would be additional operators for managing the sensors and missions. As there is much workload involved with flying the UAVs manually, this leads to a high number of operators needed to fly a few drones (Cummings, Bertucelli, Macbeth, & Surana, 2014). However, there is research being conducted to change this aspect, and decrease the number of operators needed to fly more drones, which will cause an improvement in commercial operations (Cummings et al., 2014). To be able to control multiple UAVs with a reduced number of operators, there needs to be a shift in the role of the human operators to a more supervisory control (Mouloua, Gilson, & Hancock, 2003). As a result, a change from swarms and autonomous control is expected; this results in the need for automation to deal with stochastic properties or failure management. However, when dealing with stochastic properties, this could make a situation over-constrained or "unsolvable" due to its dynamic nature. There may not be a solution present for a given problem in a specific period during mission operation, resulting in an algorithm to be not very efficient in circumstances like these. A human operator would be more beneficial, as it may avoid specific constraint(s) to provide a solution in case of an over-constrained problem in different stochastic situations.

## 1-2 Problem Statement

The shift in the role of the human operators to a supervisory control leads the human to be out of the direct control loop. The inclusion of automation can result in a decrease in Situation Awareness (SA), relying heavily on the autonomous system, and also the loss of skills to operate the UAVs manually in case the automation is not able to operate successfully (Chen, Barnes, & Harper-Sciarini, 2011). As a result, much research is being done to know the best level of automation and achieve functional human-machine interactions. The versatility and inventiveness of human beings often make a human-machine interactive system to solve unforeseen situations (Woods, 2003). Thus, in case of an over-constrained scenario, it is essential to provide the operator with the necessary information about the work done by the automation and what will be achieved next by the automation. The operator should be able to solve the problem and also be able to identify the problem. As a result, a design is needed for the human-machine interface, which is advantageous to the needs of the operator for a supervisory control (Cummings, Brzezinski, & Lee, 2007b).

Research (van Paassen, Borst, Ellerbroek, Mulder, & Flach, 2018) (Borst, Flach, & Ellerbroek, 2015) has been done on the use of interface design to aid the performance of the operator by helping to coordinate between humans and automatic systems with the help of interface design that shows the structure of the work domain in the manner which supports the human knowledge-, rule- and skill-based problem-solving activities. The focus of these articles was on the ground surveillance missions, where the visualisation of low-level information is put effort on. Koerkamp et al. had worked on providing more integration of information which would help in the higher level of mission planning (Koerkamp et al., 2019). His study was on the development of the interface for the ground station for a multi-UAV system. Additionally,

the ability of the human operator to be able to plan the mission in case of the disturbance of the UAV or failure for a payload delivery mission. The mission that was implemented is the Distance-Constrained Capacitated Vehicle Routing Problem (DCVRP), in which multiple UAVs are able to deliver a payload to customers around. However, while respecting the depot, payload capacity and distance constraint. The experiment was performed by students of the university and resulted in showing that, during the failure of the UAVs, some of the participants were not able to provide a solution to the scenarios. Besides, it was found that when the optimisation was done autonomously, it took over 30 hours of solution time. As a result, it is better to have a human-in-the-loop interface to be able to have a faster real-time solution. Moreover, it is advantageous to have human operators, as the algorithm tends to *optimise* the problem, whereas a human tends to *satisfy*. This feature would be beneficial when there is no solution available from an algorithm possibility due to its over-constrained nature. Thus, when there is no possible solution available for a particular constraint, a human can relax one of the constraints and still be able to solve the problem. Therefore, the goal of this research will be to analyse the approach taken by an operator for an *over-constrained* or *unsolvable* situation, and then further analyse the approach to see the difference in solution with different mission objectives, in case of different stochastic situations during mission operation. A problem is considered over-constrained when all the constraints would not be able to be satisfied, thus needed to relax one of them (Lau, Sim, & Teo, 2003) also, the interface design was done by Koerkamp et al. (Koerkamp et al., 2019) will also be looked at, to add more complexity to the interface design as he currently considered a generic vehicle in his design.

### 1-3 Research Questions, Aims, and objectives

Even though the *satisfy* feature of the human is observed in this research, the *optimise* feature needs to be observed to see the limit of the algorithm. There needs to be information collected about Vehicle Routing Problem (VRP) to get a better insight into the different situations possible with using an algorithm. The VRP algorithm is researched in order to get an insight into the *optimise* feature of an algorithm. Additionally, a stochastic property during mission operation is similar to the dynamic VRP. Thus there will be a focus on the dynamic algorithm too. On the other hand, to understand the *satisfy* feature, the human performance on the Traveling Salesman Problem (TSP) is observed. TSP is a variant of VRP. The performance can show how well humans are to make optimal routes just by looking at the locations of the customers and the possible vehicle routes (MacGregor & Chu, 2011). Besides, it would provide an idea on the development of the experiment, as similar research would take place in this research. Moreover, as the operator would be operating the system on a computer, the supervisory control of the Multiple UAVs are considered. This will provide the necessary information needed to know the different level of automation and workload that is required from the human and the automation, which will be efficient for both the cases. Knowing about the supervisory aspect will also aid in the design of the additional features in the interface of the ground station of the UAV. The relation between human and automation is evaluated for the successful functioning of the supervisory control of multiple UAVs. This aids in providing information about the collaboration between the *optimise* and *satisfy* feature, thus evaluating the necessary aspect needed to judge the amount of automation needed.

The research framework, in combination with the research goal, can help formulate the research question. The research question that is formulated is the following:

*How does the ecological ground station visualisation, for additional vehicle complexity, affect the approach taken by a human to solve an over-constrained case for different mission objective in planning for distinct disturbances for a multi-UAV payload delivery mission during operation?*

As this research question includes much information that needs to be answered, it is divided into several other sub-questions that need to be answered:

- What level of automation is required in the interface for it to be efficient to the operators?
- How does the visualisation help the human operator with the mission planning in case of stochastic scenarios during mission operation?
- What are the limits and scope of a VRP algorithm currently present?
- How does a human recognise a pattern, and solve problems in a mission planning for disturbance and failure management for a multi-UAV payload delivery mission?
- How should the tasks be divided between human and automation?
- What are the possible circumstances that may affect human thinking, thus affecting the results of the solution?
- What visualisation can assist the operator for additional vehicle complexity?

The objective of this research is to observe how the *satisfy* feature of a human can solve scenarios with no possible solution, depending on the different circumstances and distinct dynamic scenarios. In order word, how the human performs **constraint relaxation** dependent on different circumstances. The human would be able to adjust one of the constraints to be able to achieve the global mission. Additionally, test the use of human operators on different stochastic cases during mission operation. Moreover, as the current interface developed by Koerkamp has the use of one generic vehicle, there will be research done to add a layer of complexity in the interface design (Koerkamp et al., 2019).

The objective will be achieved by initially evaluating the scenarios taken by Koerkamp, and seeing how the variable vehicle specifications can alter the solution with the failure of the vehicles, and then for unsolvable scenarios, how relaxing one of the constraints will be able to give a solution for a simplified situation. Additionally, looking from theories regarding ecological design, the interface developed will be updated for additional vehicle complexity and then evaluated with the participants with over-constrained scenarios in different situations.

## 1-4 Research Scope

As discussed in Section 1-3, the aim is to observe how humans solve problems in case of an over-constrained situation for different dynamic failures during mission operation. Additionally,

another aim is to add a layer of complexity to the interface regarding the vehicle properties. When taking into account the complexity of the vehicle and scenario, several options can be considered to make the interface more realistic. The complexity of a problem could either increase by adding more properties, or it might also occur by increasing the problem size, to evaluate the scalability of the operator performance.

The complexity could either be added before the start of the mission (static), or after the mission has started (dynamic), and these variables would be added to any problem dimension as complexity may arise when the dimension of the problem is increased. Having a dynamic problem may involve coming with a solution in real-time. In case of the static case, the different load capacity, different customer demands, multiple depot and time window constraints was not considered. Moreover, the wind conditions was not considered for the dynamic condition. *In this research, the UAV will begin with battery deficit and changing customer location will be considered.* These stochastic properties are considered to see how an operator can tackle the different stochastic situations during mission objective. Additionally, the scope of this research is to *add variable speeds and battery capacity to the existing problem.* Also, due to the over-constrained problem, the algorithms do not provide a quick solution, it is interesting to understand the approach taken by participants when given a problem with more vehicle information and different dynamic properties.

## 1-5 Report Structure

The thesis report is structured in the following way. Part I includes the thesis paper. Part II includes all the appendices to the paper. The Appendices is structured as following: Appendix A contains the Literature Study that is done to complete this research. Appendix B is describing the Experiment Design that is subject to this research. Appendix C is providing the Experiment Briefing which was given to the participant prior to the start of the experiment. Appendix D is the Experiment survey that the participants had to complete during the experiment. Appendix E displays the Results of the Experiments. Appendix F shows the code architecture that is used during this research. Appendix G provides a final remark and recommendations for furture research.



## **Part I**

# **Master of Science Thesis Paper**



# Human Performance in Solving Multi-UAV Over-Constrained Dynamic Vehicle Routing Problems

Ankit Gupta

Supervisors: Clark Borst and Max Mulder

**Abstract**—In case of finding an optimised solution in real-time, automation may not be a helpful tool to be able to select preferable decisions and implement actions due to the complexity involved. More notably, in the case of an over-constrained dynamic vehicle routing problem as there is no solution which can satisfy all the constraints in real-time with a limited number of vehicles. This also resembles a real-life situation. However, as humans are good at problem-solving, there is a proposal to introduce a human to improve the performance by presenting an interface. Thus, the automation will be used to acquire and analyse the necessary information and display it in the interface, the human can then use this information to decide a preferable action and then implement it during mission operation. An interface design from previous research, with additional features, was used for a payload delivery mission to control Unmanned Aerial Vehicles. The human performance and the interface effectiveness is evaluated in an over-constrained dynamic vehicle routing problem for different mission objectives. Results show that the interface supported the humans, and additionally, the participants came up with a solution to satisfy the individual goal for a particular mission objective by relaxing specific constraints. It could be established that humans can come up with a solution for the over-constrained problem in a limited time required, thus it is an acceptable alternative which can be used to be able to come up with solutions. Having a human-in-the-loop is beneficial in case of a vehicle routing problem.

**Index Terms**—Over-constrained Dynamic Vehicle Routing Problem, Interface Design, Mission objective, Human Control Performance, Multi Unmanned Aerial Vehicles

## 1 INTRODUCTION

UNMANNED Aerial Vehicles (UAVs) are pilot-less aircraft which have the potential to be used in many logistical applications for civilian, military or commercial purposes. Some examples of the use of UAVs are to monitor crops, survey animals or borders, aid in search and rescue operations, or deliver packages [1]. Increased availability of UAVs in the market and their benefits have caused an increase in their use [2]. The vehicles can be used to access difficult locations, which may be problematic for a human to reach. Moreover, UAVs promote safety for the workers, as it reduces the exposure of hazardous situations to humans [3]. However, when introducing multiple of these vehicles in an area, there needs to be a route that each vehicle can follow when there needs to be a delivery of goods to multiple customers from a single point of origin, the depot. Considering the objective function, an optimised route for each of the vehicles needs to then be determined. This problem is similar to a Vehicle Routing Problem (VRP) [4].

VRP are observed every day by a significant number of distributors worldwide, and its solution have great economic importance [5]. Recently, various suppliers and distributors are establishing the design of efficient strategies for distribution to better the level of customer service. A few market sectors, including delivery services, have also reported that the use of an automated process of transporta-

tion makes a significant saving, which ranges from 5% to 20% of the total costs [5].

Over the years, there have been much insights and algorithms obtained for the classical static deterministic VRP [4]. However, in real life, the events may be more dynamic. As during mission operation, there could be an occurrence of stochastic events. For instance, there could be vehicle failures, defects in the vehicle battery, or changing/additional/removal of customer locations [6].

Additionally, while optimising the routes, a limit on the number of the vehicles along with the dynamic events, may not enable a solution to satisfy all constraints while satisfying all customers, which leads to an **over-constrained dynamic VRP** [7].

One of the possibilities to retrieve a solution is to use automation. But, there are several drawbacks identified when using automation to solve VRPs:

- 1) Typically, automation is favourable in familiar situations, and for the aspects for which it is designed. However, the execution of them in unexpected circumstances may be ambiguous. The algorithm for optimisation needs to be formulated explicitly. Even though in the decades of research, there is a great variance of algorithms present, there remains a challenge in developing an algorithm which considers every stochastic behaviour during mission operation. Thus, these theoretical solutions may not well translate into real-life missions during a disturbance

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[8] [9].

- 2) As VRPs require the most optimal solution in a wide combination of possibilities, the algorithms may take a great amount of time to solve. This might not be an issue when the problem is static but, it may become a liability in case of re-optimisation during mission operation due to changing variables [10] [11].
- 3) Algorithms usually assume an unlimited number of vehicles when computing the optimised solution, differing from a real-life situation. A limit on the number of vehicles is one of the factors of an over-constrained problem. The optimising algorithm will be unable to produce the most efficient route while satisfying all the constraints. In these cases, constraint(s) would need to relax to come up with a solution which is known as constraint relaxation. Additionally, contrasting mission objectives might require the need to relax a different constraint [7] [12].

When considering the different levels of automation, having a high level of automation may be an obstacle in case of an over-constrained dynamic VRP. The automation may not be reliable enough due to its inability to solve these situations, dependent on the different mission objectives [13]. A proposed solution is to place a human in the control loop to be able to make decisions and implement changes. This will reduce the level of automation, and involves the human operator during certain dynamic situations. Past research shows that humans can perform well in solving the Travelling Salesman Problem (TSP). Humans are good at problem-solving and can produce a satisfactory (possibility optimal) solution on the bases of visual depiction of the location of customers and the routes of the vehicle [14], [15], [16], [17]. In the case of over-constrained dynamic VRPs, this versatile nature of humans can help them relax a constraint during re-optimisation dependent on the mission objective which provided to them.

To investigate this, this research paper utilises an interface to be able to adequately represent the over-constrained dynamic VRP to an operator in an experiment. The interface would involve a certain level of automation, as it would acquire and analyse the information, for the human to make decisions with. The goal is to evaluate the performance of the human along with the interface design.

For the experiment, the interface will demonstrate a multi-UAV payload delivery system to represent a VRP. The stochastic property presented in the scenarios will be battery defects for the vehicles, and the addition of extra customers to make an over-constrained dynamic VRP. Moreover, the set of scenarios will be rotated 180-degrees to see a difference in the performance of diverse mission objectives. The objective of the human-operator will be to relax constraint caused by perturbations for limited vehicles during real-time in a variety of mission.

The paper is composed as follows. Section 2 provides information about VRP algorithms. Section 3 discusses the interface that is used for the experiment. The experiment is then explained in Section 4, after which, the results of the experiment are delivered in Section 5. Moreover, the

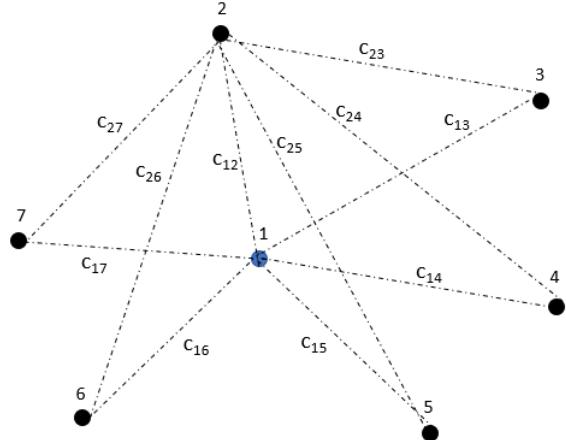


Fig. 1: Representation of VRP

discussion of the results is in Section 6. Lastly, Section 7 provides the conclusion.

## 2 THE VEHICLE ROUTING PROBLEM

As this research is observing a solution regarding the VRP, this section explains the concepts which will be covered throughout the paper, and the proposed implications that will take place.

### 2.1 Definition

VRP can be defined as "*the problem of designing optimal routes from a depot to geographically scattered customers, subject to side constraints*" [4].

To depict this, let  $B = (N, A)$  be a graph in which  $N = \{1, \dots, n\}$  is a set of vertices which represent the delivery locations. The depot is represented as vertex 1, as observed in Fig. 1.  $A$  expresses the set of arcs. Each arc  $(i, j)$  where  $i \neq j$  is a non-negative distance matrix  $C = c_{ij}$ . The  $c_{ij}$  can be associated as the *travel cost* or the *travel time*. Fig. 1 displays the  $C$  for  $c_{1j}$  and  $c_{2j}$  with all the other vertices. Moreover, consider there are  $K = \{1, \dots, k\}$  vehicles available at the depot. The VRP designs its least cost vehicle route in such a way that:

- Each location is visited at least once by exactly one vehicle,
- All of the vehicles start and end at the depot, and
- Any other side constraints are completed.

### 2.2 Distance-Constrained Capacitated Vehicle Routing Problem with Depot Constraints

There is an extensive variety of VRPs, subjected to a particular set of side constraints. This paper focuses on the Distance-Constrained Capacitated Vehicle Routing Problem (DCVRP), with an additional capacity constraint at the depot. In other terms the side-constraints will be the distance constraint for each vehicle limited by its battery flight time life, the capacity constraint which is the inability to deliver to more customers than the vehicle payload limit and a depot constraint, that limits the number of vehicles which

take-off and land simultaneously at the depot. Hence, every vehicle is delivering a payload to the customers from the depot and ultimately returns.

The DCVRP can be formulated as the following [4] [11]. The optimised route is determined while minimising the total cost of the summation of the vehicle routes. However, the cost function has some constraints which are considered. The vehicles are required to cover all the required customers. Additionally, each vehicle is required to depart and arrive at the depot once, and ensuring that the routes are joined, rather than having separate routes. Due to the capacity constraint, the vehicle is not able to travel to more customers than the quantity of the payload and due to the distance constraint, unable to travel to a higher distance capacity than the flight time limit. The routes are then determined for the most optimised route.

### 2.3 Dynamic Vehicle Routing Problem

The VRP is identified as dynamic if part of the problem is unknown and revealed dynamically during the execution of the routes caused by perturbations, thus requiring the route to be re-optimised [9]. The sources of this dynamic nature include: changing demands from the customer (cancelling the request, change/add/remove the location of the customer, or demands), increase in the travel time or distance due to a defect, or failure of a vehicle [6]. There are particular drawbacks when computing a dynamic problem. Firstly, an algorithm is only able to handle a specific perturbation. Thus, to come up with a solution, the problem needs to be well-defined [18]. Secondly, the problems may require a long time to solve due to the tremendous computational time required [6]. Thus, there is a need for an alternative method to solve a dynamic problem.

### 2.4 Over-constrained Vehicle Routing Problem

Most algorithms assume an unlimited amount of vehicles and the objective then is to gather the solution that would either account for the least number of vehicles or minimise the travel cost [19]. In real applications, there is a resource constraint on the number of vehicles present or additional constraints caused by disturbances. This may cause the problem to be over-constrained, where it would not be able to deliver to all customers while satisfying the constraints [20]. Most of the algorithms currently dealing with an over-constrained problem focus on a static scenario, rather than a dynamic VRP, due to the increased complexity with the uncertainty involved because of the perturbations. Due to the high number of possibilities and combinations that can take place in an over-constrained dynamic VRP; the algorithm may not be computationally viable.

Additionally, to come up with a solution, one or more of the constraints need to be relaxed [12]. The algorithms do not take into account the possibilities of relaxing a specific constraint dependent on a particular mission objective during operation. In a case where there may be a priority to provide payload to as many customers as possible during an over-constrained situation, there may also be a requirement to satisfy the payload limit and relax the depot or flight time constraint. On the other hand, for a standard delivery mission, there may be a higher priority to let the UAVs

reach the depot safely while not maximising the payload constraint. Introducing a human in the loop allows for an adaptable changing of constraints depending on the mission provided during an over-constrained dynamic vehicle routing problem.

In real life, there is a possibility that there is an over-constrained problem which occurs due to the addition of dynamic elements in them. For instance, during real-time, a stochastic dynamic element occurs and then due to the limited number of vehicles and the constraints, there is an inability to find a solution while the vehicles are continuously operating. This will be an example of an over-constrained dynamic VRP. This makes the problem increasingly complex and difficult for an algorithm to solve in real-time.

### Proposed Concept of Operation

Automation has four different levels involved: 1) information acquisition, 2) information analysis, 3) decision and action selection and 4) action implementation [21]. Rather than having a completely autonomous situation, where the automation will be able to implement the optimised action, it can be used as a tool to provide relevant information for letting humans make a proper decision. So, it acquires and analysis the information. In this case, automation is not used for decision and action selection and action implementation due to the complexity involved in the problem. For an algorithm, there needs to be a well-defined problem, and there exists an algorithm for a specific type of problem. But, when observing for a vast range of problems, automation does not deem to be beneficial. Humans, on the other hand, are good at problem-solving and can adapt to new situations.

Due to the increased difficulty in finding a solution for the VRP algorithm, there is a possibility to add a human-in-the-loop, to be able to provide with a solution. To understand the role of humans in solving problems, in previous research, it is shown that when humans were given a TSP problem and asked to provide the shortest distance possible in a limited time period, they were able to find a solution which is close to the solution provided by the algorithm, also with the increasing problem sizes and complexity [14], [15], [16], [17]. Using humans for different scales as operators would be beneficial to the experiment due to their problem-solving skills. For an over-constrained dynamic VRP, the human would be able to steer the solution in a particular way where the algorithm would not seem beneficial. Using the solving skills of the human, they would be able to provide a solution in such a manner which would suit a specific mission objective. But, there is a doubt about the increasing number of waypoints which might affect the ability of the human to solve a problem. Additionally, the experiments mostly considered a single generic type of vehicle, but, there is not much information available about the effect of a fleet of vehicles in the information.

To be able to solve the routes optimally, the humans would require a proper interface which would be able to provide the necessary information in real-time to be able to make decisions. As discussed, automation or optimisation algorithms do not perform well in an over-constrained dynamic VRP, but, there could be a certain level of automation provided in the interface for the human to make informative

decisions. Instead of letting the automation calculate the solution, it can aid in visualising the problem and the constraints. Thus, the automation would be able to compute the constraints and visualise the "solution spaces", but the human would be able to make the control actions to be able to solve the problem accordingly.

This paper will be a helpful tool in practical relevance as it considers possible implications that may take place in real life, and inspects the results of a human solution with varying dynamic aspects. Further, looking at the performance of humans with different mission objectives and testing the capability of the human to come up with a solution in a limited period.

### 3 INTERFACE DESIGN

An interface is required to be able to perform the human-in-the-loop experiment. It should be able to provide the necessary information, to efficiently re-optimise the route.

#### 3.1 Scope

This study considers the over-constrained dynamic VRP correlating to a DCVRP. The high-level constraints examined in the mission will be UAV flight time limit, the UAV payload capacity, and the depot capacity. The problem will include a single depot, and the vehicle will be permitted to leave the depot and arrive once. The mission objectives observed in the experiment is restricted to two varied applications. One is to deliver essential resources during a search and rescue mission, and the other is to deliver coffee beans. The dynamic elements introduced in the mission operation was battery deficiency and undelivered customers. To observe the difference in the reaction of different UAVs, the fleet contained two-vehicle type. The complexity was controlled according to the payload capacity and the perturbation severity. The dynamic elements were the addition of customers and battery deficiency. This research left the weather, vehicle separation requirements (including the separation between the vehicles or the terrains), airspace restriction, the characteristics of the UAV flight performance and the communication range between the vehicle and depot, outside the limits of the research.

#### 3.2 Information Requirement

Based on the properties of DCVRP and the research on human performance in dealing with the TSP, the interface would require the following to be able to help the operator in achieving its goal:

- 1) A scaled-map visualising the customer location and the depot.
- 2) Payload capacity for each vehicle.
- 3) Routes taken by the vehicles.
- 4) The time of arrival for the vehicles, to visualise the limit of the depot capacity.
- 5) Battery level of each vehicle.
- 6) Ability to differentiate the fleet of vehicles used.

The interface developed by Koerkamp et al. is used as it provides most of the parameters which would aid the human operator to solve the over-constrained DCVRP [22].

This design for the interface was inspired by a design from air traffic control, which focused on the spatio-temporal arrival management of aircraft, and the perturbation management in real-time. Also, in the experiment conducted in the previous research, the interface was deemed beneficial for the human-operators in finding an optimised solution in case of failure of UAV in real-time with an increase in the problem size. However, points 5) and 6) from the list had to be added to the interface.

#### 3.3 Additional Aspects Added to the Interface

##### 3.3.1 Battery Level of the UAV

As defined in the scope, one of the dynamic elements in the experiment was the battery deficiency, there was a need for a battery icon to be able to visualise the UAV flight time. The battery indicator from Fuchs et al. was adapted to this interface, as it indicated the required performance of the system (required battery level), the expected performance of the system (predicted battery level) and lastly, the current performance of the system present during the mission (current battery level) [23]. Using the battery icon, the operator will be able to observe the amount of irregularity during the mission, and then be able to formulate and implement a solution accordingly.

To inspect the battery condition, an indicator was created as seen in Figure 2b. The height of the coloured bars represents the amount of battery that was present in the vehicle ranging from 0% to 100%. The dashed lines represent the battery capacity for future customer locations. The colour of the block would go red below the battery icon to represent the lack of battery present to go to that location or be green otherwise.

The green represents that there is sufficient battery to cover all the waypoints. Anything below the red line represents the extra battery that is left in the battery after reaching the depot, as it can be seen in UAV 1 in Figure 2b. If the block turns red, the waypoint would not be able to be reached. When considering UAV 2, it would safely cover D5-D8 but, when the vehicle is going towards the depot, the battery will drop below the icon as it represents that there is not enough energy to ensure safe arrival to the depot. The same information can also be visualised in the map view, as depicted in Figure 2a also.

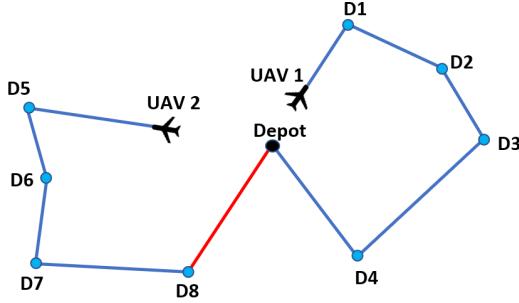
This is implemented in the interface by considering the following relation:

$$a_n = \sum_{i=1}^n i \quad (1)$$

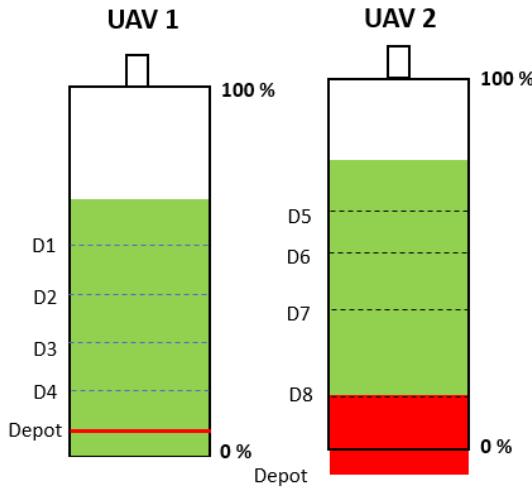
where  $n = \{1, \dots, N\}$ ,  $N$  is the total number of waypoints which the UAV is travelling too. The specific waypoint ( $n - th$ ) of the battery indicator will turn red when  $a_n$  will exceed the total energy ( $t_{total}$ ) in the battery, or also visualised by:

$$a_n > t_{total} \quad (2)$$

For short term memories, humans perform better with relative information than absolute based on the research by Henson [24]. Thus, the battery icons will show the battery levels relative to the highest amount of battery in the fleet, as the operator would be able to make a judgement about the battery remaining relative to the other vehicles.



(a) The map view shows the area that can be covered by the two UAVs. The leg where UAV 2 will run out of battery is visualised by red.



(b) UAV 1 has enough energy to visit all the waypoints, however, UAV 2 does not have enough energy to reach the depot after delivering to customer D8.

Fig. 2: Side by side view of the map view along with the battery indicator. The battery icon is depicted similar to the battery view.



Fig. 3: The use of different icons to represent the difference in the type of vehicle used.

### 3.3.2 Icons for the fleet of vehicles used

As each scenario included two types of vehicle which had different speeds and battery capacity, there needs to be a differentiation between them. As humans respond well to different icon sizes, it was adapted to the interface usage [25]. The vehicles used in this experiment were the following: one of them had a maximum flight time of 900 s and airspeed of 20 m/s, and the other vehicle had a maximum flight time of 750 s and an airspeed of 13 m/s.

Figure 3 displays the varying size of icons that were used. The more prominent icon will represent the vehicle

with higher battery capacity and higher speed than the other alternative vehicle.

The visualisation of the flight time constraint is done using an ellipse as a guidance reference in the map view. The definition of the ellipse can be seen in Figure 4. From this representation,  $a$  is the semi-major axis,  $b$  is the semi-minor axis,  $c$  is the linear eccentricity and  $(c_1, c_2)$  is the centre.

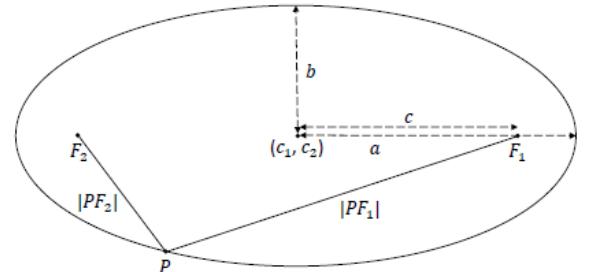


Fig. 4: Definition of the ellipse

The ellipse can be defined as

$$(c_1 + a \cdot \cos \theta, c_2 + b \cdot \sin \theta), 0 \leq \theta \leq 2\pi$$

In addition, the semi-minor axis,  $b$  can be defined as

$$b^2 = a^2 - c^2$$

The semi-major axis  $a$ , is the sum of  $t_{available}$  and half of the sum of the flight time between  $F_1$  and  $F_2$ .

$t_{available}$  can be defined as:

$$t_{available} = t_{total} - t_{used} - t_{flightplan} \quad (3)$$

$t_{total}$  is the total time that the UAV is beginning with. In this case, there are two vehicle types with random battery deficiency defined in the beginning. When the vehicle goes from one waypoint  $(x_1, y_1)$  to another waypoint  $(x_2, y_2)$ , the time of the vehicle reduces by Equation 4, which is the  $t_{used}$

$$t_{used} = t_{1-2} = v \cdot \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (4)$$

Lastly,  $t_{flightplan}$  is the total time that the vehicle is planned to travel still. Thus, using all these variables would provide the  $t_{available}$  that is left. The centre  $(c_1, c_2)$  is determined as the halfway between the two waypoints. So, every time a vehicle passes a waypoint, the envelope of the vehicle reduces by the distance that is travelled and the total distance it has to travel. The ellipse needs to be oriented dependent on the direction of the waypoints. The ellipse is oriented by using the relation:

$$x' = x \cdot \cos \theta - y \cdot \sin \theta$$

$$y' = y \cdot \sin \theta + x \cdot \cos \theta$$

With the presence of different vehicle speed and flight time limit, the ellipse will be visualised differently for the different type of vehicles according to these formulas.

### 3.4 Layout, Structure and Functionality of the interface

Figure 5 gives a representation of the layout and the structure of the user interface design for a particular example. This scenario includes two vehicles with four payload levels each to deliver to five customers from the depot. In Figure 5a, the interface has four separate views. The map is seen in (A), the payload detail in (B) and the timeline in (C). The battery view will appear at (D) when clicking on an individual vehicle. At  $t_0$  (Figure 5a), the interface shows the mission overview by displaying the customer (1) and the location of the depot (2). Besides, it shows the pre-optimised flightplans (3) of the vehicle. The dashed lines mean that the UAV has not left the depot yet.

At  $t_1$  (Figure 5b), the first UAV has left the depot, and is flying towards the first customer. The first UAV left from the depot (5), and is flying to the first customer (6). The arrival time of the vehicle to the depot is indicated in the timeline view with a block (7). As seen in the map view, three customers - D1,D2,D5- appear who do not have a pre-optimised route planned (4). The colour of the UAV icon is similar to the arrival time block corresponding to the payload level of the vehicle. In which bright yellow is used when all the payload is available, dark yellow is used when the payload capacity is reduced and amber when there is no more payload available.

At  $t_2$  (Figure 5c) the departure of the second vehicle (8) occurs. The difference in the size of the icons would help the operator to identify the different type of vehicles that are being used. It can be observed in the timeline view (9), the arrival time overlaps with the first UAV, and so exceeding the capacity of the depot. This can be avoided by either *stretching the path* of the vehicle so that it would reach later, or *divert the path* by delivering to undelivered customers. Due to the overlap in the depot, the UAV icon along with the arrival time block in the interface is coloured red to bring it to attention to the operator and take a particular action.

Now that the two UAVs have launched, the user can use these vehicles to change the trajectory to the undelivered customers.

At  $t_3$  (Figure 5d) one of the UAVs is selected as indicated by the green colour of the UAV icon and the arrival time block. When the vehicle is selected, the payload view (12) indicates the payload that is available for the vehicle. The map view (10) displays the envelope around the guidance reference, which shows the area that can be reached with the energy left. This is the locomotion constraint of the vehicle. The battery icon (11) indicates the battery level of the vehicle. The battery does not start from the top due to the battery deficiency that is present. Thus, the operator would have to make a decision using the current level of battery level.

Figure 5e displays the flightplan leg which is selected at  $t_4$  and the corresponding flight time constraint as indicated by (13) in the map view and the timeline view, in which the vertical line displays the maximum flight time. Moreover, the particular segment is also selected in the battery view to represent a single leg. The red UAV icon and the arrival time overlap (14) displays depot congestion.

At  $t_5$  (Figure 5f) the customer D2 is included in the flightplan, indicated by a dashed line (15). The battery icon

includes the additional waypoint (16), and the payload level is then decreased by one at (17).

In  $t_6$  (Figure 5g), the modified plan is confirmed, and the arrival time changed to (18).

At  $t_7$  (Figure 5h) displays that the other UAV has enough capacity (19) to go to D1. The battery capacity of the vehicle is much lower than the capacity of the other vehicle.

At  $t_8$  (Figure 5i) the flightplan leg is selected, in addition to the flight time constraint, the required delay in clearing the depot arrival time problem as conferred in (20). The UAV would have to travel outside the red circle to avoid depot congestion.

In  $t_9$  (Figure 5j), customer D1 is added to the flightplan as there is enough battery to cover that region, and it would successfully avoid the depot congestion. The effect of adding the waypoint to the battery is seen in (22), a warning for zero payloads is visualised in (21).

In  $t_{10}$  (Figure 5k), the updated flightplan is confirmed. The vehicle colour changes to amber to signify that there is no payload left in the vehicle. The vehicles (23) managed to deliver to 2 more customers, using an efficient route (24), while satisfying all the constraint.

However, there is still one customer left without the payload. In this case, even though one of the vehicles has enough payload left to provide to customer D5, there is not enough battery left to deliver the payload and reach the depot as it can be seen in (25) in  $t_{11}$  (Figure 5l).

In such a case, the operator does have an option to relax the battery constraint such that it would deliver to the customer, but maybe not be able to reach back to the depot. So in  $t_{12}$  (Figure 5m), the operator then selects a particular flightplan leg (26) to deliver to customer D5.  $t_{13}$  (Figure 5n) displays the effect of adding customer D5 to the flightplan leg. The red flightplan and the red battery bar shows the last part of the plan will not be able to occur. So even though the vehicle is delivering to the customer, there is not enough left to reach the depot as it can be seen in (27). Lastly,  $t_{14}$  (Figure 5o) displays the confirmed flightplan, and the red bar in the timeline view and the red line in the map view to visualise the lack of battery to cover the last leg.

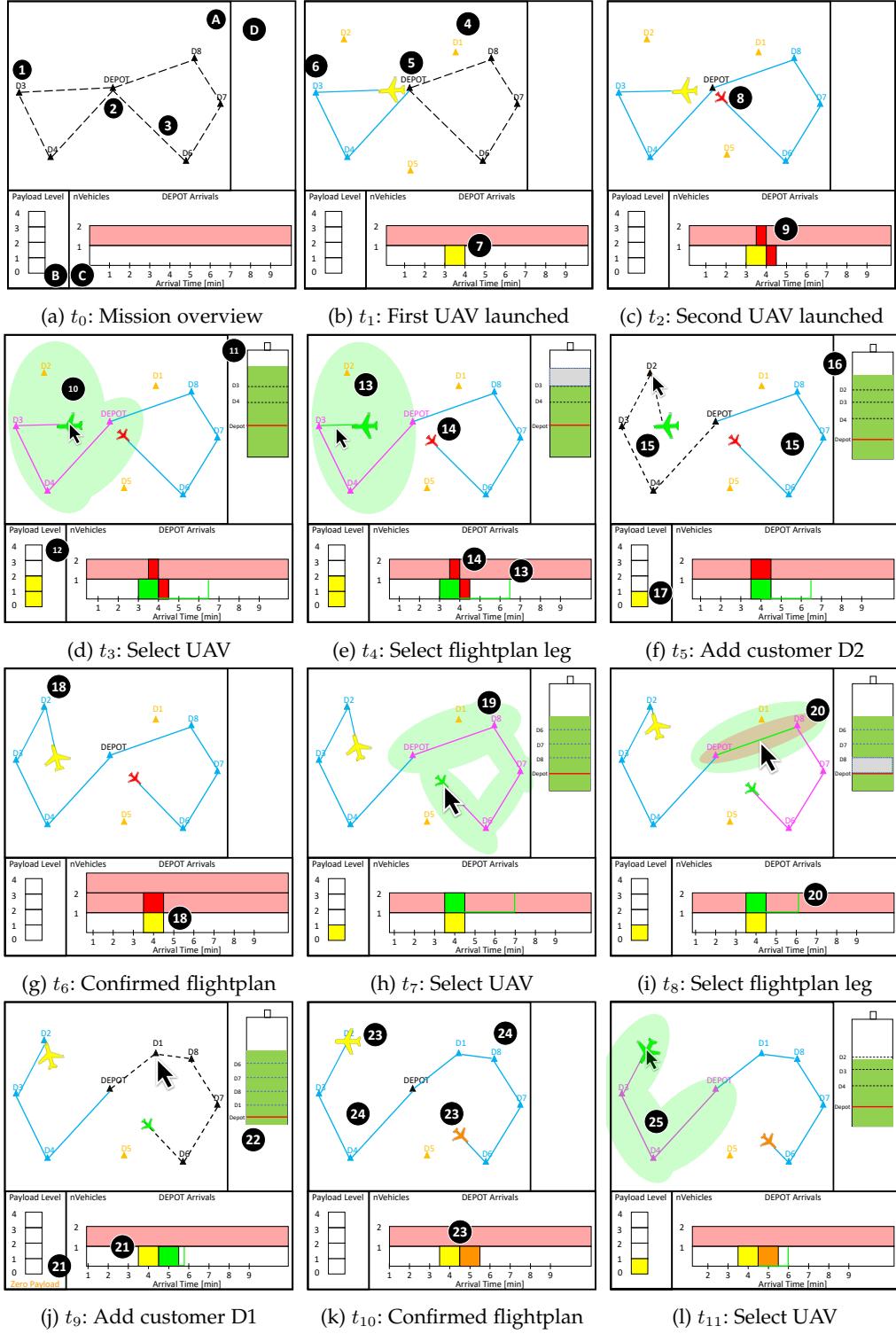


Fig. 5: Step-by-step overview of the interface workings for a simple scenario.

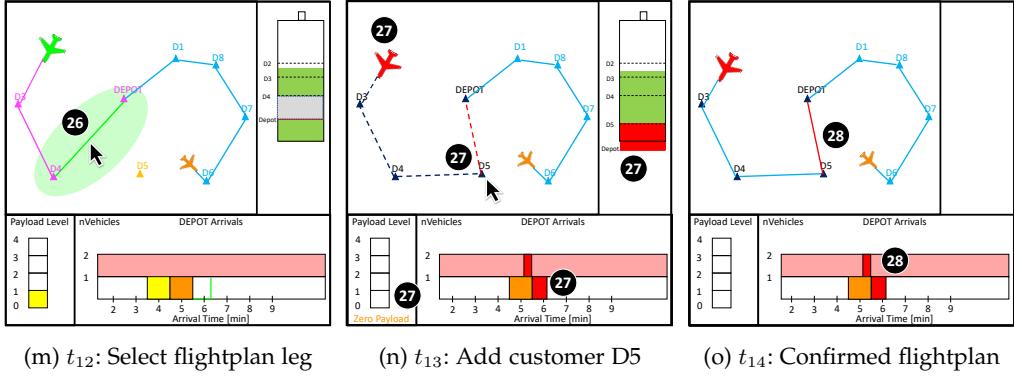


Fig. 5: (continued) Step-by-step overview of the interface workings for a simple scenario.

## 4 EXPERIMENT

To examine human performance in over-constrained DCVRP in different mission objectives, an experiment is performed with the human involved. The experiment evaluates the approach taken by the participants in different mission objectives for a similar DCVRP, but with varying scalability. The over-constrained DCVRP was constructed and configured in a manner where the interface would be able to aid the human operator. The objective and subjective data from the experiment are gathered to conclude the interface usage and the performance of the mission.

### 4.1 Participants

The experiment was completed by sixteen participants, who were graduate students or staff from Delft University of Technology (TU Delft), with an average age of 25.38 (SD = 7.1923). The group had fourteen males and two females. Additionally, eight of the participants considered themselves as regular gamers, and the rest did not.

### 4.2 Independent Variable

The experiment had three with-in subject independent variables, which were the following:

- 1) Payload Capacity: The problem size of the over-constrained DCVRP dependent on the payload capacity of a single UAV. There were four payload levels used: 4, 5, 6 and 7 payloads for each vehicle. Each of the vehicles was provided with the same number of payloads in every scenario
- 2) Perturbation Severity: To produce an over-constrained problem, each scenario was either given a single low-level vehicle, or double low-level vehicles at the beginning of each scenario. The low-level vehicle was defined as the vehicle which will initially deliver to 2 customers and has the least amount of battery capacity. In other words, at the beginning of each scenario, this vehicle will have the highest payload margin-left with the lowest amount of battery.
- 3) Mission Objective: As the aim of the experiment was to observe the difference of performance in varying mission objectives given to the operators, there were two objectives chosen. The initial one was a search

and rescue and the other one was to deliver coffee beans.

The payload capacity variable sets the size of the scenario, which is provided to the participant. Using the number of payload capacity, the number of customers and the quantity of the vehicles can then be determined. The scenarios were designed in a manner which would allow enough payload capacity in each of the vehicles to be able to serve the undelivered customers. Increasing the payload in each scenario would lead to an increase in the number of customers in the area, and also the number of vehicles which needed to be operated by the operator. The reason for this variable was to first, observe the scalability of the interface. This can provide information on how the information is perceived with the increased number of vehicles and customers. Secondly, to investigate human performance with the different complexities of problems provided. Thirdly, to observe if the strategy taken by the operator differs with the difference in the problem size.

The perturbation severity decides the complexity of the problem by having vehicles with the least amount of battery with the most significant number of payload margin at the beginning of the scenario. This variable was used to define the complexity of the over-constrained DCVRP. In the case of a single low-level vehicle, there was one vehicle which delivered to two customers initially and had the least amount of battery capacity. Thus the user would lose at least one vehicle if they choose to serve all customers in a scenario. Which means that it is possible to serve the payload to all the customers, however, for one of the vehicles, there may not be enough battery to reach the depot after delivering to its last customer safely, or the user would have to accommodate as many customers as possible while considering the amount of battery and the depot conditions, to ensure a proper arrival to the depot. Whereas, in the double low-level vehicle scenarios, there are two vehicles present which deliver to two customers and have the least amount of battery capacity. The participant will be unable to deliver to all customers without meeting the battery capacity of at least two vehicles. The reasoning behind this variable was to investigate the effect of the different scale of perturbation on the solution quality provided by the human.

The mission objective is provided to the operator to observe which constraints the operator chooses to relax

TABLE 1: Experiment Condition - Mission (M), Number of low-level vehicle (L) and Payload (P).

	Mission: Search and Rescue				Mission: Delivery Coffee Beans			
	Payload 4	Payload 5	Payload 6	Payload 7	Payload 4	Payload 5	Payload 6	Payload 7
Single low-level vehicle	M1L1P4	M1L1P5	M1L1P6	M1L1P7	M2L1P4	M2L1P5	M2L1P6	M2L1P7
Double low-level vehicle	M1L2P4	M1L2P5	M1L2P6	M1L2P7	M2L2P4	M2L2P5	M2L2P6	M2L2P7

dependent on the mission provided. The mission goals were chosen to observe the constraint priorities that are set. The two contrasting missions are chosen from the applications of multi-UAVs.

In case of a search and rescue mission, there may be a higher relevance to provide payload to as many customers, and lesser on the well-being of the vehicle, while it may be the other way around when delivering coffee. To observe the difference in the effect of mission objective for the same scenario, one set of the problem was given for one of the mission objectives, and provided for the second mission objective.

In search and rescue, the participants were asked to solve the experiment with the following description:

*There has been an avalanche in the mountains, and there are people stuck in the area around. A Search & Rescue team is then called upon to rescue the victims. However, in the meantime, the team is providing the victims with some necessities, such as medicine, food and water to be able to help them survive longer.*

On the other hand, the delivery of coffee beans mission entailed the following:

*Every morning, a company delivers fresh coffee beans to various customers around the area.*

This variable is chosen to see the different constraints that are prioritised dependent on the mission objectives are given. As this is an over-constrained problem, it is interesting to see which constraints will be prioritised by the human. Additionally, it would also be possible to see if there is a difference in the results provided by the human if they are given a mission objective. Furthermore, the over-constrained DCVRP has been found challenging for optimisation algorithms, as it is difficult to constraint relax dependent on the mission objective provided during operation.

### 4.3 Scenarios

The participants were asked to mitigate the effects caused by battery deficiency and additional customers. While assigning the unassigned customers, the participants had to relax constraints as prioritised by themselves, according to the mission goals provided. The constraints considered in this experiment were the flight time of the vehicles, payload capacity of each vehicle and the depot capacity. Each mission was given eight different experiment conditions, see Table 1. To investigate the effects of the mission objective, the experimental conditions for the two missions were similar. However, to avoid recognition, the set of experimental conditions for one mission was rotated 180-degrees with respect to the other mission. Thus, each participant was given 16 experiment conditions. As both the missions have similar experiment conditions, Table 2 defines the lists of customers and number of vehicles per condition for one of

TABLE 2: The vehicles and customers per condition

	nCustomers	nVehicles
M1L1P4	14	4
M1L1P5	23	5
M1L1P6	34	6
M1L1P7	47	7
M1L2P4	29	8
M1L2P5	46	10
M1L2P6	67	12
M1L2P7	92	14

the missions, which is dependent on the payload capacity and the number of over-constrained vehicles.

To minimise the carry-over effect between the scenarios, a balanced Latin square was utilised to sequence the experiment conditions.

Each scenario lasted for five minutes. In all the scenarios, a batch of UAVs was deployed every thirty seconds (equal to the depot service time). The number of UAVs deployed was equivalent to the depot capacity. The experiment only allowed lateral waypoint modification control. Additionally, there were two types of vehicles used in the scenario. One of them had a higher maximum flight time of 900 s and airspeed of 20 m/s, and the other vehicle had a maximum flight time of 750 s and an airspeed of 13 m/s. In case of an even number of vehicles, the two types of vehicles were equally divided, whereas, in the case of an odd number of vehicles, there was one more of the lower performing vehicle.

To create the scenarios for the experiment, there was an off-line VRP optimisation algorithm developed, which allowed the inputs for different properties of vehicles used and varying payload level. The scenario was first optimised for the static case (before the addition of customers during mission operation). The level of customers, in this case, was determined by the payload margin for each of the vehicle and the number of the low-level vehicles. Disregarding the low-level vehicle, the rest of the fleet was given a payload margin of one during mission operation. The number of customers for the static condition was given in Table 3. Once the number of customers was determined, the location for them was then randomly generated. A minimum distance criterion was applied to avoid the cluster of locations in a particular area. The optimising algorithm then routed this static scenario considering the DCVRP. For the algorithm, the Google Optimisation (Google-OR) Tools was adapted to feature the variable fleet capacity and properties [26]. The Google-OR tool is a software which is suitable to solve the combinatorial optimisation problem. The algorithm begins by first finding the route from the start node, and then it connects to the nodes which produce the lowest route section. The next node is then added by iterating from the previous node position while considering the constraints. The guided local search algorithm is used to find the solution for the

TABLE 3: The number of customers per condition for the static case.

	nCustomers in the static case
M1L1P4	11
M1L1P5	18
M1L1P6	27
M1L1P7	38
M1L2P4	22
M1L2P5	36
M1L2P6	54
M1L2P7	76

TABLE 4: Control variables.

Variable	Value
UAV 1 - Max flight time [s]	900
UAV 1 - Airspeed [m/s]	20
UAV 2 - Max flight time [s]	750
UAV 2 - Airspeed [m/s]	13
Service Time [s]	30
Scenario Duration [s]	300
Payload Margin for high-level vehicles [-]	1
Sector Size [m <sup>2</sup> ]	5000 x 5000
Depot Capacity (Rounded to the nearest integer)	30% of nVehicles

algorithm, as it is considered an efficient solution for the VRP [27].

Once the static case is represented, the stochastic elements need to be added. The rest of the customers were then placed randomly around the area. An example of the scenarios is shown in Figure 6. Figure 6a displays the condition M1L1P4, which shows that for the search and rescue mission objective, there is one low-level vehicle (UAV 1) which is delivering to two customers, and each vehicle has four number of payloads. Condition M1L1P4 will be rotated by 180-degrees to create condition M2L1P4 for the delivering coffee beans condition. Figure 6b shows the condition M1L2P7, which displays that for the search and rescue mission, there are two low-level vehicles (UAV 1 and UAV 3), and each vehicle has a total of seven payloads. Condition M1L2P7 will be rotated by 180-degrees to create condition M2L2P7 for the delivering coffee beans condition. The battery defect was randomly selected for each vehicle, but ensuring the low-level-vehicle had the lowest amount of energy in the beginning. To validate if the scenarios were over-constrained, it was run in the optimising algorithm to see if the resulting scenarios indeed produced no solutions. This was also checked with other solution strategies offered in Google-OR tools.

#### 4.4 Control Variable

The control variables considered in this experiment are the depot service time, sector size, depot capacity, duration of the scenario, UAV fleet, and the amount of extra payload that is provided in each vehicle after mission operation. The overview of the control variables can be seen in Table 4.

#### 4.5 Dependent Variable

To examine human performance, along with the scalability and functionality of the interface, the following dependent variables are observed and recorded:

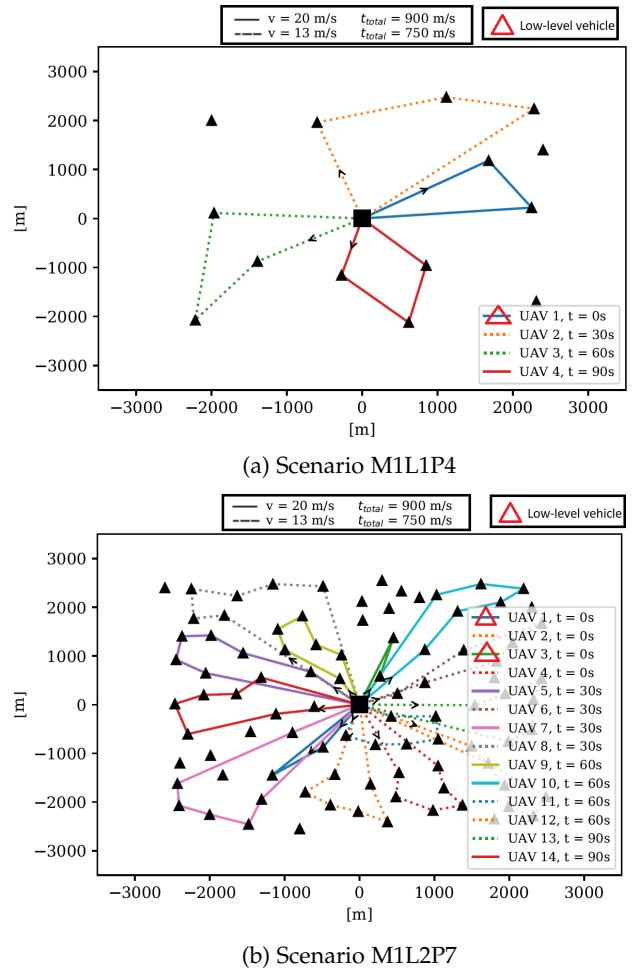


Fig. 6: Two of the scenarios which were given to the participants.

- 1) **Workload:** Rating Scale Mental Effort (RSME) scores and the total amount of clicks on the map-view of the interface. The RSME score was provided by the participants after the completion of each scenario in the survey, and the clicks are registered to see the number of changes that are done during the mission. Only the clicks for the map view are measured as the changes in the routes were done through this view.
- 2) **Control Performance:** The total distance flown, total path stretch waypoints, relative payload remaining before the mission and the relative energy margin after the mission are complete. Total distance is the sum of all the distance flown. The total path stretch waypoints are used to understand the delay allocation. The relative payload remaining at the end of the mission, in comparison with the total payload, will provide us with the information about which scenarios used the most payload and the relative battery margin, in comparison with the total battery in the beginning, is the capacity that is left after the vehicles arrive at the depot, to show the robustness in the solution.

- 3) Constraint Priority: Performance per constraint, and ranking provided for the constraints for each scenario. The performance per constraint measures the percentage of the constraints that is satisfied in each scenario. And the rank priority given for each constraint was given by the participant after each scenario in the survey.
- 4) Strategy: Satisfies versus optimise. The strategy done by the participant was given in the survey after each scenario is completed. Also, the method taken to solve the problem was noted down during solving.
- 5) Display usage rating for the different views in the interface: Map, timeline, battery, and the payload view. This rating was given by the participants after each scenario was completed in the survey. Along with the participant comments considered at the end of the experiment by each participant.

#### 4.6 Procedure

In the beginning, the participants were made to perform an intake survey. The survey included questions about age, gender, language and if they considered themselves as gamers. Additionally, to test their spatial reasoning, the survey consisted of six image-based questions. This provided information about the participants, as performing poorly in this would affect the experiment performance. The mean score of the reasoning test is 4.75 (SD = 1.2383) out of a total of 6. Even though the survey was not timed, and the participants were not asked to perform it as quickly as possible, the meantime to complete the survey was 309.12 seconds (SD = 121.42). As the mean score is greater than 3 out of a total of 6, it was considered substantial to partake in the experiment.

After the survey, the participants were given a briefing manual which explained about the over-constrained dynamic VRP, the goal of the experiment, the experiment setup, the control input, and each view of the interface. The participants were asked to alleviate the effects caused by battery defects and additional customers, causing it to be an over-constrained problem during several multi-UAV payload deliveries for two mission objectives. The control goal of the experiment is to relax constraint(s) according to their choice and optimise it for the shortest route. The briefing manual also consisted of instructions, which described the training scenarios. The participants used this instruction with the interface to have a better idea about each of the views.

The training had nine scenarios, which were untimed.

- The first three scenarios familiarised the participants with each of the view and the controls that are involved in it.
- The fourth scenario emphasised the importance of differentiating the battery icon in the interface.
- In the fifth scenario, the participant was invited to try out different combinations for a simple over-constrained dynamic DCVRP.
- The next two scenarios explained the mission objectives provided and tasked them to relax constraints

and solve the problem with a single low-level vehicle.

- The next two scenarios provided more examples of solving these kinds of problem with the different mission objective and double low-level vehicles.

Beginning with the last four training scenarios, the participants were tasked to complete a post-scenario survey after each run. The post-run survey consisted of a Rating Scale Mental Effort (RSME) score [28].

Additionally, they were asked to provide a relative amount of time interacting with the four different display elements. Next, the participants were required to rank the depot, payload, and flightplan constraint according to their choice. Finally, they were tasked to classify the approach taken to solve the problem, i.e., whether the approach taken by them is classified as *satisfies* (achieving a solution that reaches the overall goal) or *optimise* (achieving the best solution that reaches the overall goal).

After the training was completed, the participants were able to start with the experiment. The experiment run time duration for each scenario was five minutes. After each run, the participant would fill out the post-run survey, as done during the training scenarios. The experiment then concluded with a post-experiment survey. The survey inquired the participants on the usefulness of the different views in the interface: the map, battery, timeline, and payload view. Additionally, the participants were made to comment on the clarity and usefulness of the colour in the display, and also the use of the different icons to signify the different UAV type. Conclusively, the participants were permitted to express or suggest any aspect about the interface or experiment which was not covered in the previous questions.

#### 4.7 Apparatus

The experiment took place in the Air Traffic Management Laboratory (ATM Lab) at the Faculty of Aerospace Engineering at Delft University of Technology (TU Delft). The interface was presented as a software to the participants on a 30-inch display (60-Hz LED, 2560 x 1600 pixels). The display was placed in front of the participants, and the control input was done on the keyboard and the mouse.

#### 4.8 Hypothesis (H)

##### H-1

It was hypothesised that the increase in the payload capacity and an increase in the perturbation severity leads to an increase in the workload, as if the information in the interface increases, it will be more difficult for the participant to be able to come up with a solution, and so increasing the workload for the participant. Additionally, there would be a need for more re-routing with the increase in the payload and the perturbation. In case of the search and rescue mission, there would be a higher workload as the participants would most likely attempt to provide the payload to as many customers as possible, resulting in an increase in the workload for the participant.

## H-2

The increased number of payloads and perturbation severity would affect the control performance, as it would be more challenging to focus on optimising the results for the increase in customers and increase complications with the increased number of perturbations. In case of search and rescue, as the participants would focus more on delivering to more customers, the vehicles would travel longer distances in comparison to the delivering coffee beans condition. Also, the total distance should increase with the increase in the number of payload and perturbation severity since the number of customers increases, and so, the distance travelled by the vehicles would be higher too. The percentage of relative payload remaining at the end of the scenario should be lesser in case of search and rescue mission, in comparison to the delivering coffee beans since more participants would be delivering to more customers in case of the former mission. Also, there would not be a lot of relative battery margin left in case of search and rescue mission objective, in comparison to the delivering coffee beans missions, as the participants would maximise the battery of the vehicles in the fleet to be able to deliver to as many customers as possible. The path stretch should not play a major part, as it is an inefficient method to divert the path to cause a delay in case of exceeding the depot capacity constraint. It is hypothesised that the participants would rather re-optimize the route such that the depot congestion does not occur.

## H-3

Regarding the constraint priority, it was hypothesised, that in the case of the search and rescue mission, the participant would provide the solution by delivering to as many customers as possible, thus relaxing either the depot condition or the flight time limit. On the other hand, in the case of delivering coffee beans, it would be the other way around. But, there would be no significant effect of payload capacity and the perturbation severity on the constraints relaxed, as the participants would probably start optimising for the constraints kept in mind from the beginning.

## H-4

With the increase in the number of payloads and perturbation severity, there would be a shift from going to an optimised solution to a satisfying solution due to the limited time to come up with a solution due to the increase in the number of customers present. With the mission objectives, due to the over-constrained nature present, finding a solution in a limited time period would also result in a satisfactory solution instead of optimising it.

## H-5

As the map view can provide a majority of the information regarding the scenarios, it would be the display which would be utilised the most. Nonetheless, the other displays would be able to support the human to make a decision during re-optimisation. The battery view will aid in visualising the flight time limit that is there in each vehicle, and the difference in icon size will differentiate the vehicle type. This will be used to make a strategy to re-optimize during the scenario. With the increase in the perturbation severity

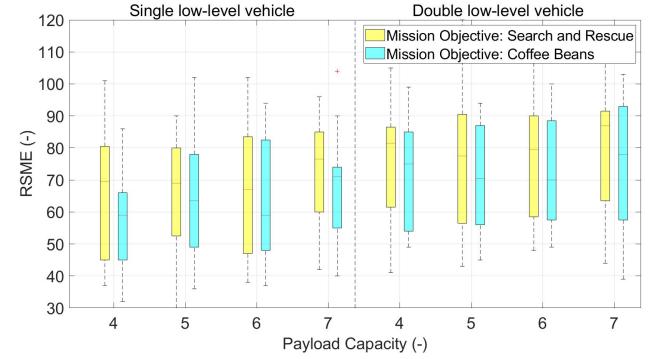


Fig. 7: Clustered Box plot for the Rating Scale Mental Effort (RSME) score for each condition and mission objectives.

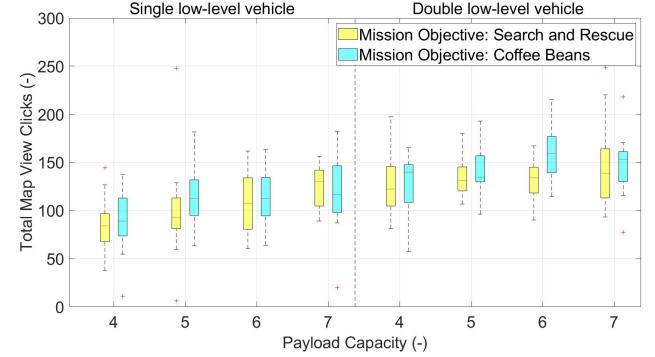


Fig. 8: Clustered Box plot for the total map view click for each condition and mission objectives.

and payload capacity, this will result in the interface being less efficient due to the cluster formed with increased routes, especially for the map view. The participants will use the interface equally to make informed decision to be able to complete a route during re-optimising the routes in both the mission objectives.

## 4.9 Data Analysis

In case the data are normally distributed, the three-way repeated measure ANOVA is used to test the within-group effects. In case the data are not normally distributed, Friedman's ANOVA test is used. For all the tests, the significance level ( $\alpha$ ) is set as 0.05. To control the Type I error when multiple hypotheses ( $m$ ) are being tested, a Bonferroni correction is used. This adjusted the significance level to  $\frac{\alpha}{m}$ .

## 5 RESULTS

In this section, the results for each dependent measure is discussed.

### 5.1 Workload

Figure 7 shows the clustered boxplot of the RSME score for each condition. When the participants were solving the scenarios, it was observed that the primary source of workload during the search and rescue mission was to accommodate the maximum amount of customers, whereas, while delivering coffee beans, there was a higher focus to have the vehicle arrive safely to the depot while attempting to deliver

to as many customers as possible. When noticing for the payload capacity, there does not seem to be a clear difference with the increase in the number of payloads. Additionally, comparing for the difference between the number of low-level vehicles with the RSME score, there seems to be higher workload in the use of double low-level vehicles, than single low-level vehicle ( $F(1, 15) = 59.331, p < 0.05$ ). Moreover, there is a higher RSME score given for the search and rescue mission, compared to the objective to deliver coffee beans ( $F(1, 15) = 9.784, p < 0.05$ ).

Figure 8 displays the clustered boxplot of the total number of clicks that were performed on the map view. As the map view is used to make the changes, the amount of clicks is proportional to the number of variations that were done by the participant. Thus, a higher number of clicks with correlate to a higher workload. It can be observed that there is an increase in the total number of clicks with an increase in the number of payloads per scenario ( $F(3, 45) = 7.632, p < 0.05$ ). Furthermore, there is a higher number of clicks in case of the double low-level vehicle than the single low-level vehicle ( $F(1, 15) = 102.669, p < 0.05$ ). When comparing the difference in the total number of clicks between the two scenarios, it can be seen that there is a higher number of clicks in the map view in case of delivering coffee beans compared to the search and rescue mission objective ( $F(1, 15) = 4,929, p < 0.05$ ), other than for the case of single low-level vehicle and the 7 payload capacity case. During search and rescue, the participants were just providing the payload to all the customers and not about optimising for any solution. These results indicated that increasing the number of payloads and the total number of low-level vehicles increases the total number of clicks for the delivering coffee beans scenario; however, there is an increase in the mental effort due to the number of low-level vehicles and for the search and rescue mission objective.

## 5.2 Control Performance

Figure 9 shows the clustered box plot of the total distance flown for each condition and mission objective. It can be seen that the increase in the level of payload causes an effect on the total distance flown ( $F(2.505, 37.578) = 730.853, p < 0.05$ ). Observing the number of low-level vehicles, there is a higher distance flown for the double low-level vehicle, rather than a single low-level vehicle ( $F(1, 15) = 3595.119, p < 0.05$ ). This was expected, as increasing these variables provide an increase in the problem size of the over-constrained DCVRP, which leads to more distance to be flown. There is an effect with the mission objective on the distance flown ( $F(1, 15) = 16.223, p < 0.05$ ). A higher distance is flown for the search and rescue mission, in comparison with delivering coffee beans. This is due to the fact that as the vehicles were made to travel around more to be able to cover a larger amount of customers to deliver to during search and rescue, and in case of coffee beans, the participants were delivering to lesser customers around the area, and getting the vehicles safely back to the depot. It can also be observed in the figure that, for each scenario, results of the participants were close to each other. As also seen in Table 5, the standard deviation is not high relative to the magnitude of the total mean distance. Thus, the performance of humans tended to be close to the mean.

TABLE 5: The statistical information of the total distance for each experiment condition.

	Standard Deviation [km]	Mean [km]
M1L1P4	2.10	32.10
M1L1P5	2.32	40.26
M1L1P6	2.34	50.77
M1L1P7	4.92	59.05
M1L2P4	4.24	59.71
M1L2P5	4.00	66.46
M1L2P6	5.43	83.23
M1L2P7	5.52	93.30
M2L1P4	2.33	29.58
M2L1P5	2.14	38.25
M2L1P6	3.41	48.65
M2L1P7	4.72	57.39
M2L2P4	3.98	58.04
M2L2P5	3.34	63.43
M2L2P6	4.38	83.24
M2L2P7	5.16	92.52

Figure 10 displays the clustered boxplot for the amount of relative battery left after each condition and mission objective aiding to understand how the performance of the participants is affected. Knowing the battery margin, relative to the total battery before the mission start, available at the end explains about how the participants were solving these problems, even though, it was not asked to optimise for this. This analysis shows the combined battery level of all vehicles when they complete their route and return at the depot. There is no effect on the level of payloads on the battery margin following the completion of each scenario. However, it can be seen that there is an effect caused by the number of low-level vehicle. There is a higher vehicle battery margin-left for the double low-level vehicle, than the single low-level vehicle ( $F(1, 15) = 49.105, p < 0.05$ ). Thus, the vehicles were used for greater capacity in case of the double low-level vehicle. There is also a higher margin-left in case of the delivery of coffee beans in comparison with the search and rescue mission ( $F(1, 15) = 2.234, p < 0.05$ ).

Figure 11 displays the clustered boxplot for the amount of relative payload left after each condition and mission objective to understand how the different dependent variables affect this result. This analysis is done through evaluating the sum of the payload that is left in the vehicle once it arrives at the depot, and comparing it to the total number of payloads to judge the relative margin. There is no effect on the number of low-level vehicles on the percentage of payload that is remaining at the end of the scenario. However, it can be seen that there is an effect caused by the payload level and the mission objective provided. As the payload capacity increases, the percentage of payload remaining decreases ( $F(3, 45) = 100.899, p < 0.05$ ). So relative to the total number of payloads, the participants left lesser payloads at the end with the increasing number of payload capacity. When observing for the different mission objectives, there is also a higher payload-margin remaining in case of the delivery of coffee beans in comparison with the search and rescue mission ( $F(1, 15) = 68.655, p < 0.05$ ).

Figure 12 displays the bar chart for the total number of path stretch done by participants at each condition and mission objective. This was done by the participants to delay the vehicles in case the depot capacity constraint. It

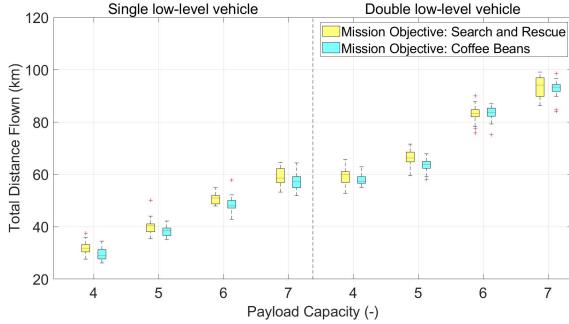


Fig. 9: Clustered Box plot for the total distance flown for each condition and mission objectives.

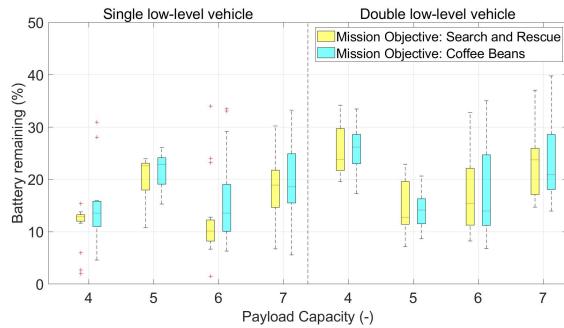


Fig. 10: Clustered Box plot for the total battery remaining after each condition and mission objectives.

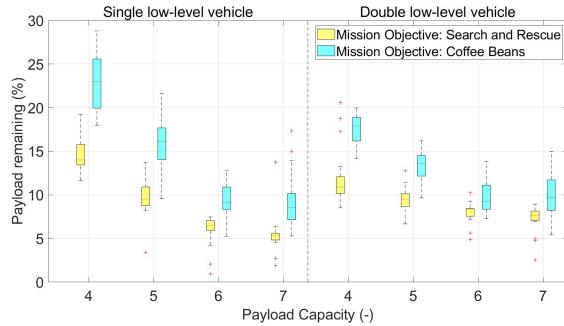


Fig. 11: Clustered Box plot for the total payload remaining after each condition and mission objectives.

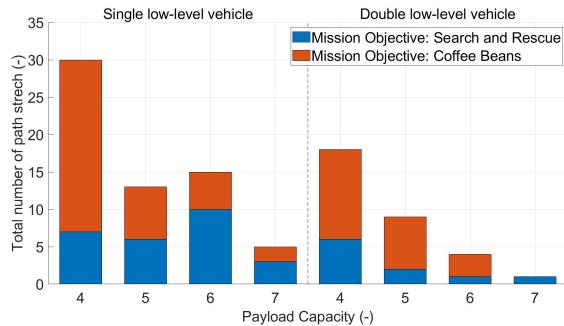


Fig. 12: Bar Chart for the total path stretch waypoints used in each condition and mission objective.

is analysed that there is no effect on the number of payload level, payload capacity and mission objective on the number of path stretch done. This was not used much through the experiment.

### 5.3 Constraint Priority

Figure 13 displays the clustered bar chart for the feasibility of each of the constraints for every condition and mission objective. The constraints were considered infeasible if: unable to serve as many customers as possible by using the limited payload of the vehicle, overrunning the provided flight time limit or by congestion in the depot. For each of the figure, there is no effect on the number of payload level and number of the low-level vehicles on the variable. Figure 13a observes the total percentage of customers that were served in each scenario provided. In case of search and rescue, there was more customers delivered in comparison to the case of delivering coffee beans. The next constraint analysed was in Figure 13b. This figure depicts the number of vehicles which satisfies the battery constraint in each of the scenarios. The vehicles which satisfy the battery constraints are higher in case of delivering coffee beans than compared to the search and rescue mission. Figure 13c displays the vehicles which satisfy the depot constraint for each of the scenarios. There is a higher number of vehicles which satisfy the depot constraint while delivering coffee beans in comparison with the search and rescue mission.

Figure 14 displays the clustered bar chart for the priority rank given for each constraint after every scenario by the participants. Figure 14a provides the ranking given to the payload constraint, in which the priority was to provide the payload to as many customers as possible. For each of the ranks, there seem to be no effects of payload level and the number of low-level vehicle on the rankings given, however, there is an effect by the mission objective provided to the participants. Most of the participants gave the highest rank to the payload constraint in case of search and rescue.

Additionally, when observing the rankings given for this constraint for delivering coffee beans, the majority of the participants gave a second or third ranking. Figure 14b provides the rank given by the participants for the flight time constraint. As similar to the ranking for the payload constraint, there is no effect of payload level and the number of low-level vehicles on each of the rank given to the flight time constraint. However, the mission scenario provides a difference in the rank given. For search and rescue, the majority of participants gave it a second priority for this variable. Whereas, in the case of delivering coffee beans, most of the participants ranked it first. Figure 14c provides the rank given by the participants for the depot constraint. Similar to the other two clustered bar charts for the constraints, the payload level and the number of the low-level vehicle does not affect the ranks given for the depot constraint. In both of the missions, the depot constraint was mostly given the lowest rank.

### 5.4 Strategy

Figure 15 displays the clustered bar chart of the ratings given by the participants regarding providing a solution which satisfies or optimises post every scenario. It can be analysed that perturbation severity and the payload capacity do not affect the assessment done by the participant. But considering the different mission objective, the participants tended to satisfy more in case of search and rescue missions,

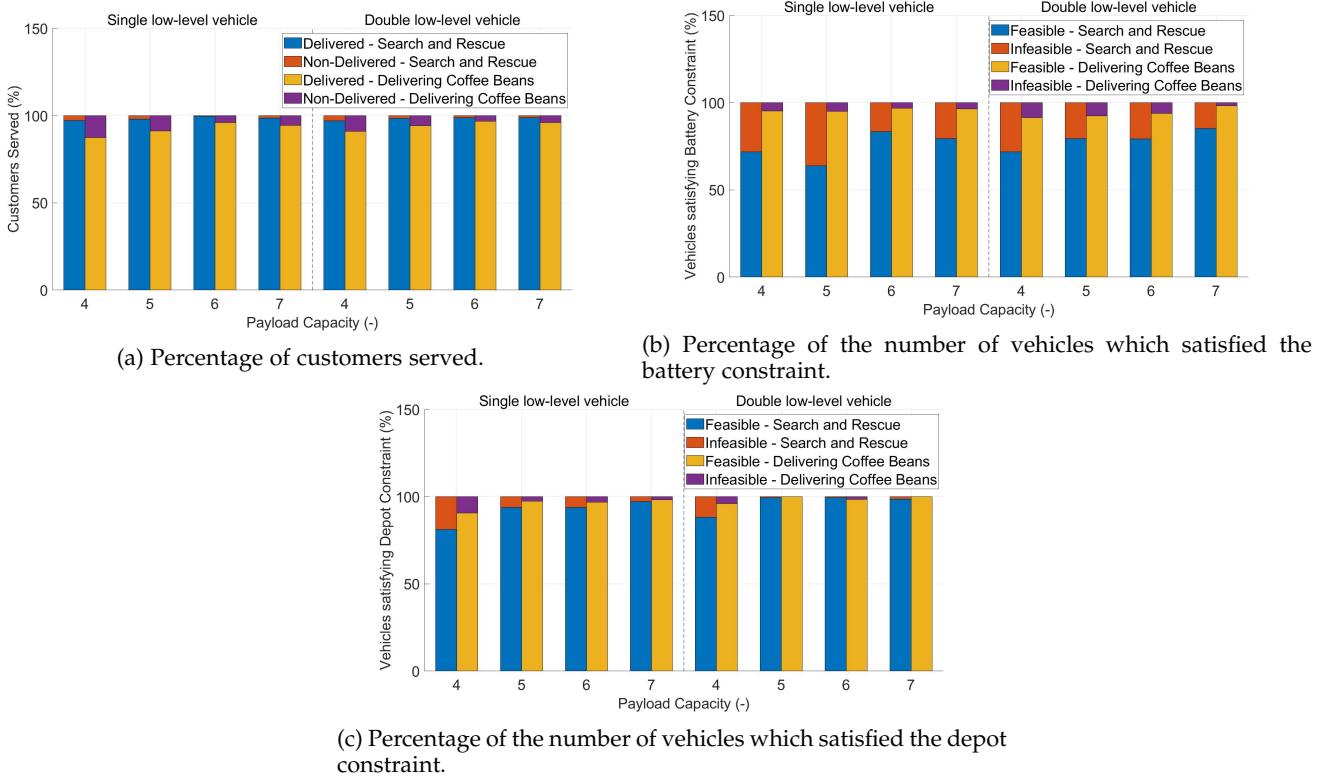


Fig. 13: Clustered Bar chart for the feasibility of each of the constraints for every condition and mission objectives.

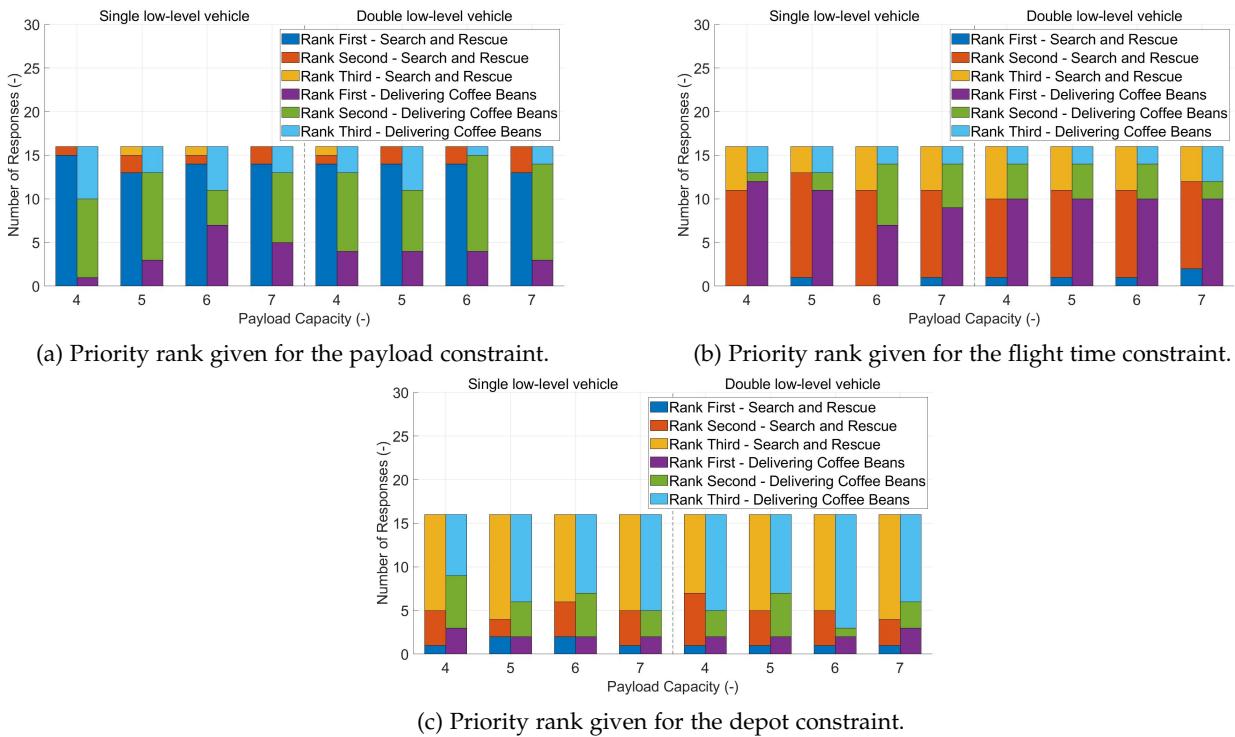


Fig. 14: Clustered Bar chart for the Priority rank given for each constraint at the post scenario survey for every condition and mission objectives.

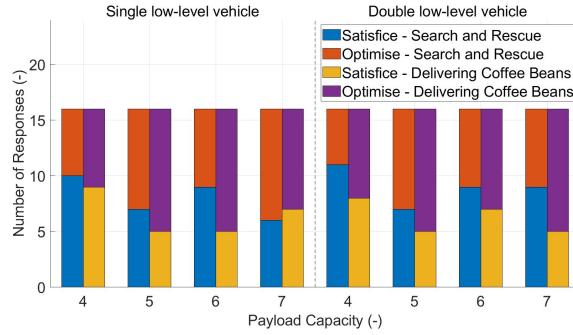


Fig. 15: Clustered Bar chart of the ratings given for satisfies and optimise given by the participants per condition and mission objective.

in comparison to delivering coffee beans, except for the condition with single low-level vehicle and 7 payload capacity. This means that the participants attempted to optimise the results in case of delivering coffee beans and use the vehicles efficiently, but, in case of the search and rescue missions, there was more effort on delivering to as many customers as possible while relaxing the battery and the depot constraint.

When observing the results of each of the participants, there was some interesting strategy. While sacrificing the vehicles, the participants were able to deliver the payload to as many customers as attainable and letting it fail while it is performing the last leg to fly towards the depot. As a result, the failed vehicle would drop down somewhere close to the depot.

Additionally, the strategy taken by most of the participants was to use the vehicles with the higher battery capacity and higher speed to go to customers further away from the depot, whereas the vehicles with the lower battery capacity and speed were used to provide the customers closer to the depot. The participants attempted to provide the payload to the customers farther away from the depot, and if needed, neglected the customers closer to the depot. Moreover, the participants tended to sacrifice the smaller icon vehicle if needing to provide to as many customers as possible.

## 5.5 Display Usage

Figure 16 displays the clustered box plot for the usage of each view per condition and mission objective. From the graphs, it is clear that there is no significant effect of the payload level, the number of low-level vehicles, the mission scenario or a combination of them on the map view usage. Figure 16a focuses on the map view. It can be observed that, in comparison to the other views, the map view has the highest usage. The mean for every scenario and mission are all about the same range. Figure 16b displays the usage of the battery view for each of the conditions. Figure 16c displays the usage of the timeline view for each of the condition. Figure 16d displays the usage of the payload view for each of the condition.

## 6 DISCUSSION

Unlike hypothesised in H-1, the workload as judged by the RSME score of the participants was not affected by the

payload level. But the participants provided a higher score in case of an increase in the perturbation severity and for the search and rescue mission objective. This implies that the growth in the number of customers did not provide a significant workload on the participants, but, increasing the complexity by varying the number of the low-level vehicle made it more difficult to re-optimize the solution. Also, in case of a search and rescue mission, the participants felt a higher workload as they tried to deliver to as many customers as possible with the limited resource and time limit.

The number of clicks on the map view does increase with the increment of payload level and perturbation severity. So, the participants had to make more changes during the mission. These variables aided in an increase in the number of customers and the vehicle. Thus, this also resulted in a higher click count on the map view to re-optimize the solution for the dynamic situations due to the higher number of factors on the screen. In a limited period, having a higher click on the map-view means that the participant had to make more changes, and so increasing the workload. Further, in case of search and rescue missions, the participants clicked more on the interface to attempt to provide the payload to as many customers as possible. When looking at the individual solution of the participants, they tended to be very close to each other. So, in the case of each problem, they tended to take a similar strategy in place.

As hypothesised in H-2, The control performance is influenced by the dependent variables. Increasing the perturbation severity and the payload level increased the total distance flown because more customers needed to be covered for the limited number of vehicles. In the search and rescue mission objective, as more customers are delivered too, this is increasing the total distance flown in comparison to the delivering coffee beans. But, as it can be seen that the distance travelled by the participants were not deviated comparing to the mean, the solution provided by them were close to each other. Thus, the human have a similar solution strategy in mind when re-optimising the solution.

The effect of the mission objective is visualised in the relative battery margin and the relative payload, after the mission is complete, as there is lesser capacity left in case of search and rescue for both the factors thus attempting to minimise the two and so delivering to as many customers as possible. When considering the total number of path stretch done, it was observed that there was no effect on the dependent variable on this number. The participants were rather re-optimising the routes to deliver customers in such a way as to avoid a collision in the depot due to the efficiency involved.

When looking at the control performance for each of the participants, they were still getting used to the interface in the initial runs of the experiment. Not all the participants reached a steady-state at the beginning of the experiment. Therefore, there should be more emphasis on adding some extra training scenarios before the start of the experiment to be able to get the participants more familiar with the interface.

Unlike optimisation algorithms, the participants were able to relax a constraint to be able to provide their goal in a limited amount of time for a dynamic situation. Even though this time limit may not allow making an optimised

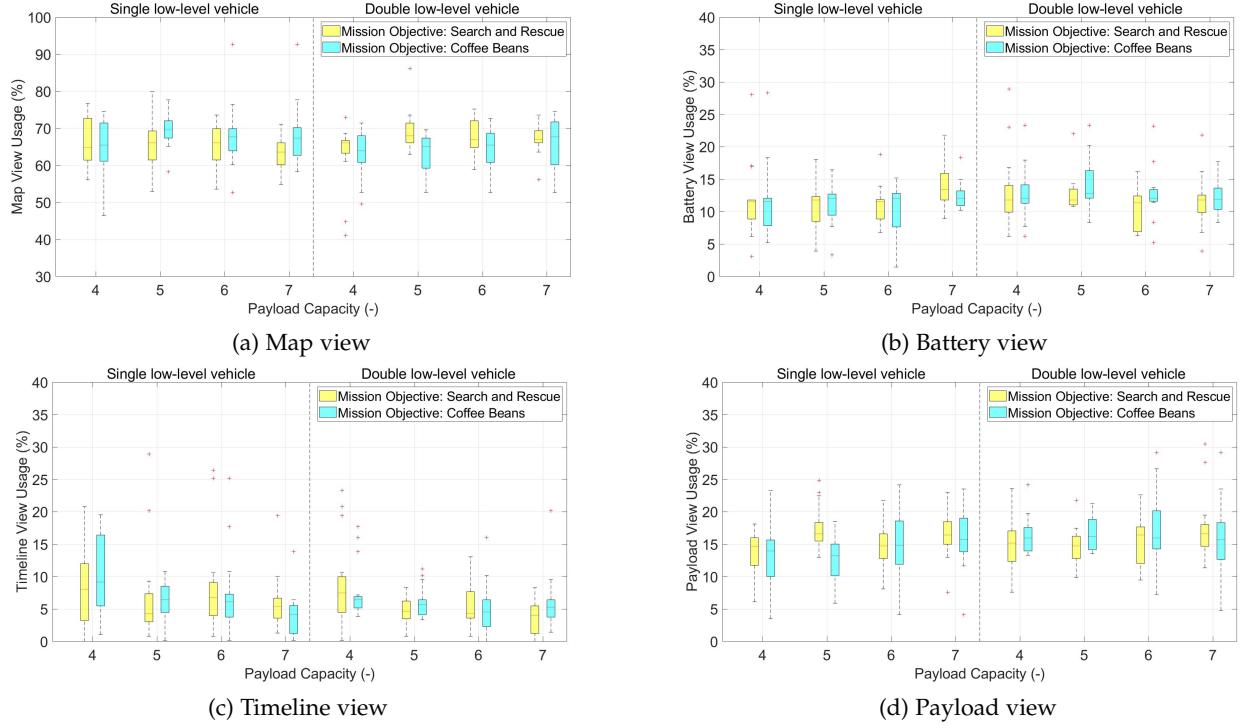


Fig. 16: Clustered Box plot for the usage of each view per condition and mission objective.

solution, but the subjects tended to come up with more of a satisfying approach. Additionally, dependent on the mission provided to them, they were able to come up with a solution conditional on the mission objective for a varying dynamic situation for an over-constrained problem. Hence, as this problem is more similar to a real-life situation, it is beneficial to have human in the control-loop because they at least reach a certain solution to their choosing. As discussed with the different level of automation, humans are thus able to make decisions and implement actions while the automation is used to provide information and analysis with the information to provide the user with the necessary information. The automation is helpful to give quick information which can be further used by a human due to there problem-solving skills.

Hypothesis H-3 holds, and also clearly seen in the results that there is no real significant effect of the perturbation severity and the payload level on the constraints that were relaxed in each scenario. But, the mission objective provides a distinction in the results for the perturbation. The subjects differentiated the priorities set dependent on the missions given. Future research could attempt to providing more mission objectives to see the effect of them on the constraints that are relaxed.

Unlike as hypothesised in H-4, the payload severity and the number of payloads did not affect the judgement of strategy given by the participants, whether the result provided was more towards the satisfy or optimise. But they claimed that in case of search and rescue, they tended to satisfy the result, so just trying to get a result at the end of the time limit. Furthermore, in the case of delivering coffee beans situations, as there was more focus on the vehicles, the humans attempted to optimise the problem and got an effi-

cient result. When considering the participant strategies in the post-scenario survey, the information provided seemed to be unreliable to gain insight into the strategy taken. It was observed that often, the participants chose the answer opposing the strategy executed.

As hypothesized in H-5, the interface adapted from the previous study was deemed adequate for human performance in case of solving an over-constrained multi-UAV dynamic DCVRP as the participants were able to come up with a solution in a limited amount of time.

The interface assisted the participants to satisfy the goal set in place by them. The additional aspects added to the interface also provided support in the strategy taken in the experiment. The battery icon presented the visual aid to be able to predict the amount of battery in the interface and predict future performance. Consequently, informing the user of the possible customers could be reached effectively. The distinctive icon size was able to differentiate the vehicles that are used in the interface. According to the type of vehicle, the participants tended to deliver to further customers by using the vehicle with higher battery capacity and speed while using the other vehicles to deliver to the customers nearby. If needed, the smaller icon vehicles were used more to sacrifice in comparison to the big icon vehicles. Thus, the different icon sizes influenced the solution provided.

The elements in the interface were considered useful for the participants. The map view was able to provide a very definite overview of the situation. Notably, the ellipses which display the flight time constraint provided the participants with the essential information about the maximum reach that can take place for the vehicles and was beneficial during re-routing. The battery, timeline and the payload

view were less helpful. The colour scheme on the map view was able to provide the same information as the payload view. Thus, the participants did not spend much time interacting with it. The participants observed the payload view during re-routing to help grasp the payload margin. A possible improvement would be to have the payload margin located within the map view to provide quicker feedback. The battery icon was used to know the current, future and planned battery capacity at each customer waypoint once clicked on a particular vehicle. Thus letting the participants plan a re-route depending on the battery left in the vehicle. The participants provided positive feedback for this view, as it provided them with the necessary information to be able to re-optimize to customers. However, it seemed that when the problem size was increasing, it was getting increasingly more challenging to interact with the battery icon. Moreover, as the colour of the flightplan leg in the map view represents the same aspect as the battery icon, it was deemed unnecessary at some points. Lastly, the timeline view was used to determine the depot congestion that is occurring.

Due to the limited time, participants focused on re-routing according to the mission objective and observed the depot congestion at the end. The view was not regarded as very significant during re-optimisation. The participants were getting entangled with the colour scheme, as it provided to be messier to observe with the increase in the problem size. Thus, the timeline view would only be significantly used during smaller mission scenarios, giving the participants enough time to observe the depot congestion.

## 7 CONCLUSION

Some of the drawbacks involving using automation to solve problems is that: 1) the problem needs to be well defined, and may not work efficiently in ambiguous situations, 2) the time it takes to solve the problem and 3) the difficulty to solve over-constrained problem, as there is no particular solution which satisfies all the constraint. Thus, as humans are good at problem-solving, they could be an alternative in solving these algorithms. So, the goal of this study is to investigate the human performance in multi-UAV over-constrained dynamic DCVRP, to investigate how the human performs in the drawback situation of automation. This was solved on the interface, which used automation to be able to acquire and analyze the information and the humans would decide and implement the action. The interface design and the performance was judged on the bases of workload, control performance, constraint priority, strategy and display usage. The human was able to re-optimize the over-constrained problem during real-time, with the introduction of dynamic situations with increasing problem sizes and relaxed constraints dependent on the mission operation. Thus, it can be concluded that humans are a good option when considering solving complicated problems, and so beneficial to have a human-in-the-loop.

Further research can be done on introducing a higher level of automation in the interface or achieving a balance between automation and human. This may result in a more optimal solution. For instance, the human would input its re-optimized route in a dynamic problem in the interface, and the automation could use that to optimise the problem

further, also dependent on humans judgement on the constraints that need to be relaxed dependent on the mission objective.

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## **Part II**

# **Thesis Book of Appendices**



*The content in this chapter has been graded as part of the preliminary thesis report under AE4020.*

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## Appendix A

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# Literature Study

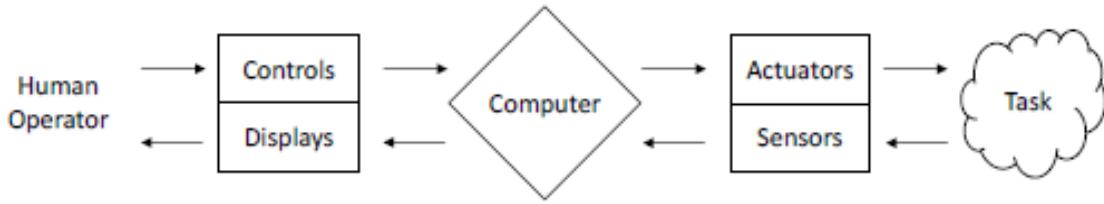
This chapter presents a review of literature on the supervisory control of Multiple UAVs in Section A-1, vehicle routing problem in Section A-2 and human performance in solving travelling salesmen problem in Section A-3.

### **A-1 Supervisory control of Multiple UAVs**

This section is about the human supervisory control of multiple UAVs. It deals with how the human and the automation work with each other. The relation between human and automation is evaluated for the successful functioning of the supervisory control of multiple UAVs. This aids in providing information about the collaboration between the optimise and satisfy feature, thus evaluating the necessary aspect needed to judge the amount of automation needed from the interface. This section begins by discussing the supervisory control loop, followed by the operator workload. Moreover, the effects of situational awareness to the system are discussed. Lastly, an explanation is given about the *optimise* and *satisfy* feature due to different levels of automation.

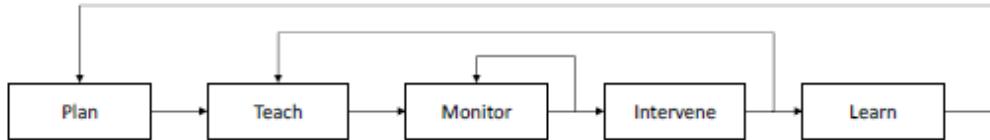
#### **A-1-1 Supervisory control**

As it can be illustrated in Figure A-1, in supervisory control, a human is supervising a computer system, which in return controls the process. As the human is not controlling the process directly, there is some sort of automation and processing present in the computer system. Generally, for a few variables sometimes, the computer can close the automatic control loop, thus the role of the human operator is to be able to guide the automation (Sheridan, 1992). In such a case, the human is observing the actions done by the automation. The human assesses the desirability and the quality of the actions and intervenes if needed.



**Figure A-1:** Human Supervisory Control (Sheridan & Verplank, 1978)

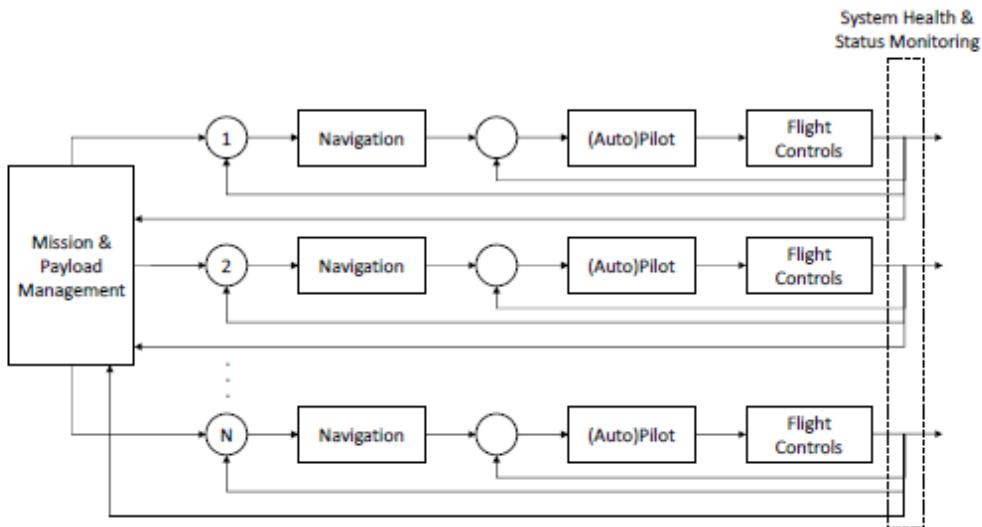
There are five sequential functions of the human supervisory present: planning, teaching, monitoring, intervening and learning (Sheridan, 1992). During planning, the human determines a strategy after which can allocate and prioritise tasks. Moreover, the human teaches or is instructing the computer on the plan, after which monitors the automation and then identifying any anomalies that are present during the execution of the plan and the possible failures that exist with it. However, in case of emergency cases or to improve the performance, the operator will be able to intervene to re-guide the system or overrule the automation. The operator can learn from past experiences to be able to increase performance in the future. Figure A-2 shows the human supervisory function shown as a nested loop. In the research, as the operator would need to plan and execute information in case of dynamic scenarios, the interface should be able to provide relevant information to the operators. The information should be necessary to be able to aid the operator to make proper decisions.



**Figure A-2:** The human supervisory function displaced as nested loops (Sheridan, 1992)

The concept of the human supervisory function can be used for the command and control of the multi-UAV. As discussed in (Cummings, Bruni, et al., 2007), the representation of the system can be seen in Figure A-3. The figure represents  $N$  UAVs the accompanying low-level control loops and an underlying global mission and the payload management loop. The most inner loop is for the flight controls and the basic guidance involved with it. After which, the second loop involves the navigation loop, which is responsible for the avoidance of the obstacle and the waypoints of the route. Lastly, the global loop can find the mission level control where the information from the sensors and payload is established, and the guidance of the global goals and the performance of the mission is given. The monitoring of the system health and status is also represented by comparing the state of the UAV with the information with the nominal performance of the model.

However, for this research, the focus lies on the failure management of a multi-UAV system by the human operator; the navigation and flight control loop is expected to be fully automated. This limits the scope of the research, and also, provides the operator with enough cognitive resources to be able to make proper control performance. In this research, the user must



**Figure A-3:** The system control loop for Multiple-UAV (Cummings, Bruni, et al., 2007)

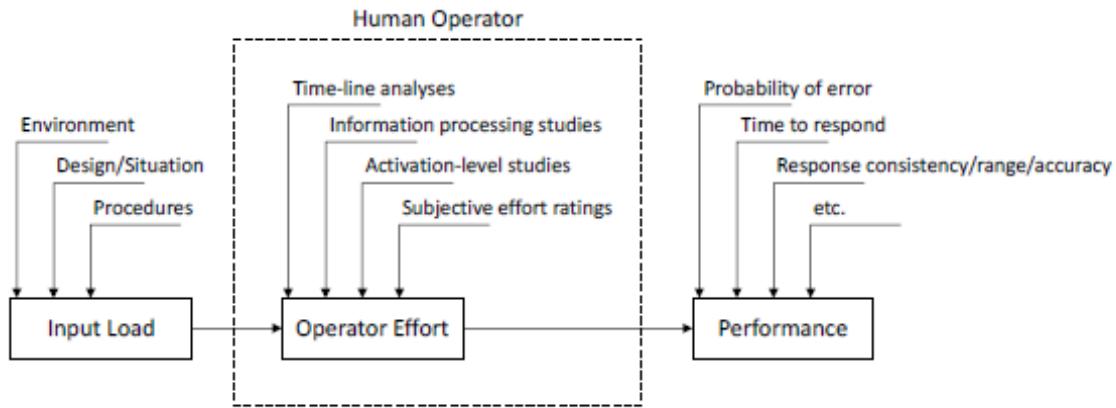
have enough information to be able to intervene and provide the best solution possible. This can be achieved when providing the user with useful information to be able to make useful decisions.

## A-1-2 Workload by the operator

As this research is considering the case of Multi-UAV supervisory control, attaining tolerable operator workload is essential for the overall effectiveness of the mission, and it deserves attention when designing the interface and display. As mentioned in (Jahns, 1973), it is divided into several functions: input load, operator effort and performance. The input loads are about the events or the factors which are external to the human operator, operator effort is related with the internal factors involved and performance is related to the capacity of the data output which is generated by human operator (Johannsen, 1979). Figure A-4 displays the attributes of operator workload besides with the number of measures of performance.

When looking at a human-machine system, the input load is usually a predetermined factor, which is established by the experiment and system design, and the effort and performance are assessed.

Regarding the operator effort, the *Subjective effort ratings* should be able to provide the workload faced by the human during operation. The subjective effort rating is a technique to get information about the operator effort, and it was based on questionnaires. One of the majorly accepted and a well known subjective effort rating is the NASA- Task Load Index (TLX) (Hart & Staveland, 1988). As this research focuses on how the operator is relaxing the constraints dependent on the circumstances provided for an over-constrained problem during mission objective, it is relevant to observe the actions taken by the operator. The performance will be able to judge how the interface can assist the humans in solving problem, and which constraints are relaxed dependent on different circumstances.



**Figure A-4:** Attributes of operator workload (Jahns, 1973) (Johannsen, 1979)

### A-1-3 Situation awareness

Situation awareness (SA) is defined as *” the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future”* (Endsley, 1988). In this research, there needs to be a sufficient level of SA of the mission by the operators. According to the definition, there are three levels of SA: the perception of data and element in the environment, understanding the current situation and showing the future states and events. These are Level 1,2 and 3 of SA respectively. To get the SA, the information needs to be obtained from the environment. The information from the real world is put into the system. However, the system usually does not take all the information from the real world. After which, the system displays the information gathered in the interface. However, not all of the information gathered is displayed on the interface. Finally, the information that is gathered from the real world and the interface might not be complete when transmitting it to the human operator due to the constraints involving perceptual, attention and working memory.

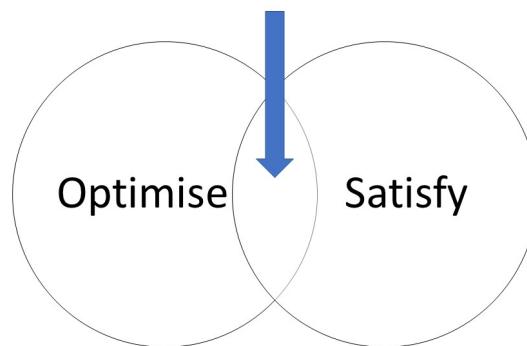
Additionally, M. R. Endsley presents several system characteristics that would improve the situational awareness of the operator (Endsley, 1988). The level of availability of the appropriate environmental features given to the operator affects the persons' ability to obtain SA. Also, SA is affected in the way the information is presented. Using automation has a bad influence on situational awareness if it is used for human decision making and active system control. However, it is a positive aspect if it is used for peripheral tasks. As a result, when developing the interface for the operators, it is essential to provide the user with the necessary information to make decisions during mission operation. The user should be able to see which constraints are not being satisfied to be aware of the decisions that are made. Giving too much information to the user may also hamper the decisions made by the operator.

The operator workload and situational awareness are not independent concepts. However, the operator workload can affect the SA. The SA decreases when the operator is made to have a high workload due to the limit of cognitive resources, and it can even decrease when the operator does not have much to do, as the operator may experience boredom and complacency (Andre & Wickens, 1995) (Rodgers, Mogford, & Strauch, 2000).

#### A-1-4 Effects of Automation

Usually, automation is used to help the operator in performing tasks, which would help in reducing the workload and preventing overload of information (Cummings, Brzezinski, & Lee, 2007a). Even though there are positive impacts, automation can degrade human performance rather than making it better (Council et al., 1998). As the level of automation increases, there might be too much reliance by the operator to the system and also result in loss of skills for performing the tasks manually, in case of an emergency involved. Thus, it may increase the workload, and decrease the situational awareness (Chen et al., 2011).

On the other hand, when considering the solution solving taken by the human to solve a problem, it is evaluated that approach taken tends to go towards *satisfying* the problem. This would result in the solution to have possible errors, and there is high reliability on the user. Whereas, when considering the utterly autonomous system, it tends to *optimise*. This uses higher processing power, and would possibly require more time to solve considering the nature of the problem. As a result, as it can be seen in Figure A-5, the research would focus on the combination of the two as it can use the advantage of the quick solution time of the human to provide a solution for an over-constrained problem in varied situations for different dynamic cases. So, the human will be able to relax some of the constraints to achieve results. Additionally, the interface given should complement the human performance and not make it too complicated when making a solution.



**Figure A-5:** The approach that is evaluated in this literature review

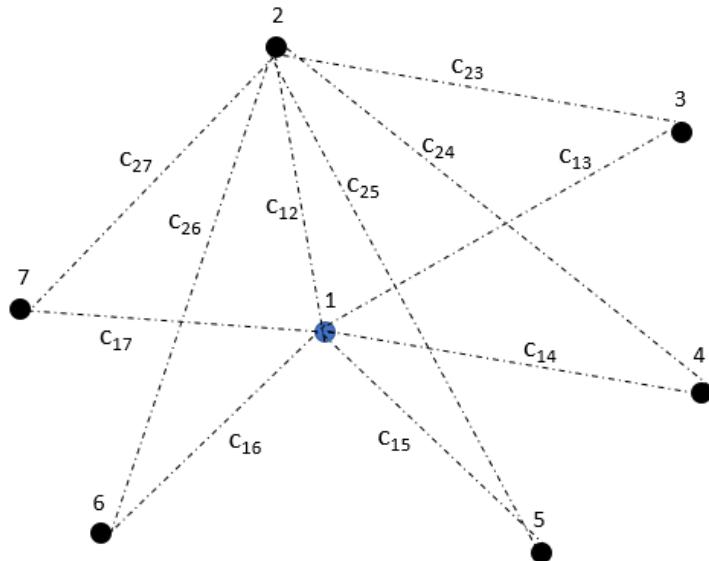
## A-2 The Vehicle Routing Problem

This section presents the definition of VRP and the various types of VRP that are currently present and used for research purposes. When considering the distribution of goods and planning, VRP is a central aspect. There is a wide variety of VRP that are currently present to solve the different kinds of problems. This chapter would provide a more in-depth insight about the *optimise* part of the algorithm, and the scope at which the algorithm is extended towards as this research would be based on the over-constrained dynamic problem. The limits of the research on VRP is also evaluated.

### A-2-1 Definition

The VRP can be defined as "*the problem of designing optimal delivery or collection routes from one or several depots to several geographically scattered cities or customers, subject to side constraints*" (Laporte, 1992).

Let  $B = (C, A)$  be a graph in which  $C = (1, \dots, n)$  is a set of vertices which represent the delivery locations, however, vertex 1 is considered the depot, as it can be observed in Figure A-6. In addition,  $A$  are the arcs. Each arc  $(i, j)$   $i \neq j$  is a non-negative distance matrix  $C = c_{ij}$ . The  $c_{ij}$  can be associated as the *travel cost* or the *travel time*. The notations are shown for location 1 and 2, in Figure A-6. When considering the matrix,  $c_{ij} = c_{ji}$ . The VRP designs its least cost vehicle route in such a way that:



**Figure A-6:** Example of VRP problem

1. Each location is visited at least once by exactly one vehicle;
2. All of the vehicles start and end at the depot;
3. Some other side constraints are completed.

Some of the common side constraints that are considered for the research are :

1. Restriction of capacities: A demand ( $d_i$ ) is attached to each of the vertexes  $i \neq 1$ , and so the sum of all of the weights of the vehicle routes should not exceed the capacity of the vehicle. As a result, this is known as . Also, the number of cities that are constrained by the capacity of the vehicle.

2. Restriction of total time: the length of the route of the vehicle shall not exceed the prescribed bound. The length includes the travel time between the cities ( $c_{ij}$ ), and the stopping time in each of the cities ( $\delta_i$ ) on the route.
3. Time windows: the location  $i$  is visited within a specific time interval  $[a_i, b_i]$ , additionally, waiting would be allowed in the location  $i$ .
4. Precedence relations among the locations: there is a requirement for location  $i$  to be visited before location  $j$ .

### A-2-2 The taxonomy

The VRP can be divided into several criteria. Figure A-7 shows the overview of the different criteria that are present, but it focuses more on the due to the nature of this research (Psaraftis et al., 2016). There is a lot of different information present in the context of these problems, but not very relevant information regarding the over-constrained dynamic problem. However, due to the scope of the research, only the relevant one will be covered. These sections have a variety of types present, but, there is a dependence between the categories that are present. Only the delivery is considered in this situation (one-to-many). Additionally, the transportation mode that is considered is the air in this case, as only the UAVs are examined in this case. In addition, the number of available vehicles will be multiple and a limited number of UAVs in the scenario. This will be to test the scalability of the user in the research. Due to the scope of the research, the time constraints for the arrival of the commodity to the customer is not considered. Lastly, as the aim is not to develop an additional DVRP, thus the additional information about solution methods are not considered as this research focuses on the human performance of the over-constrained DVRP in different situations.

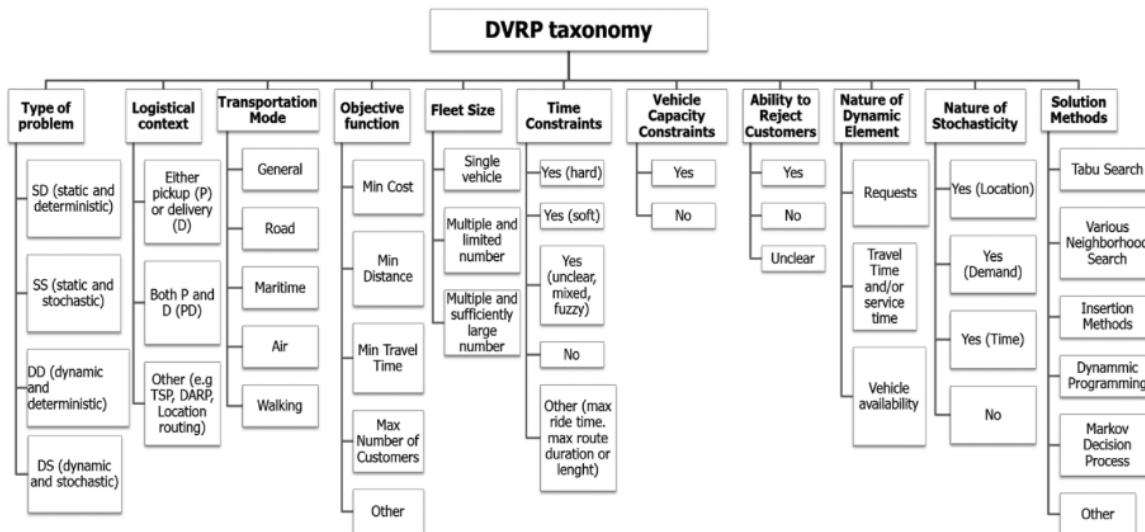


Figure A-7: The overview of the taxonomy of the VRP (Psaraftis et al., 2016)

### A-2-3 Type of problems

A VRP can either be static or dynamic. Also, the problem can either be a deterministic or a stochastic one. As a result, a combination of the two is present, which results in the following type of problems: , , , and . The VRP can be defined as *dynamic* if "the input of the problem is received and updated concurrently with the determination of the route" (Psaraftis et al., 2016). However, if all the routes are determined before the vehicle has departed, and there are no changes, then the VRP is considered static. Moreover, as the routes are not optimised overtime when the plans are determined, thus, the problem is considered static. On the other hand, if the routes are re-optimised or even if the output is a function of the inputs which evolve in real-time, then the problem will be considered dynamic.

A VRP is considered if all the inputs are known before the vehicle has departed, and there are no stochastic inputs present. Referring to Figure A-6, the VRP can be formulated as following (Laporte, 1992):

Minimise:

$$\sum_i c_{ij} x_{ij} \quad (A-1)$$

Subject to:

$$\sum_{j=1}^n x_{ij} = 1 \quad (i = 1, \dots, n) \quad (A-2)$$

$$\sum_{i=1}^n x_{ij} = 1 \quad (j = 1, \dots, n) \quad (A-3)$$

$$\sum_{j=1}^n x_{0j} = |K| \quad (j = 1, \dots, n) \quad (A-4)$$

$$\sum_{i,j \in S} x_{ij} = |S| - v(S) \quad (S \in N; |S| \neq 0) \quad (A-5)$$

$$x_{ij} \in \{0, 1\} \quad (i, j = 1, \dots, n; i \neq j) \quad (A-6)$$

Equation A-1 is the total cost of the summation of the vehicle routes, and it has to be minimised. However, the cost function has some constraints which have to be taken care of. Equation A-2 and Equation A-3 make sure that the vehicles can cover all the required customers. Equation A-4 makes sure that there are  $|K|$  vertices which leave the depot. Thus, each vehicle is leaving the depot once. Equation A-5 provides the capacity constraints and is a sub tour elimination constraints.  $v(S)$  is the required lower bound on the number of vehicles that is appropriate to visit all the vertices of  $S$  in the most optimal solution. At the end, Equation A-6 is the decision variable for  $x_{ij}$ . The variable is equal to 1 when the route needs to be taken part of the optimal solution.

Some other VRPs are considered both static and stochastic (SS). An example of this type of problem is considered in (Jaillet, 1985), which is the . In case of a PTSP, there is a *a priori* route set in place. However, at each of a node, there is a probability  $p$  that the customer is present. The a priori route is determined before it is known which customers will be present at the nodes. This information will be revealed later. As a result, even though it is a static problem, but due to the stochasticity of the customer, it is considered a SS problem. Even though the 'posteriori PTSP' is a problem which is close to the actual PTSP; however, due to the different solution it provides, it is a different problem. The contrary to SS problem is called the dynamic and deterministic (DD). However, when calling it deterministic, it may seem misleading as it may show that the inputs are already known before the start of the mission, which is, however, not the case. A VRP is considered DD whenever the problem is Dynamic, but, there is no stochastic information provided in the future. The dynamically evolved inputs are known beforehand. For example, the location of a customer may not be known until the customer in question requested the service. Alternatively, also, nothing is known about the quantity that is demanded until the information is represented. As a result, the input is only revealed when it appears.

Some papers which had showed instances of using DD are (Psaraftis, 1980), (Ichoua, Gendreau, & Potvin, 2003) and (Gendreau, Guertin, Potvin, & Séguin, 2006). Thus, it is observed that each dynamic scenario had a different solution method involved to solve the problem. When there are several dynamic situations present into the system, a very technology advanced system is needed, or several types of algorithms would need to be considered. As a result, this research would focus on how a human operator would solve different dynamic cases with the aid of the interface.

#### A-2-4 Objective function

A major criterion that is considered in the taxonomy is the objective function of the algorithm. Certain aspects can be maximised or minimised when considering a function. This is important to know as it would mention how the optimisation of the VRP algorithm would be achieved. When the different papers were seen regarding the VRP problems that are present, the objective function that was presented was of a wide variety. Some **examples** of the objectives function that was observed was :

To be minimised:

- Route Cost or the money that is spent
- Route Distance
- Travel time
- Total delay
- number of vehicles

To be maximised:

- Quality of service, thus, optimising for the possible request of the customer

- Profit

However, in this research, as an over-constrained problem will be observed, there may be a need for a constraint relaxation to be able to have a suitable solution (Lau et al., 2003). An approach taken for static over-constrained is to make a hierarchical cost structure and observing the results. This means observing the different constraints as a sequence. This approach may seem more favourable for static situations or for a particular circumstance in which the user is under. However, for different circumstances, there might be a need for different constraints that need to be relaxed in a dynamic situation. Also, when observing over-constrained problem for dynamic situations, they tend to have complexity issues and tend to focus only on a specific problem (Jussien & Boizumault, 1997). Thus, the focus of this research will be on having a better understanding of how human operators would be able to provide a solution in dynamic cases, for over-constrained problems in different circumstances. The humans could be able to cover a broader range of problems, and so may prove more effective during dynamic situations due to their versatility.

#### **A-2-5 Nature of Dynamic Element**

The nature of the dynamic element in the dynamic VRP can be in some forms. This may include how the request takes place, in which the order that is taken can be cancelled or the demand changes according to the scenario. There may also be a change in travel time or service time. Additionally, there could also be an observation of changing customer locations. However, for this research, the dynamic element that occurs is the lack of the vehicle or the availability due to the breakdown of the vehicle. To have a better understanding of the resulting problem, different approaches regarding the failure of vehicles were observed (Li, Mirchandani, & Borenstein, 2009), (Chang, Chen, & Hsueh, 2003) and (Mu, Fu, Lysgaard, & Eglese, 2011). However, the algorithms were observed to be for a specific problem. This research will thus use the problem-solving skills of the human operator and test the capability for different circumstances.

### **A-3 Human performance in solving Travelling Salesman Problems**

This section deals with how the human can solve the Travelling Salesman Problem (TSP). The TSP represents a classic VRP. The difference is that the VRP considers a greater number of vehicles, as compared to the one vehicle for TSP (Restori, 2004). As there will be participants involved in the experiment, it is important to know the human performance in solving the TSP. The TSP is evaluated as it would provide feedback of how well is the human ability to contribute in the problem solving of the problem that is in hand, hence give a better understanding about the *satisfy* feature of an operator. There are several papers which analyse the behaviour and the performance of the human, such as (MacGregor & Ormerod, 1996), (Dry et al., 2006), (MacGregor & Chu, 2011) and (Vickers, Butavicius, Lee, & Medvedev, 2001).

As a TSP will have a significant number of possible solutions. Finding a "reasonable" solution may take an extended amount of time. For instance, a 20-node problem would require around 8000 calculations (MacGregor & Ormerod, 1996). Due to the characteristic of the problem, it

is interesting to see how human beings solve TSP. It would provide an exciting physiological task to explore, as it is testing the performance of humans for visually represented problems. To test this performance, MacGregor and Ormerod took 29 subjects which were students from the university (MacGregor & Ormerod, 1996). The students were given seven TSP problems, which included 20 points. Thus the performance of the subjects on these scenarios would provide a better understanding of the human performance for a lower number of customers regarding this research. As the data points of the problem were given, the problems were plotted and can be seen in Figure A-8.

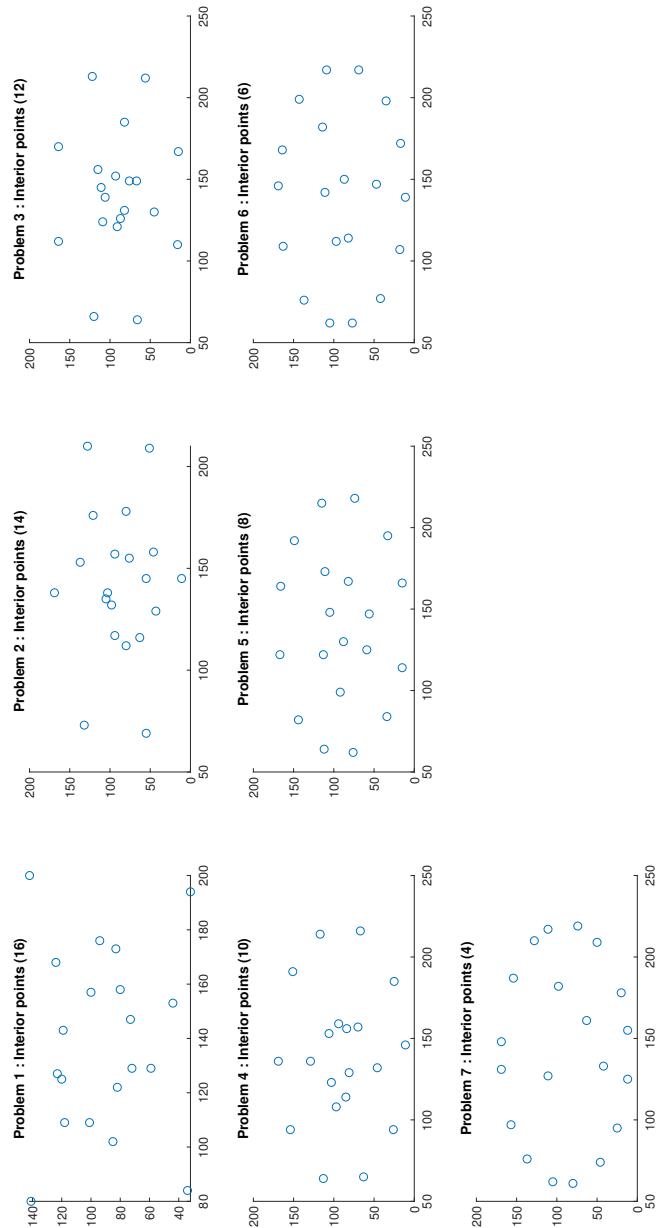
To create the problem: the coordinate of the points on the boundary of the hull was first determined with the vertices of the regular polygon with the number of sides, using the polar coordinates with a radius of 80 mm. For instance, for 4 points on the boundary of the hull, the coordinates were then determined with the interior angles of  $45^\circ$ ,  $135^\circ$ ,  $225^\circ$ , and  $315^\circ$ . To introduce some irregularity in the point, random angles were added between  $+5^\circ$  and  $-5^\circ$ . After the points in the boundary of the hull were determined, the polar coordinate of the central points was then randomly generated with a constraint that the points should fall within 40 mm from the centre of the original regular polygon. Once all the 20 points were generated for the problems, these were the problems that were given to the student.

The problems were presented on separate sheets of 11 x 8.5 in. Each subject was tested on the problems that were given to them. They were presented in three different orders. The data was taken in a classroom setting. The students were given booklet with the problem with a page of instructions provided. The instructions asked them to select a starting point for each of the problem, and then draw what they thought is the shortest path, and passing through all the points and returning to the starting point chosen. The subjects were also asked to indicate the direction of the travel and the starting point taken for each of the problems. There was no time limit provided to them. However, the instructions provided a limit of 5 minutes for each of the problem given to them. When completed, the students handed in the booklet with the solutions, and the times were noted to the nearest minute.

The results had shown that nine subjects had left one or more of the problems incomplete by not able to incorporate all the points. The path lengths were taken and then provided for the primary data to analysis. The first results can be observed in Figure A-9. It shows the minimum, mean and maximum values produced from the different problems by the subjects, along with the standard deviation ( $z$ ). A random sample of 100 solutions was generated for the problem, to get a sample mean and standard deviation. These values were used to judge the performance of the subjects to the standard scores. When converting the standard score to percentile, it was observed that the subjects path lengths for each problem were beyond 99.99th percentile.

When comparing it with the heuristic algorithm, the best solution which is obtained by the human was similar to the best solution which was obtained by one of the algorithms, as it can be observed in Figure A-10. Thus, the best rational solution is comparable to the optimum solution. This experiment thus proves that a human is capable of providing a suitable solution based on visual representation, and so will be a positive aspect during the experiment in this research.

Moreover, to test the scalability of the human performance on the varying number of TSP, the experiment conducted by Dry, Lee, Vickers and Huges were seen (Dry et al., 2006). They considered human solution time for the TSP with the increase in the number of nodes. Forty



**Figure A-8:** The 20 node problems which were given to the subjects (MacGregor & Ormerod, 1996)

Number of Interior Points	Subjects' Path Lengths					
	Minimum		Mean		Maximum	
	Score	<i>z</i>	Score	<i>z</i>	Score	<i>z</i>
4	707.49	8.26	724.27	8.15	816.03	7.53
6	703.89	7.16	746.32	7.16	846.50	6.50
8	737.61	7.34	762.40	7.34	830.16	6.82
10	708.93	7.60	721.81	7.60	745.03	7.39
12	692.60	7.79	719.70	7.79	828.50	6.57
14	675.80	7.68	727.36	7.68	830.68	6.42
16	599.72	6.23	644.14	6.23	734.54	5.18

**Figure A-9:** The minimum, mean and maximum path length that is produced from the results, with the corresponding *z* value (MacGregor & Ormerod, 1996)

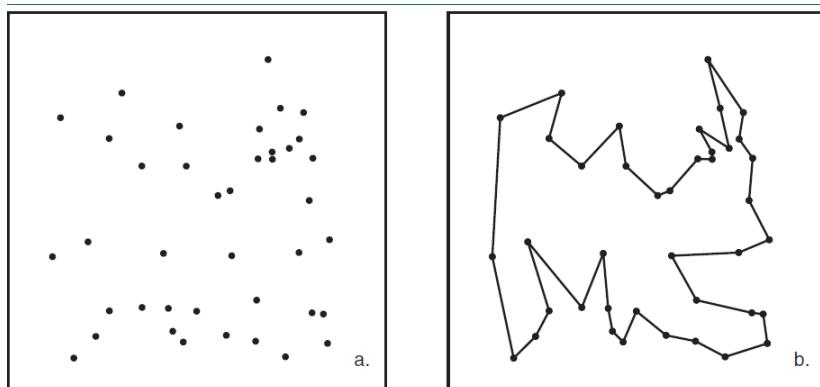
Number of Interior Points	Optimal Solution	Percentage Above Optimal					
		Subject Minimum	NN Minimum	LA	CHCI	Subject Mean	NN Mean
4	703.81	3.0	4.1	3.1	2.5	5.4	8.4
6	703.89	1.2	1.2	20.1	5.3	7.3	8.8
8	725.31	1.7	3.3	13.7	5.8	5.2	9.4
10	698.83	1.4	0	6.0	4.8	3.3	9.5
12	688.33	0.6	0	23.4	3.6	4.6	7.1
14	663.61	1.9	1.5	10.0	4.4	9.6	15.4
16	593.81	1.0	15.0	0.8	0.05	8.5	21.7

Note—NN, Nearest Neighbor; LA, Largest Interior Angle; CHCI, Convex Hull, with cheapest insertion criterion.

**Figure A-10:** The comparison between the Heuristic solution with respect to the human solution (MacGregor & Ormerod, 1996)

participants completed the TSP condition. The nodes were presented on a 14 x 14 cm square. The nodes chosen were black dots which had a diameter of 1.5 mm.

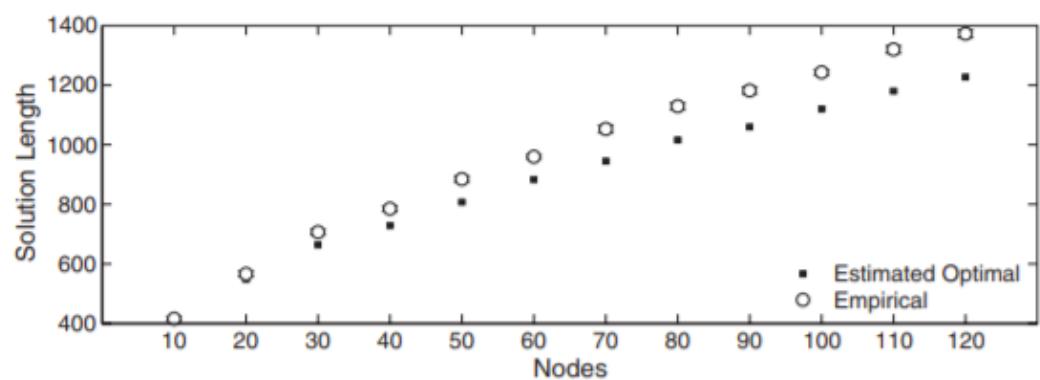
For the TSP condition, there were 10,000 random problems created with 10, 20, 30, ..... 120 nodes. According to some parameters chosen, a total of 20 problems were chosen from the sample for the experiment. Figure A-11 displays an example of the problem given to the participants, and the solution which gave the least distance. The participants were given three problems (with 30, 60 and 90 nodes) to do before commencing the experiment.



**Figure A-11:** Example of the 40 node TSP along with the optimal solution (Dry et al., 2006)

The array was presented to a coloured monitor computer. The participants were required to left-click on the starting node. After which by dragging the cursor of the mouse, to the next node, a straight line was drawn between the two. It was possible to delete the line by right-clicking on the line and clicking the delete option. The participants were given the freedom to connect the nodes, however. The only instruction provided was to draw the shortest continuous pathway, which passed through all the nodes. There was no time restriction imposed. The participants were given the result on how far were they from comparison with the optimal solution which was obtained through different heuristic solutions.

Figure A-12 compares the average length of the participant solution concerning the optimal solution obtained from different heuristic approaches. The graph can display that the estimated optimal solution is closely approximated to the estimated solution length, with the deviation asymptotic around 0.11 when the problem size increases over 70 nodes. As a result, regarding this research, it can be established that human performance is still excellent by increasing the number of nodes. Thus, using humans for different scales as operators would be beneficial to the experiment due to their problem-solving skills.



**Figure A-12:** The comparison between the estimated Optimal with respect to the Empirical (Dry et al., 2006)



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## Appendix B

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# Experiment Design

### B-1 Experiment Conditions

The experiment conditions that is used in the experiment can be seen in Table B-1. The number of customers is determined by the number of low-level vehicles and the number of payload for each of the vehicle, which were two of the independent variable. The number of vehicles and the customers is determined by using Equation B-1 and Equation B-2, respectively. The resulting value for the experimental condition can be seen in Table B-2. The control variable for the experiment can be seen in Table B-3.

$$nVehicles = nLowLevelVeh \cdot nPayload \quad (B-1)$$

$$nCustomers = nPayload \cdot nLowLevelVeh \cdot (nPayload - 1) + (nPayload - 2) + (3 \cdot nLowLevelVeh - 3) \quad (B-2)$$

**Table B-1:** Experiment Condition - Mission (M), Number of low-level vehicle (L) and Payload (P).

	Mission: Search and Rescue				Mission: Delivery Coffee Beans			
	Payload 4	Payload 5	Payload 6	Payload 7	Payload 4	Payload 5	Payload 6	Payload 7
Single low-level vehicle	M1L1P4	M1L1P5	M1L1P6	M1L1P7	M2L1P4	M2L1P5	M2L1P6	M2L1P7
Double low-level vehicle	M1L2P4	M1L2P5	M1L2P6	M1L2P7	M2L2P4	M2L2P5	M2L2P6	M2L2P7

**Table B-2:** The vehicles and customers per condition

	nCustomers	nVehicles
M1L1P4	14	4
M1L1P5	23	5
M1L1P6	34	6
M1L1P7	47	7
M1L2P4	29	8
M1L2P5	46	10
M1L2P6	67	12
M1L2P7	92	14

**Table B-3:** Control variables.

Variable	Value
UAV 1 - Max flight time [s]	900
UAV 1 - Airspeed [m/s]	20
UAV 2 - Max flight time [s]	750
UAV 2 - Airspeed [m/s]	13
Service Time [s]	30
Scenario Duration [s]	300
Payload Margin for high-level vehicles [-]	1
Sector Size [ $m^2$ ]	5000 x 5000
Depot Capacity (Rounded to the nearest integer)	30% of nVehicles

## B-2 Experiment Matrix

**Table B-4:** Experiment matrix for the conducted experiment. Each participant first goes through 9 training runs, followed by 16 experiment runs, with one break halfway the experiment.

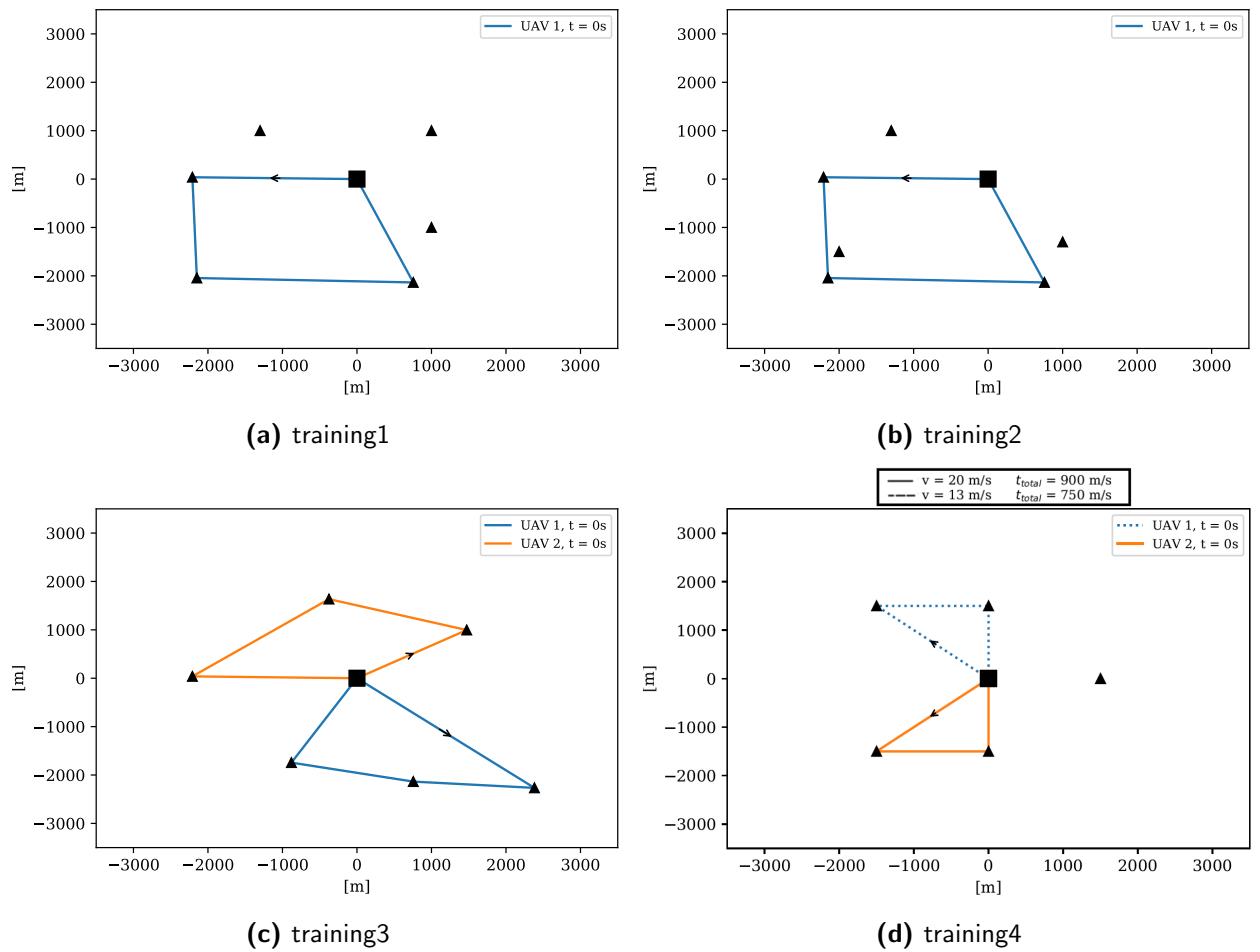
P1	T1	T2	T3	T4	T5	T6	T7	T8	T9	M2L2P7	M1L1P4	M2L2P6	M1L1P5	M2L2P5	BREAK	M1L1P6	M2L2P4	M1L1P7	M2L1P7	M1L2P4	M2L1P6	M1L2P5	M2L1P5	M1L2P6	M2L1P4	M1L2P7	M2L2P7
P2	T1	T2	T3	T4	T5	T6	T7	T8	T9	M1L1P4	M2L2P6	M1L1P5	M2L2P5	M1L1P6	BREAK	M2L2P4	M1L1P7	M2L1P7	M1L2P4	M2L1P6	M1L2P5	M2L1P5	M1L2P6	M2L1P4	M1L2P7	M2L2P7	M1L1P4
P3	T1	T2	T3	T4	T5	T6	T7	T8	T9	M2L2P6	M1L1P5	M2L2P5	M1L1P6	M2L2P4	BREAK	M1L1P7	M2L1P7	M1L2P4	M2L1P6	M1L2P5	M2L1P5	M1L2P6	M2L1P4	M1L2P7	M2L2P7	M1L1P4	
P4	T1	T2	T3	T4	T5	T6	T7	T8	T9	M1L1P5	M2L2P5	M1L1P6	M2L2P4	M1L1P7	BREAK	M2L1P7	M1L2P4	M2L1P6	M1L2P5	M2L1P5	M1L2P6	M2L1P4	M1L2P7	M2L2P7	M1L1P4	M2L2P6	
P5	T1	T2	T3	T4	T5	T6	T7	T8	T9	M2L2P5	M1L1P6	M2L2P4	M1L1P7	M2L1P7	BREAK	M1L2P4	M2L1P6	M1L2P5	M2L1P5	M1L2P6	M2L1P4	M1L2P7	M2L2P7	M1L1P4	M2L2P6	M1L1P5	
P6	T1	T2	T3	T4	T5	T6	T7	T8	T9	M1L1P6	M2L2P4	M1L1P7	M2L1P7	M1L2P4	BREAK	M2L1P6	M1L2P5	M2L1P5	M2L1P6	M1L2P7	M2L2P7	M1L1P4	M2L2P6	M1L1P5	M2L2P5		
P7	T1	T2	T3	T4	T5	T6	T7	T8	T9	M2L2P4	M1L1P7	M2L1P7	M1L2P4	M2L1P6	BREAK	M1L2P5	M2L1P5	M1L2P6	M2L1P4	M1L2P7	M2L2P7	M1L1P4	M2L2P6	M1L1P5	M2L2P5	M1L1P6	
P8	T1	T2	T3	T4	T5	T6	T7	T8	T9	M1L1P7	M2L1P7	M1L2P4	M2L1P6	M1L2P5	BREAK	M2L1P5	M1L2P6	M2L1P4	M1L2P7	M1L1P4	M2L2P6	M1L1P5	M2L2P5	M1L1P6	M2L2P4		
P9	T1	T2	T3	T4	T5	T6	T7	T8	T9	M2L1P7	M1L2P4	M2L1P6	M1L2P5	M2L1P5	BREAK	M1L2P6	M2L1P4	M1L2P7	M2L2P7	M1L1P4	M2L2P6	M1L1P5	M2L2P5	M1L1P6	M2L2P4	M1L1P7	
P10	T1	T2	T3	T4	T5	T6	T7	T8	T9	M1L2P4	M2L1P6	M1L2P5	M2L1P5	M1L2P6	BREAK	M2L1P4	M1L2P7	M2L2P7	M1L1P4	M2L2P6	M1L1P5	M2L2P5	M1L1P6	M2L2P4	M1L1P7	M2L1P7	
P11	T1	T2	T3	T4	T5	T6	T7	T8	T9	M2L1P6	M1L2P5	M2L1P5	M1L2P6	M2L1P4	BREAK	M1L2P7	M2L2P7	M1L1P4	M2L2P6	M1L1P5	M2L2P5	M1L2P4	M1L1P7	M2L1P7	M1L2P4		
P12	T1	T2	T3	T4	T5	T6	T7	T8	T9	M1L2P5	M2L1P5	M1L2P6	M2L1P4	M1L2P7	BREAK	M2L2P7	M1L1P4	M2L2P6	M1L1P5	M2L2P5	M1L1P6	M2L2P4	M1L1P7	M2L1P7	M1L2P4	M2L1P6	
P13	T1	T2	T3	T4	T5	T6	T7	T8	T9	M2L1P5	M1L2P6	M2L1P4	M1L2P7	M2L2P7	BREAK	M1L1P4	M2L2P6	M1L1P5	M2L2P5	M1L1P6	M2L2P4	M1L1P7	M2L1P7	M1L2P4	M2L1P6	M1L2P5	
P14	T1	T2	T3	T4	T5	T6	T7	T8	T9	M1L2P6	M2L1P4	M1L2P7	M2L2P7	M1L1P4	BREAK	M2L2P6	M1L1P5	M2L2P5	M1L1P6	M2L2P4	M1L1P7	M2L1P7	M1L2P4	M2L1P6	M1L2P5		
P15	T1	T2	T3	T4	T5	T6	T7	T8	T9	M2L1P4	M1L2P7	M2L2P7	M1L1P4	M2L2P6	BREAK	M1L1P5	M2L2P5	M1L1P6	M2L2P4	M1L1P7	M2L1P7	M1L2P4	M2L1P6	M1L2P5	M2L1P5		
P16	T1	T2	T3	T4	T5	T6	T7	T8	T9	M1L2P7	M2L2P7	M1L1P4	M2L2P6	M1L1P5	BREAK	M2L2P5	M1L1P6	M2L2P4	M1L1P7	M2L1P7	M1L2P4	M2L1P6	M1L2P5	M2L1P5	M1L2P6		

## B-3 Training Scenarios

The following table visualises the condition provided for the training scenarios.

**Table B-5:** Training Runs

	Category	Scenario				
T1	Interface acclimatization		Flight Time Constraint			
T2	Interface acclimatization		Payload Constraint			
T3	Interface acclimatization		Depot Congestion			
T4	Interface acclimatization		Different vehicle icons			
T5	Over-constrained DVRP	nCustomers: 6	maxPayload: 3	nVehicles: 2		
T6	Over-constrained DVRP	nCustomers: 12	maxPayload: 5	nVehicles: 4	nLowLevelVeh: 1	Mission: Search and Rescue
T7	Over-constrained DVRP	nCustomers: 12	maxPayload: 5	nVehicles: 4	nLowLevelVeh: 1	Mission: Delivering Coffee Beans
T8	Over-constrained DVRP	nCustomers: 18	maxPayload: 5	nVehicles: 4	nLowLevelVeh: 2	Mission: Search and Rescue
T9	Over-constrained DVRP	nCustomers: 18	maxPayload: 5	nVehicles: 4	nLowLevelVeh: 2	Mission: Delivering Coffee Beans



**Figure B-1:** Training scenarios

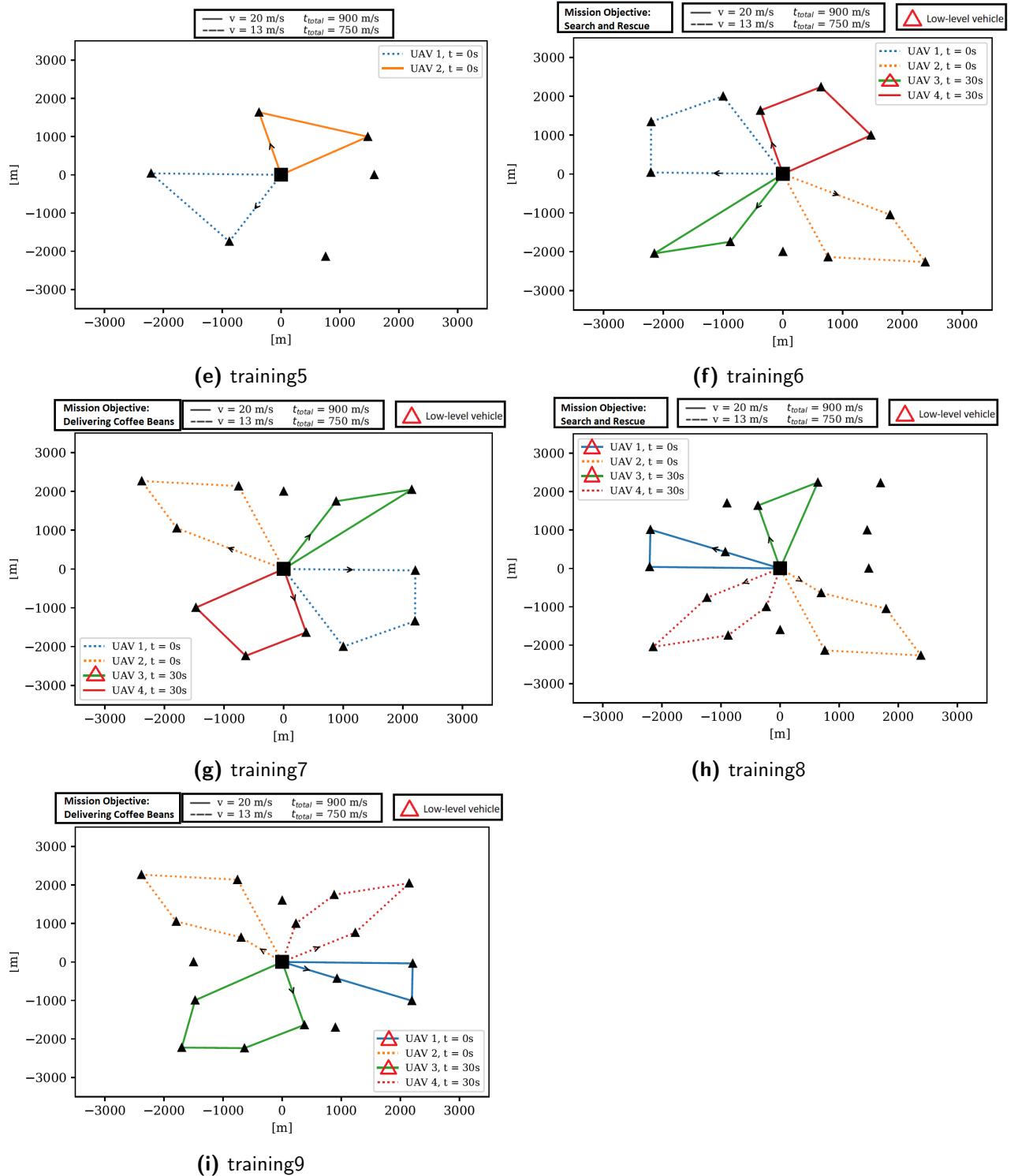
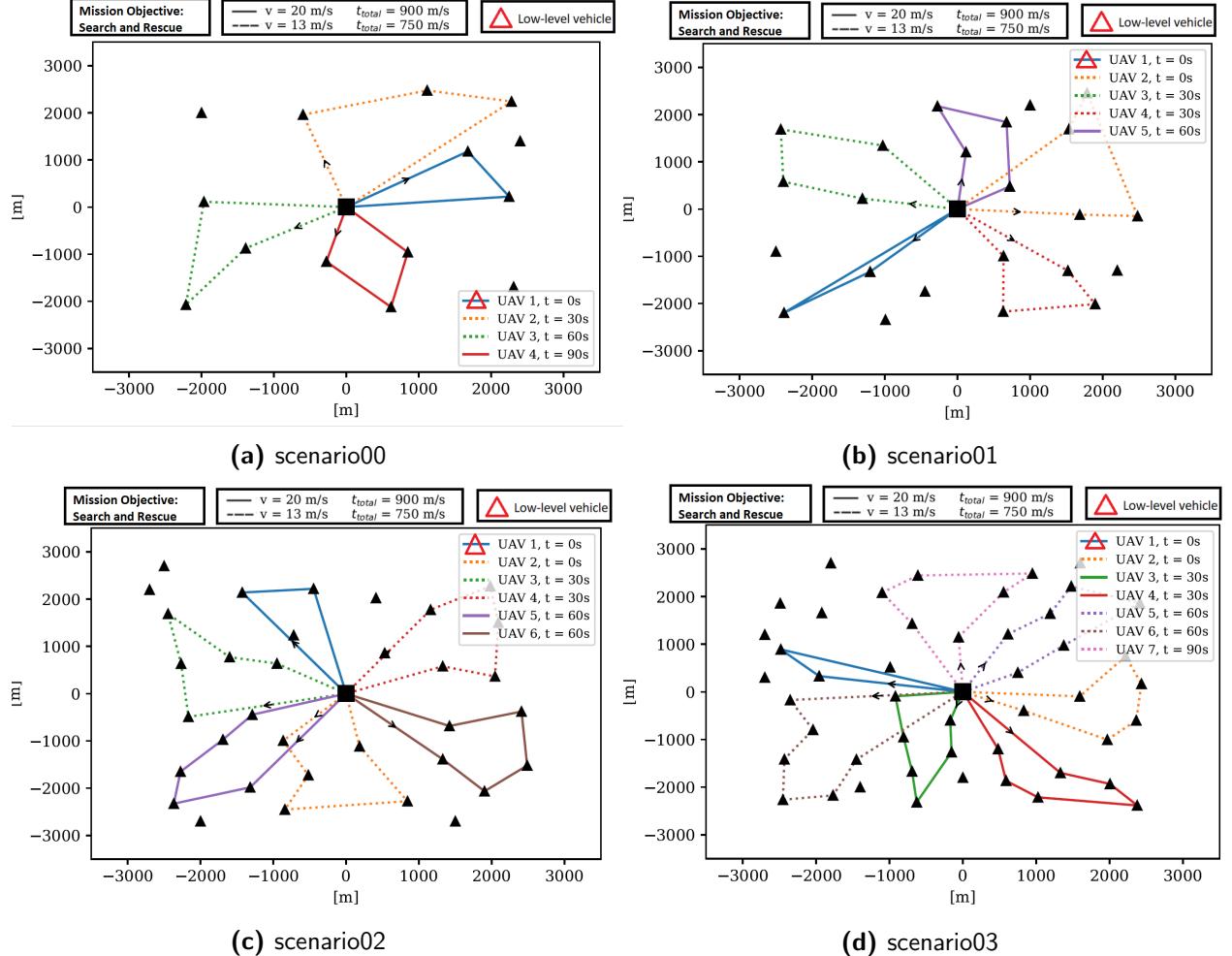


Figure B-1: Training scenarios (continued)

## B-4 Experiment Scenarios

The following are the experiment scenarios which were given to the participants.



**Figure B-2:** Experiment scenarios

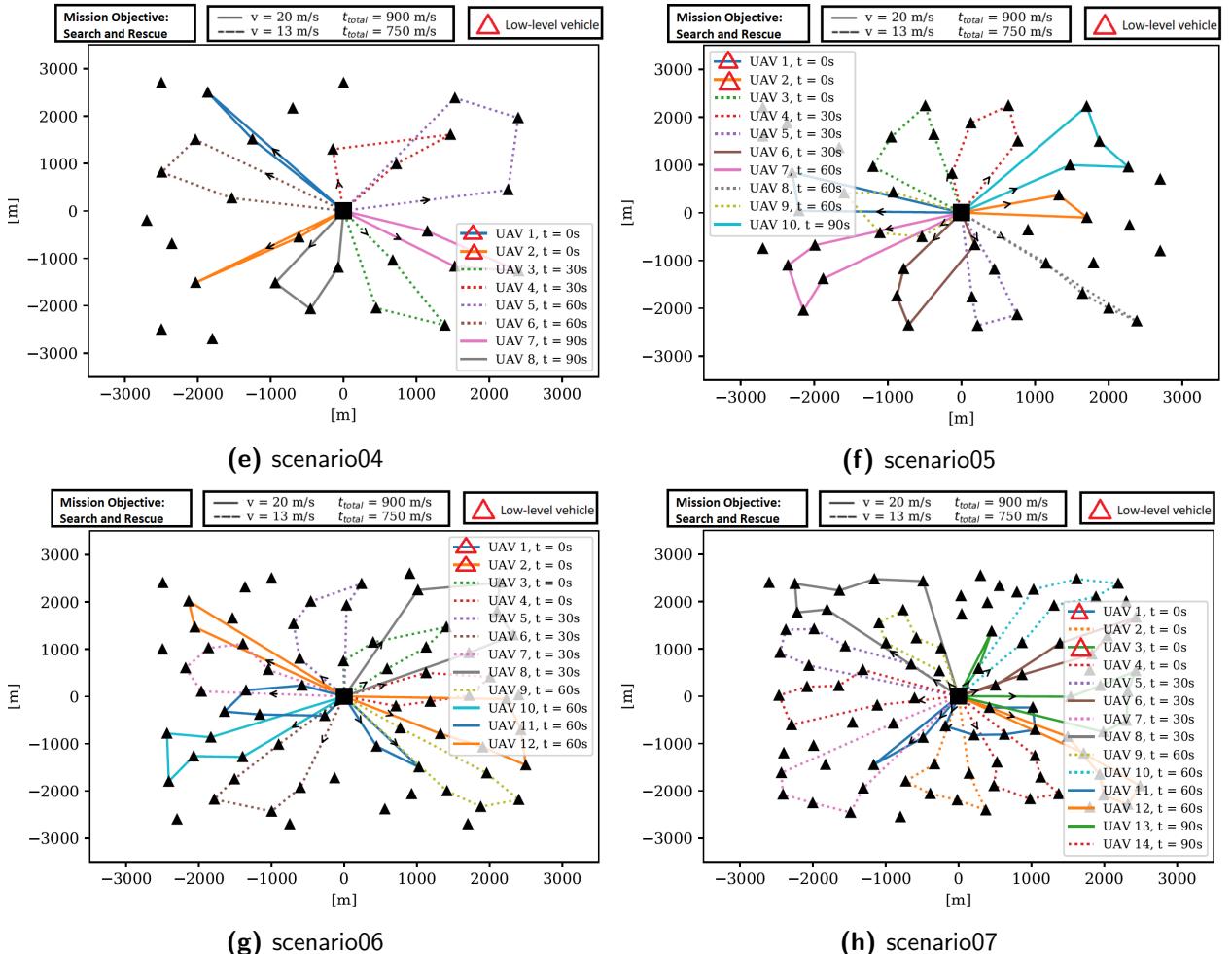
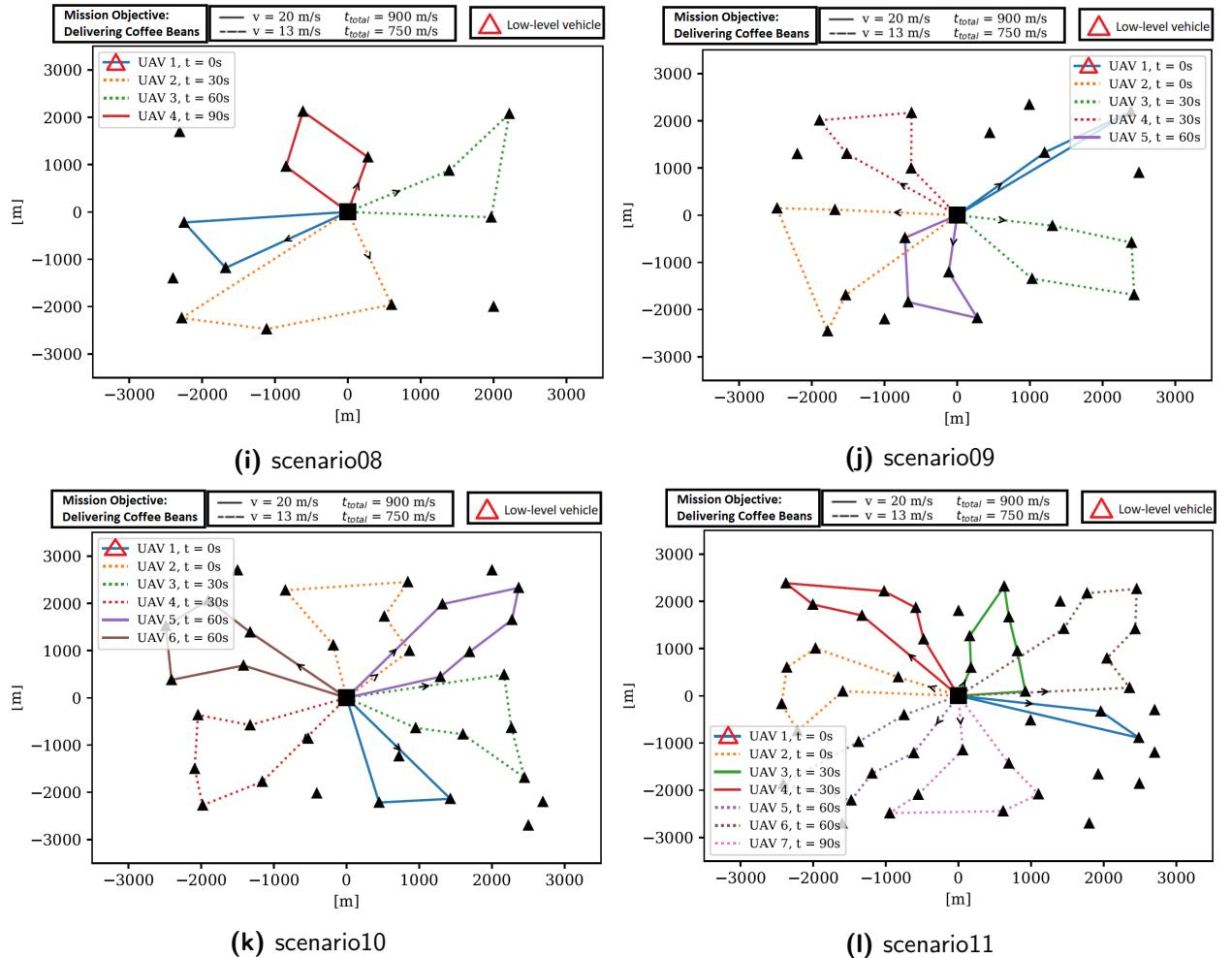
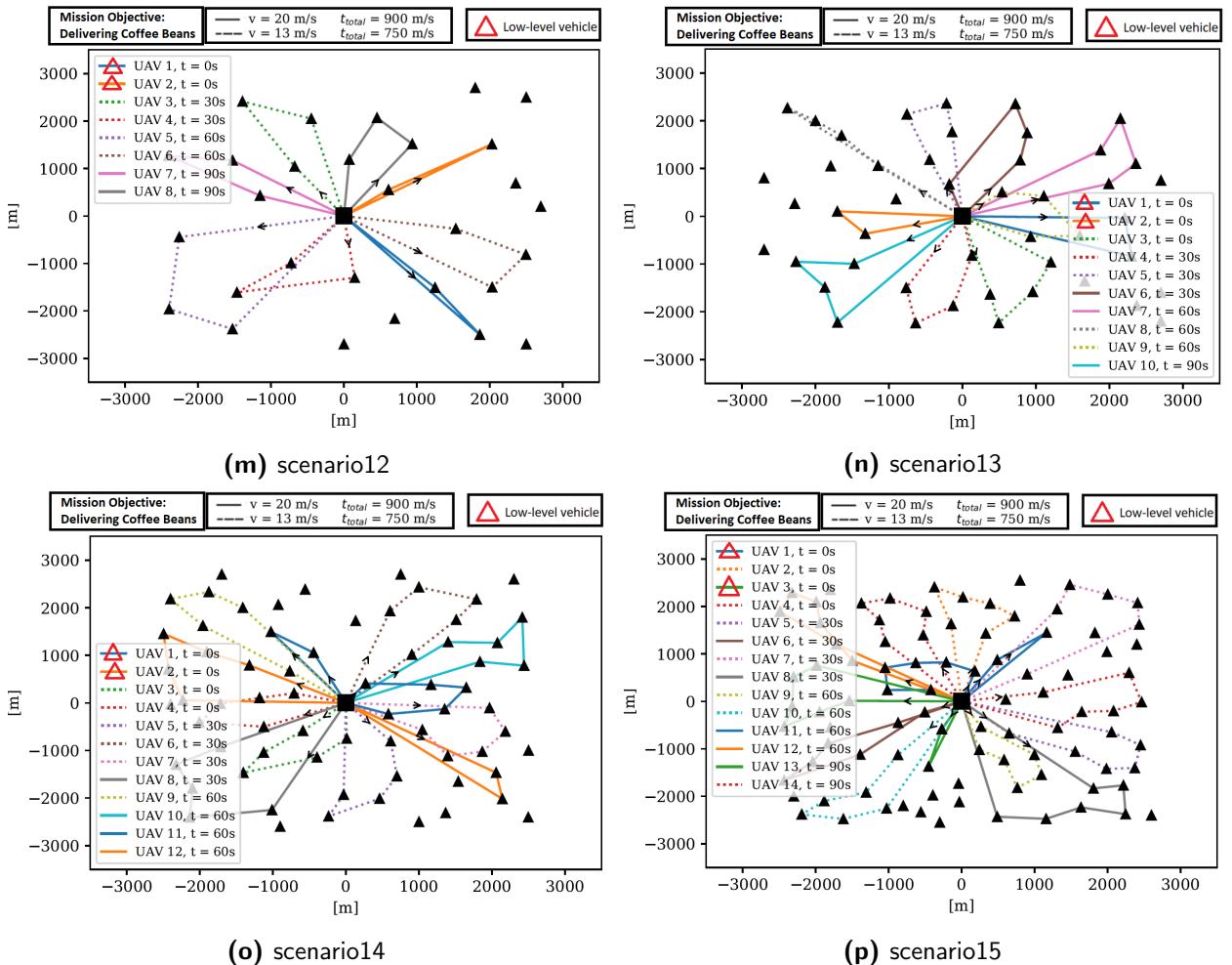


Figure B-2: Experiment scenarios (continued)







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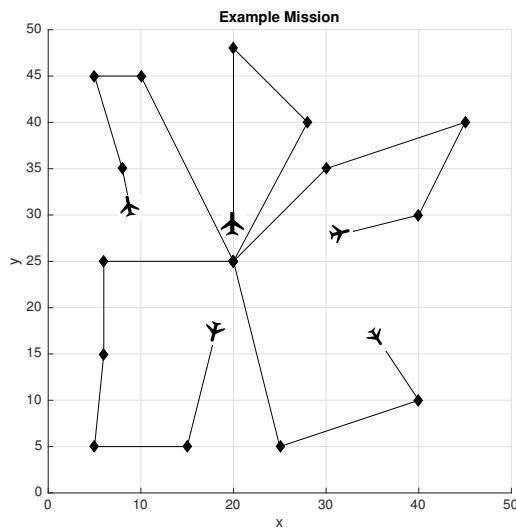
## Appendix C

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# Experiment Briefing

### C-1 Introduction

Thank you for participating in this experiment! The goal of this experiment is to investigate human control performance for an over-constrained multi-UAV (Unmanned Aerial Vehicle) dynamic vehicle routing problems (DVRP) in varying mission objectives. Consider a scenario in which payload needs to be delivered to customer locations using multiple payload carrying UAVs. The vehicles all start and end their flight at the depot. The assignment of all the customer locations to specific vehicles is the essence of the VRP. Figure C-1 shows a visual representation of an example mission.



**Figure C-1:** Example mission of a multi-UAV vehicle routing problem, with the depot at the center (20;25), 5 vehicles and 14 customer locations.

*In this experiment, it is your task to mitigate the effects caused by battery defects and additional customers causing it to be an over-constrained problem during several multi-UAV payload delivery missions.*

You will be presented with several VRP scenarios in which there will be vehicles present with battery defects, additionally, there will be presence of extra customers within the location. These unassigned locations will somehow have to be included in the flightplans of the remaining vehicles, while considering the constraints (flight time, payload capacity and depot capacity). However, due to the presence of dynamic situations and the limited number of vehicles, it would not be possible to satisfy all constraints while assigning payload to all the customers, thus making the problem over-constrained. So, it is your decision on which constraints to relax or what is priorities by you (providing payload to customers, or ensuring a safe arrival of the UAVs or a combination of both) in different missions.

Please consider the following goals during the execution of your control task:

**1. Optimize all UAV routes for shortest distance.**

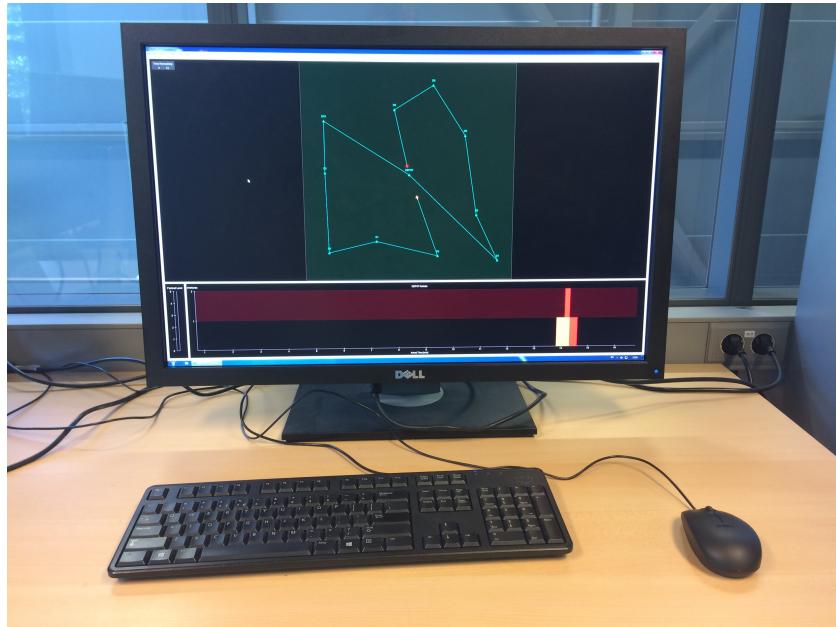
The experiment starts with a number of training scenarios, which allow you to familiarize yourself with the control task and the interface. At the end of each scenario you will fill out the web-survey. You are also asked to fill out the web-survey for a large portion of the training scenarios to familiarize yourself with the usage of this tool.

*Note: each scenario is time limited to 5 minutes, which means you only have limited time to identify and execute an updated routing.*

An explanation of the experiment setup is up next, followed by a review of the training scenarios, which you will use as a guide to follow along. If you have any questions when reading the subsequent chapters or during the training phase of the experiment, please do not hesitate to ask!

## C-2 Experiment Setup

The interface you will use consists of three distinct windows: the map view, the payload view and the timeline view. Additionally, there is also a battery view that is available when clicked on a certain vehicle. Each of these windows show relevant information for successful execution of your control task. Figure C-2 shows a visual representation of the interface and experiment setup you will use.



**Figure C-2:** Experiment setup consisting of keyboard, mouse, display and desktop PC (not shown).

The map view (as depicted in Figure C-3b and Figure C-3e) shows all UAVs, their routes and all customer locations. Also, after selecting a vehicle, the area that is within range given the available flight time is shown. If relevant, superimposed on this view is the area that needs to be avoided when the depot capacity is exceeded. This will help you in determining the required path stretching to introduce sufficient delay to solve the depot conflict.

The payload view (as depicted in Figure C-3a and Figure C-3d) shows the remaining payload for the selected vehicle. It will also show this information when hovering over a UAV without selecting it. When zero payload remaining is reached and when insufficient payload is available for successful mission execution, a corresponding textual warning will appear. Also, the color of the payload level indicator corresponds to the UAV color in the map view display.

The timeline view (as depicted in Figure C-3c and Figure C-3f) shows the arrival times of all vehicles at the depot. After arrival at the depot, UAVs require a 30 second service window. Due to constraints at the depot, the amount of vehicles allowed to arrive at the same time is limited. This ensures a safe arrive of the vehicle to the depot. This constraint is indicated by the red zone in the timeline view. Also, the color of the arrival block corresponds to the color associated with the payload level.

Lastly, the battery view (as depicted in Figure C-4) appears when selected on a certain vehicle.

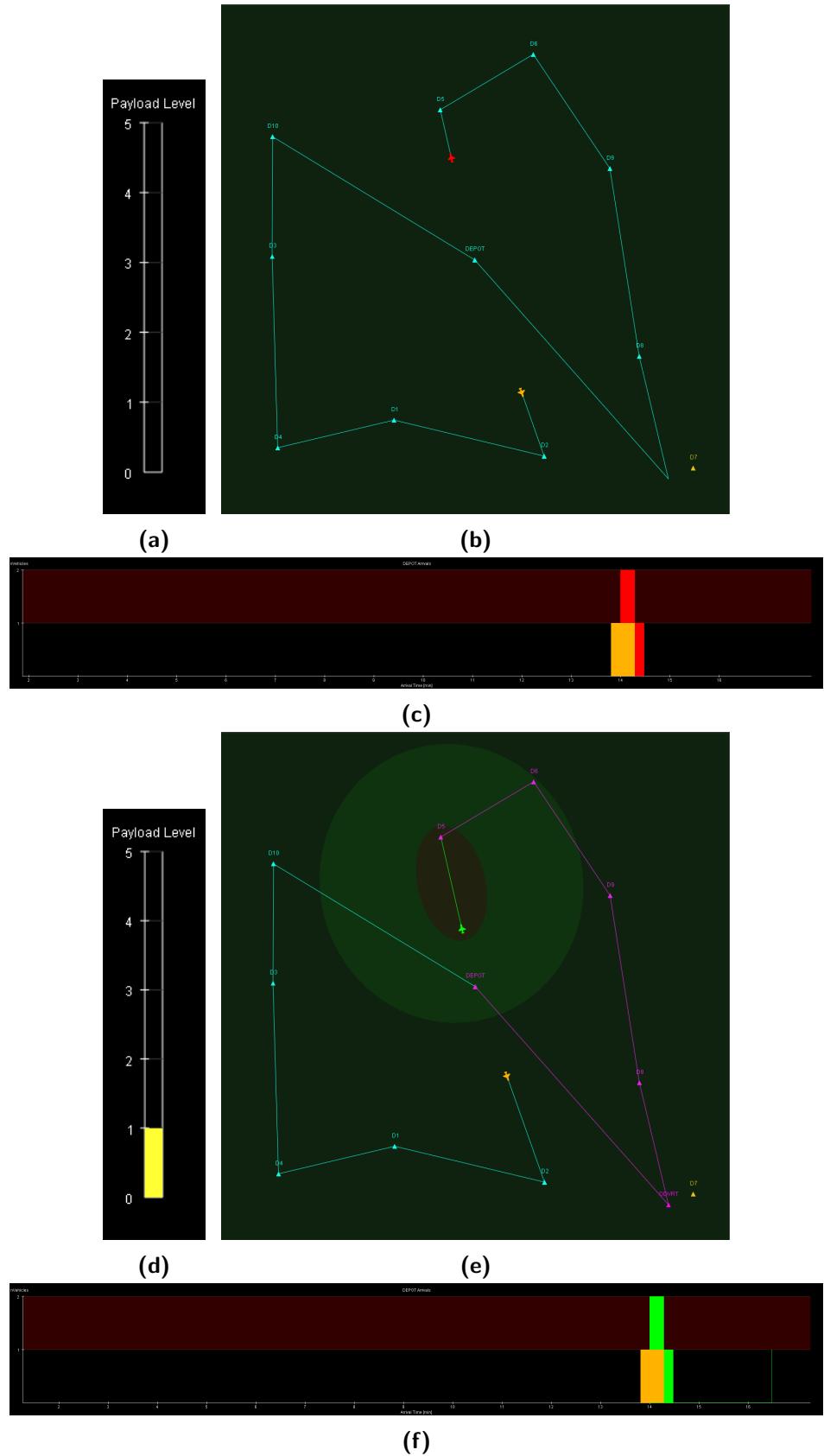
The icon shows the battery level that is currently available with the height of the coloured column provided. The dashed lines at the lower positions indicate the level of battery that is available after delivering to a respective customer. The level below the red line indicates the amount of battery that is still available after the vehicle reaches the depot. When adding or removing a certain customer, the battery will display an updated battery indication. Also, when hovering over a certain location in the battery, the indicated flight plan will lighten up. Green represents a good status of the battery, and red indicates that there will not be sufficient battery to reach the customer at all (as depicted in Figure C-5).

The following control inputs are available for you to interact with the interface:

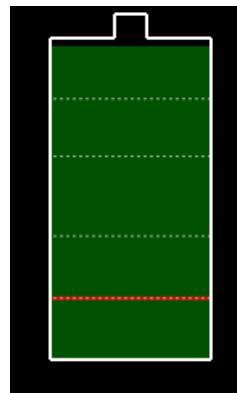
- $P$ : start scenario
- *LMB click*: select UAV / select leg
- *RMB click*: deselect UAV / deselect leg / discard FLTPLN change
- *Enter*: confirm FLTPLN change
- *CTRL + LBM click + leg selected*: add WPT
- *CTRL + LBM click + UAV selected*: remove WPT

The following colors are used in the interface:

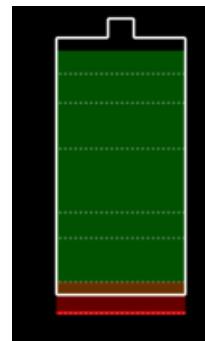
- *Grey*: flightplan and customer locations associated with UAV that is to depart the depot in the future.
- *Cyan*: flightplan and customer locations associated with inactive UAV.
- *Magenta*: flightplan and customer locations associated with active UAV.
- *White*: flightplan and customer locations associated with active and modified UAV flightplan.
- *Green*: selected UAV.
- *Amber*: unvisited customer locations.
- *Red*: infeasibility due to insufficient available flight time, payload or depot capacity.
- *Green*: (on battery view): Sufficient battery to reach the customers
- *Several shades of yellow* (on payload view): UAV payload level.



**Figure C-3:** Interface views for an example inactive and active UAV case.



**Figure C-4:** battery indication that shows when clicking on a certain vehicle



**Figure C-5:** Insufficient battery to complete the last leg

### C-3 Training Scenarios

You will now go through a number of training scenarios to familiarize yourself with solving dynamic vehicle routing problems and with the use of the interface. Please double-click on the “UAV-sim” icon on the desktop, fill out your participant ID, press “Enter”, and maximize the screen.

### C-4 Training 1: Flight Time Constraint

Observe the cyan colored depot in the center of the map view, the three amber colored unassigned customer locations and the dashed gray colored flightplan with customer locations associated with a UAV that is to depart the depot in the future in the bottom left.

» Click inside the map view and press “P”.

Observe the gray flightplan with associated customer locations now turn cyan, indicating a flying UAV.

» Select (LMB) the UAV.

Observe the payload level in the payload view and the flight time available in both the map and timeline view (green vertical line depicts latest feasible depot arrival time). Also, observe the battery in the UAV, and the available battery that is left in the vehicle. Observe the reduction in battery with time. Now incorporate customer location D4 that lies within range into the flightplan.

» Select (LMB) a specific flightplan leg.  
 » Add (CTRL + LMB) the customer location D4.  
 » Click (Enter) to confirm the changed flightplan.

Adding a customer to the flightplan is also updated in the battery icon to observe the quantity that is left after. Now also incorporate the other unvisited customer location D5 into the flightplan.

» Select (LMB) the UAV.  
 » Select (LMB) a specific flightplan leg.  
 » Add (CTRL + LMB) the customer location.

Observe, the red leg, indicating the UAV will not be able to fly back from the last customer to the depot location. This can be seen in the battery view too, as there is not sufficient energy left. This means that even though the last customer will get the payload, however, the UAV will die off at a point before the depot.

- » Confirm (Enter) the changed flightplan.

Observe, the same red leg, but now also the red UAV icon and the red arrival block indicating an infeasibility. Proceed to remove the last customer location from the flightplan.

- » Select (LMB) the UAV.
- » Remove (CTRL + LBM) the last waypoint.
- » Confirm (Enter) the changed flightplan.

Lastly, add Customer D6. The waypoints can also be selected through the **battery icon**

- » Select (LMB) the UAV.
- » Hover the mouse over a specific block over the battery to observe the flightplan leg it is associated with.
- » Select (LMB) a specific block on the battery which displays the flightplan leg which is closest to the Customer D6.
- » Add (CTRL + LMB) a waypoint at any desired location.
- » Deselect (RMB) the UAV.

Observe the changes made to the flightplan now being discarded. Observe, the battery indicator which shows that there is sufficient battery to reach this customer, also indicated by the green eclipse which gives the range of the vehicle.

Please now close the simulator. Double-click on the “UAV-sim” icon on the desktop, fill out your participant ID, press “Enter”, and maximize the screen to get set up for the next training scenario.

## C-5 Training 2: Payload Constraint

This scenario is similar to the previous one. Observe the single gray UAV flightplan and unassigned customer locations.

- » Click inside the map view and press “P”.
- » Include all unassigned customer locations in the UAV flightplan.

Observe, after including the last unassigned customer location into the UAV flightplan, the waypoint color change to red. Also note the red UAV icon color and red arrival block indicating an infeasibility.

- » Hover over the UAV and notice the textual warning in the payload view.

- » Remove one of the customer locations from the flightplan, to make it feasible again.
- » Remove some more customer locations from the UAV flightplan.

Notice the payload level indicator come up. Also notice the change of color of the UAV icon, the payload level indicator, and the arrival block to more and more brighter shades of yellow.

Please now close the simulator and re-open it to get set up for the next training scenario.

## C-6 Training 3: Depot Congestion

Observe the gray UAV flightplans, the payload capacity and the depot arrival constraint.

- » Click inside the map view and press “P”.

Notice the red UAV icon and the red arrival block.

- » Select the red arrival block in the timeline view.
- » Select the last flightplan leg (the one connected to the depot) in the map view.

Observe the green zone around the flightplan leg.

- » Place a waypoint inside the zone.
- » Select the UAV and the leg again and place a waypoint in this zone.

Notice how the zone helps you to introduce sufficient path stretching to solve the conflict. It is also possible to solve depot arrival infeasibilities by rearranging customer locations within a flightplan or by exchanging customer locations between UAVs.

Be aware that the Depot capacity may defer in each of the scenarios

Please now close the simulator and re-open it to get set up for the next training scenario.

## C-7 Training 4: Different vehicle icons

Now that you are familiar with using the interface, observe the use of the different icons used for the vehicles. When you click on the vehicles, you can observe the different battery capacity that is present in the vehicle. As a result, this effects the maximum reach of the vehicle. Also, the different icon size signify a difference in the speed. This experiment will use two different icons. The bigger icon means that the vehicle will have a higher battery capacity (max. battery capacity = 900 sec and vehicle speed = 20 m/s) and speed than the other one (max. battery capacity = 750 sec and vehicle speed = 13 m/s).

» Click inside the map view and press “P”.

Observe the different speeds at which the vehicle is moving. Additionally, the maximum reach of the two vehicles, when clicking on the icon.

» Include all unassigned customer locations in the UAV flightplan.

Note that even though the flightleg of the two vehicles are similar, due to the difference in the battery capacity, one of the vehicle is not able to provide the payload to the customer.

Please now close the simulator and re-open it to get set up for the next training scenario.

## **C-8 Training 5: Over-constrained DVRP problem**

It is time to solve the first over-constrained DVRP. This means that it is not possible to be able to satisfy all customers, while following all the constraints. So in this case, one or more constraints have to be relaxed in order to achieve your goal.

» Click inside the map view and press “P”.

Observe that, even though the two vehicles have the same icon, they have different levels of battery. This is due to the battery defect that may occur during the mission.

» Incorporate all unassigned customer locations in the flightplans of the remaining UAVs.

Observe that even though the vehicle is providing the payload to the customer, one of the vehicle will not have enough battery to reach the depot, thus permanently damaging the vehicle. Observe that the customer will be served, but it will not ensure a safe arrival to the depot.

The decision to relax which constraint to keep or let go depends on you. This may also be affected by the mission given to you too. Try out different combinations that is possible within the scenario.

Please now close the simulator and re-open it to get set up for the next training scenario.

## **C-9 Training 6: Search & Rescue**

Your results may depend on the mission that is given to you. Observe the grey box on the top left of the screen. Before starting any experiment, please see this box to know the mission that is given to you.

In this case, you can observe, ”Search & Rescue”. So consider this mission when you are making changes in the flight plan:

- » There has been an avalanche in the mountains, and there are people stuck in the area around. A Search & Rescue team is then called upon to rescue the victims. However, in the mean time, the team is providing the victims with some basic necessities, such as medicine, food and water to be able to help them survive longer. This is done through very expensive UAVs provided

With keeping this in mind, now try working on the training.

- » Click inside the map view and press “P”.

Make the necessary changes according to you.

When you are satisfied with the new routing you created,

- » Close the simulator.
- » Fill out the web-survey.
- » Start the simulator.

## C-10 Training 7: Delivering Coffee beans

Here is another mission that is given to you, as observed in the grey box. Remember to always check this grey box during the experiment.

In this case, you can observe, ”Delivery coffee beans”. So consider this mission when you are making changes in the flight plan:

- » Every morning, a company delivers fresh coffee beans to various customers around the area. This delivery is done through the use of expensive UAVs.

With keeping this in mind, now try working on the training.

- » Click inside the map view and press “P”.

Make the necessary changes according to you.

- » Close the simulator.
- » Fill out the web-survey.
- » Start the simulator.

## C-11 Training 8- 9: Overconstrained DVRP

It is now time to solve more over-constrained DVRP.

» Click inside the map view and press “P”.

Try the different combinations possible within the scenario. You may prioritise the safety of the vehicles (thus ensuring that they reach the depot and maintain the depot constraint), while not satisfying all customers. Or, prioritise the delivery of the payload (thus ensuring that the payloads reach the customer, while damaging the vehicles). Or, a combination of both.

When you are satisfied with the new routing you created,

» Close the simulator.

» Fill out the web-survey.

» Start the simulator.

***You are now ready to start the experiment! Remind yourself of the goals of your control task and the 5 minute time limit on the scenarios. Also, please do not close the simulator before the timer is at zero. Good luck!***

Reminder:

- *P*: start scenario
- *LMB click*: select UAV / select leg
- *RMB click*: deselect UAV / deselect leg / discard FLTPLN change
- *Enter*: confirm FLTPLN change
- *CTRL + LBM click + leg selected*: add WPT
- *CTRL + LBM click + UAV selected*: remove WPT

Do not forget to press **Enter** after each updated flightplan



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## Appendix D

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# Experiment Survey

To process the participant survey, a web form was made for them to fill out. There were three forms created. 1) The intake survey - the survey which provides information about the participant, and tests their problem-solving ability, 2) the post-scenario survey - this survey was provided after a few of the training scenarios and all the experiment scenario, and 3) post-experiment survey - this is the survey given to the participants at the end of the experiment to be able to get a feedback. The survey was provided to the participant in a web browser. It was run through a local web server and made through PHP. The form was able to output the result per participant. This chapter displays a survey that was given to the participants.

## D-1 Intake Survey

10/10/2019

Experiment Survey | A. Gupta

# Human performance in solving over-constrained multi-UAV dynamic vehicle routing problem in different mission objectives

Please fill out your participant ID.

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localhost/index.php

1/1

10/10/2019 Experiment Survey | A. Gupta

### Human performance in solving over-constrained multi-UAV dynamic vehicle routing problem in different mission objectives

Please fill out the following questions.

Age:

Gender:

Male  Female

Language:

Dutch  English

Do you consider yourself a regular video game player?

No  Yes

Q1: Which of the bottom figures should logically take the place of the question mark in the upper set?

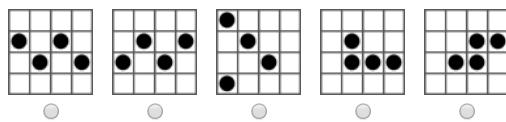
Q2: Which of the bottom figures should logically take the place of the question mark in the upper set?

127.0.0.1/intake.php?plD=4

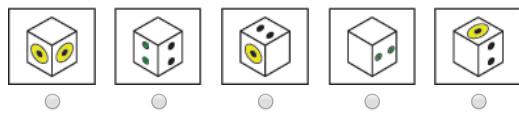
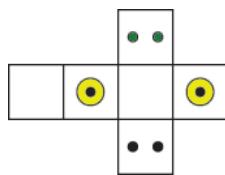
1/3

10/10/2019

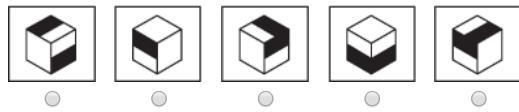
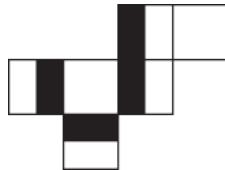
Experiment Survey | A. Gupta



Q3: Which cube results when folding the unfolded cube?



Q4: Which cube results when folding the unfolded cube?



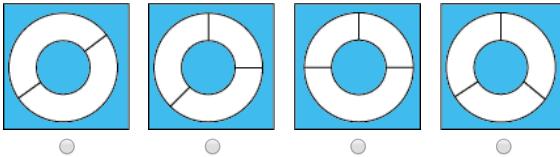
Q5: Which of the bottom figures can be composed of the individual parts?



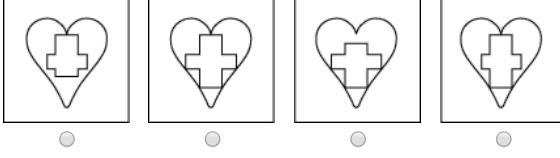
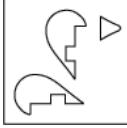
127.0.0.1/intake.php?pID=4

2/3

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Q6: Which of the bottom figures can be composed of the individual parts?



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127.0.0.1/intake.php?pID=4

3/3

## D-2 Post Scenario Survey

10/10/2019 Experiment Survey | A. Gupta

**Human performance in solving over-constrained multi-UAV dynamic vehicle routing problem in different mission objectives**

Please fill out the Rating Scale Mental Effort.

A vertical rating scale for mental effort. The scale ranges from 0 at the bottom to 150 at the top, with major tick marks every 10 units. To the right of the scale, nine levels of effort are listed, each associated with a horizontal dashed line that corresponds to a specific value on the scale. The levels are: extreme effort (115), very great effort (105), great effort (95), considerable effort (75), rather much effort (65), some effort (45), a little effort (35), almost no effort (15), and absolutely no effort (5). A small orange vertical bar is positioned to the left of the scale, starting at approximately 75 and extending upwards to 150.

Effort Level	Rating Scale Value
extreme effort	115
very great effort	105
great effort	95
considerable effort	75
rather much effort	65
some effort	45
a little effort	35
almost no effort	15
absolutely no effort	5

127.0.0.1/rsme.php?lang=1&piID=4&run=1 1/2

10/10/2019 Experiment Survey | A. Gupta

Please fill out the following questions.

Please give an estimate of the relative amount of time you spent interacting with the 4 display elements (0-100%, total 100%).

Map View

Timeline View

Payload View

Battery View

Please rank the given constraints according to their importance by you (Rank 1 is the highest)

Payload Constraints

Flight time limit

Depot Capacity

Payload constraints: Serving as many customers as possible by using the limited payload of the vehicle.  
Flight time limit: Respecting the battery limit of the vehicle. Thus ensuring to have enough battery to reach the depot safely.  
Depot Capacity: Ensuring a safe arrival and departure of the vehicle to the depot by having a time interval.

How would you describe the way you came up with a solution for the scenario?

Satisfice  Optimize

Satisfice: achieving a solution that achieves your overall goal.  
Optimize: achieving the best solution to achieve your overall goal.

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2/2

### D-3 Post Experiment Survey

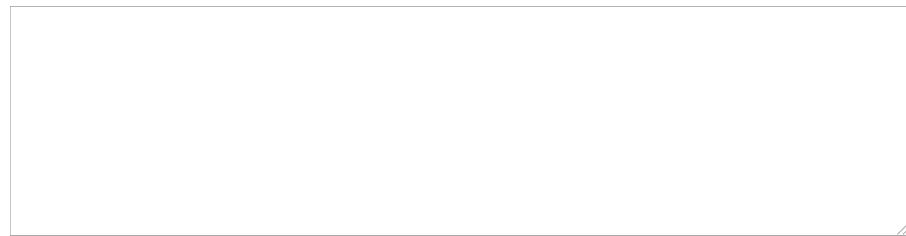
10/10/2019

Experiment Survey | A. Gupta

#### **Human performance in solving over-constrained multi-UAV dynamic vehicle routing problem in different mission objectives**

Please fill out the following questions.

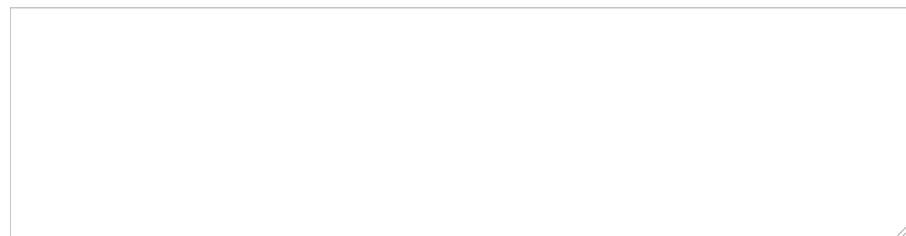
How do you assess the usefulness and the functionality of the map view?  
Please provide examples in your elaboration.



How do you assess the usefulness and the functionality of the timeline view?  
Please provide examples in your elaboration.



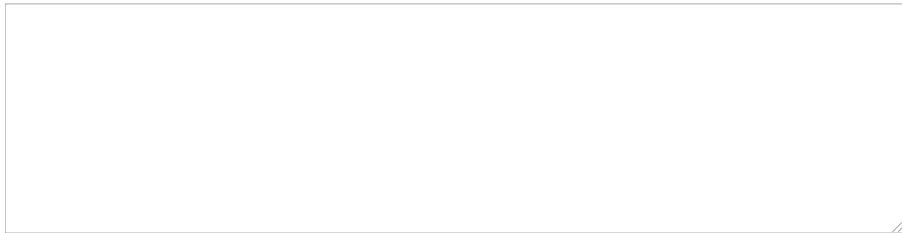
How do you assess the usefulness and the functionality of the payload view?  
Please provide examples in your elaboration.



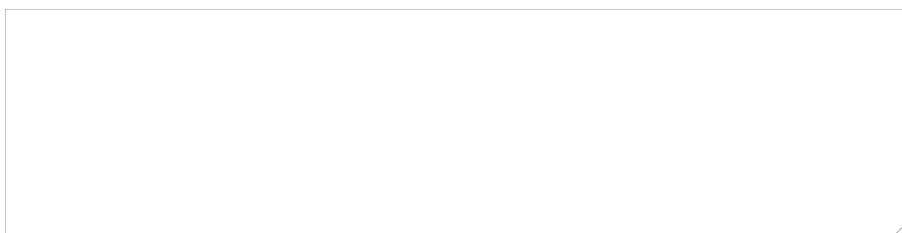
How do you assess the usefulness and the functionality of the battery view?  
Please provide examples in your elaboration.

10/10/2019

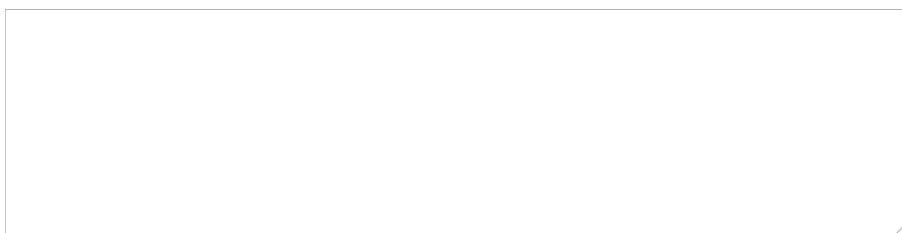
Experiment Survey | A. Gupta



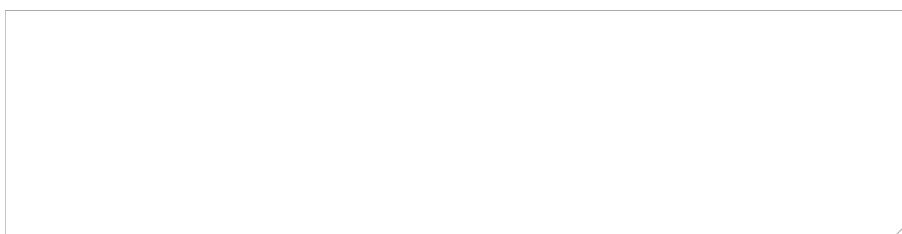
How do you assess the usefulness and clarity of the color use in the display?  
Please provide examples in your elaboration.



How do you assess the usefulness and clarity of the use of different icons to signify the different UAV type in the display?  
Please provide examples in your elaboration.



Do you have any other comments or suggestions with respect to the interface or the experiment?



10/10/2019

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## Appendix E

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# Experiment Results

### E-1 Participant Characteristics

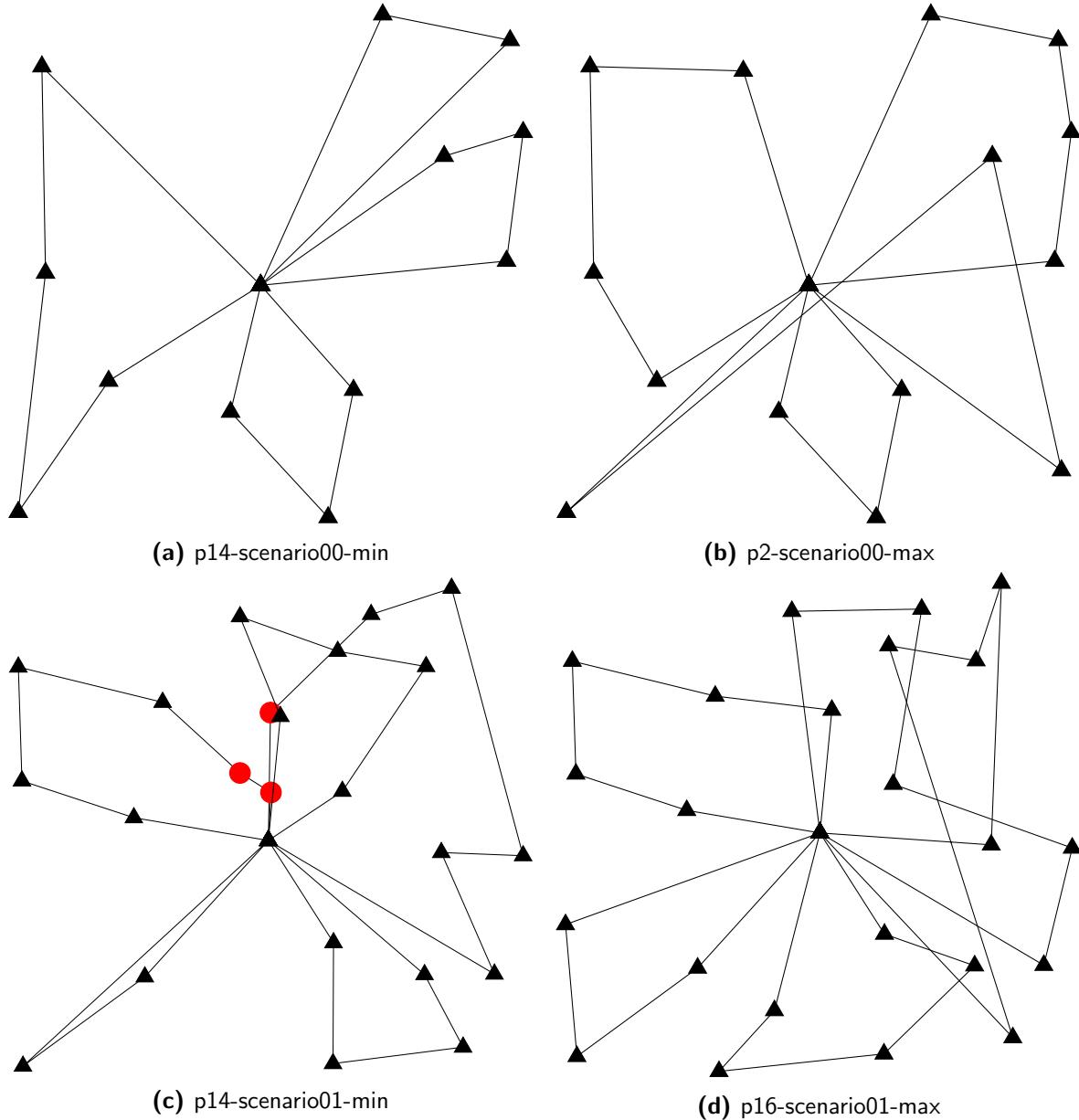
Table E-1 summarizes the information provided by the participants in the experiment. This information is obtained through the intake survey.

**Table E-1:** Participant Characteristics

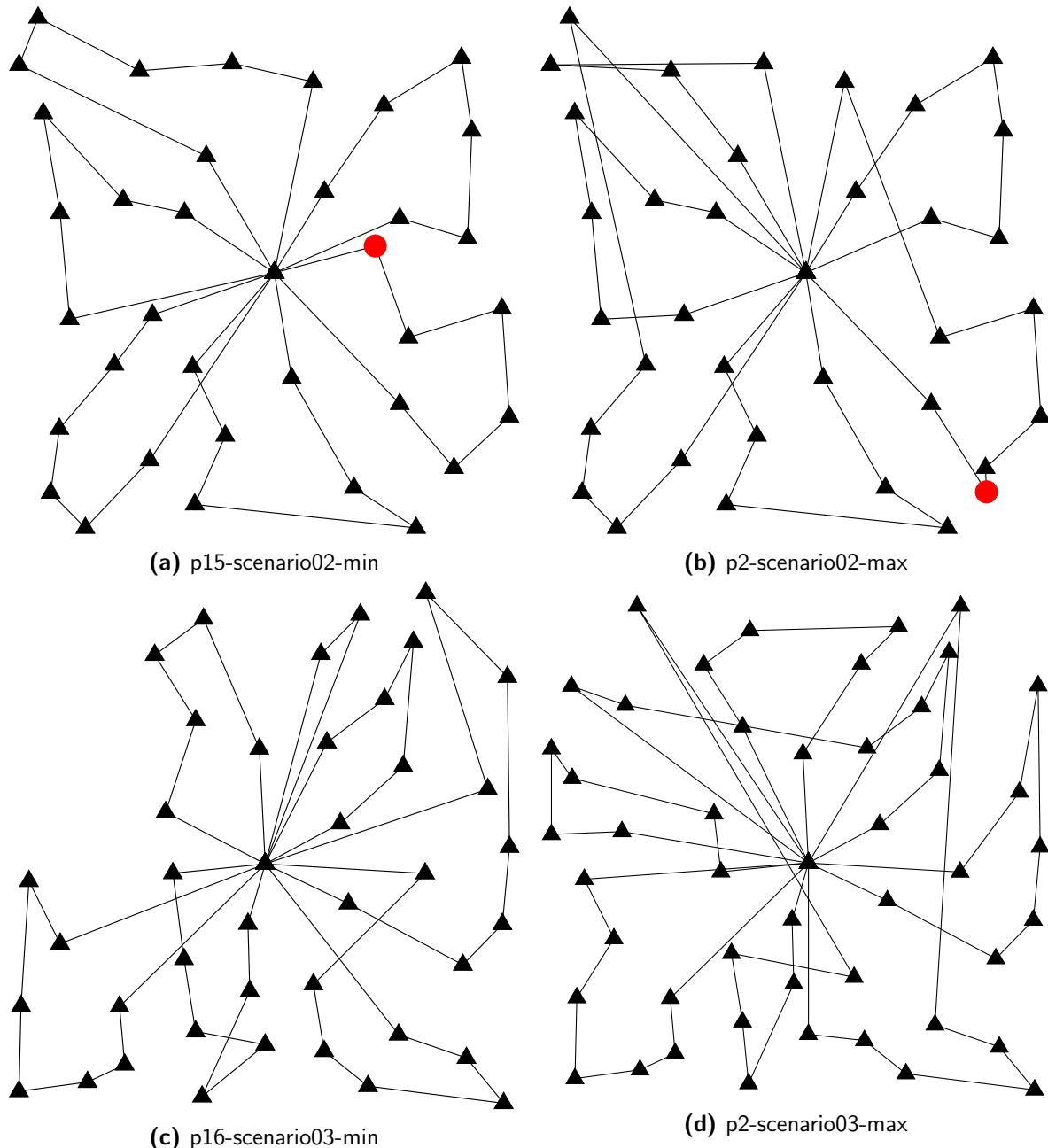
	Age	Gender	Language	Gamer	Test Score	Test Time (s)
P1	23	Male	English	True	6	251
P2	22	Female	English	False	5	262
P3	23	Male	English	True	4	130
P4	24	Male	English	True	5	357
P5	26	Male	Dutch	True	6	277
P6	23	Male	English	False	3	529
P7	24	Male	English	False	6	217
P8	23	Male	English	False	6	296
P9	24	Female	English	True	5	314
P10	24	Male	English	False	6	264
P11	52	Male	Dutch	False	4	181
P12	23	Male	Dutch	True	6	202
P13	28	Male	English	True	4	322
P14	24	Male	English	False	2	296
P15	23	Male	English	False	4	540
P16	23	Male	English	True	4	508

## E-2 Particular Participant Solution

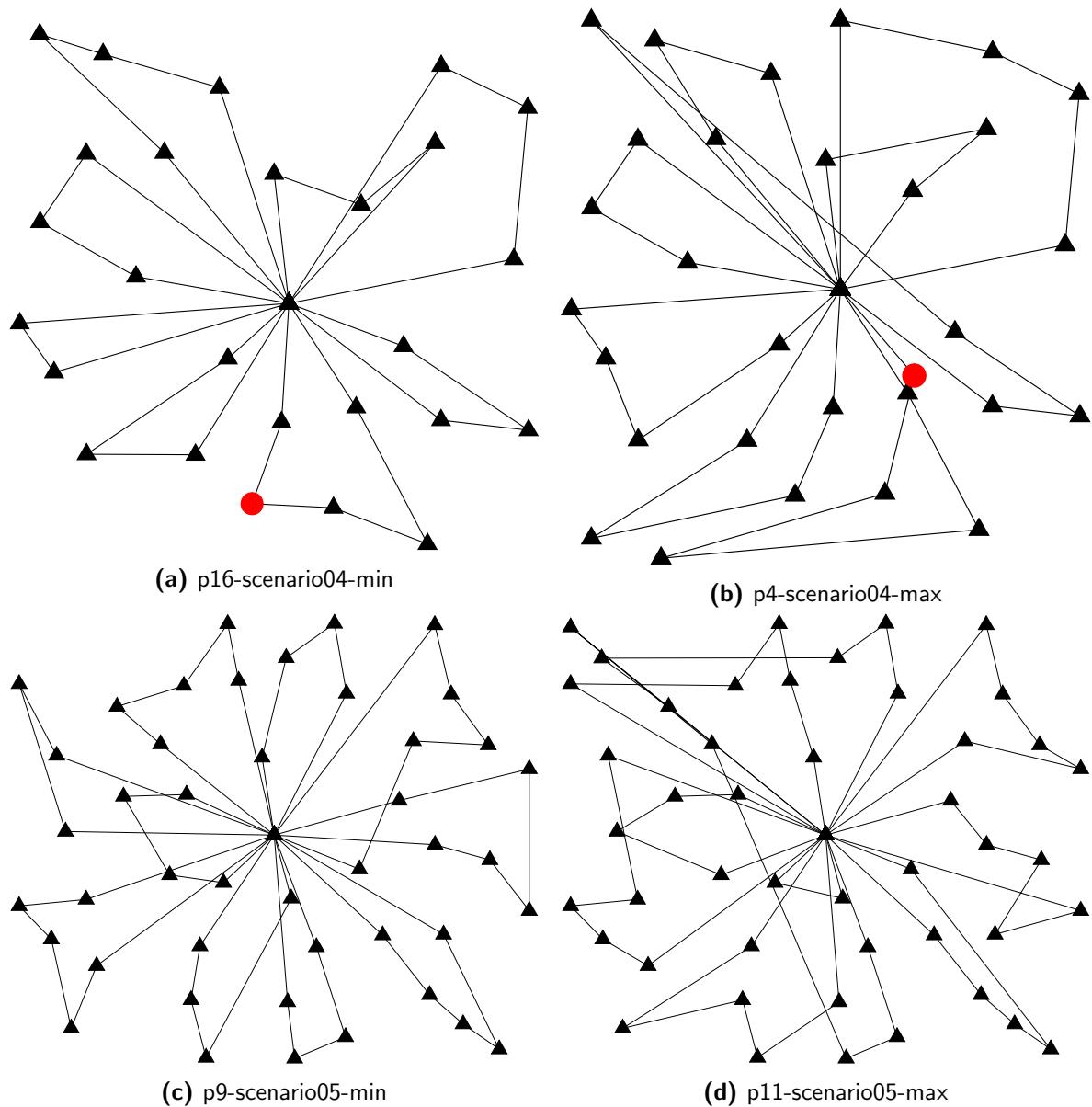
This section displays the participant solution for the maximum and minimum travelled distance for the participants. The figures only display the routes chosen by the participants, and do not visualise the constraints.



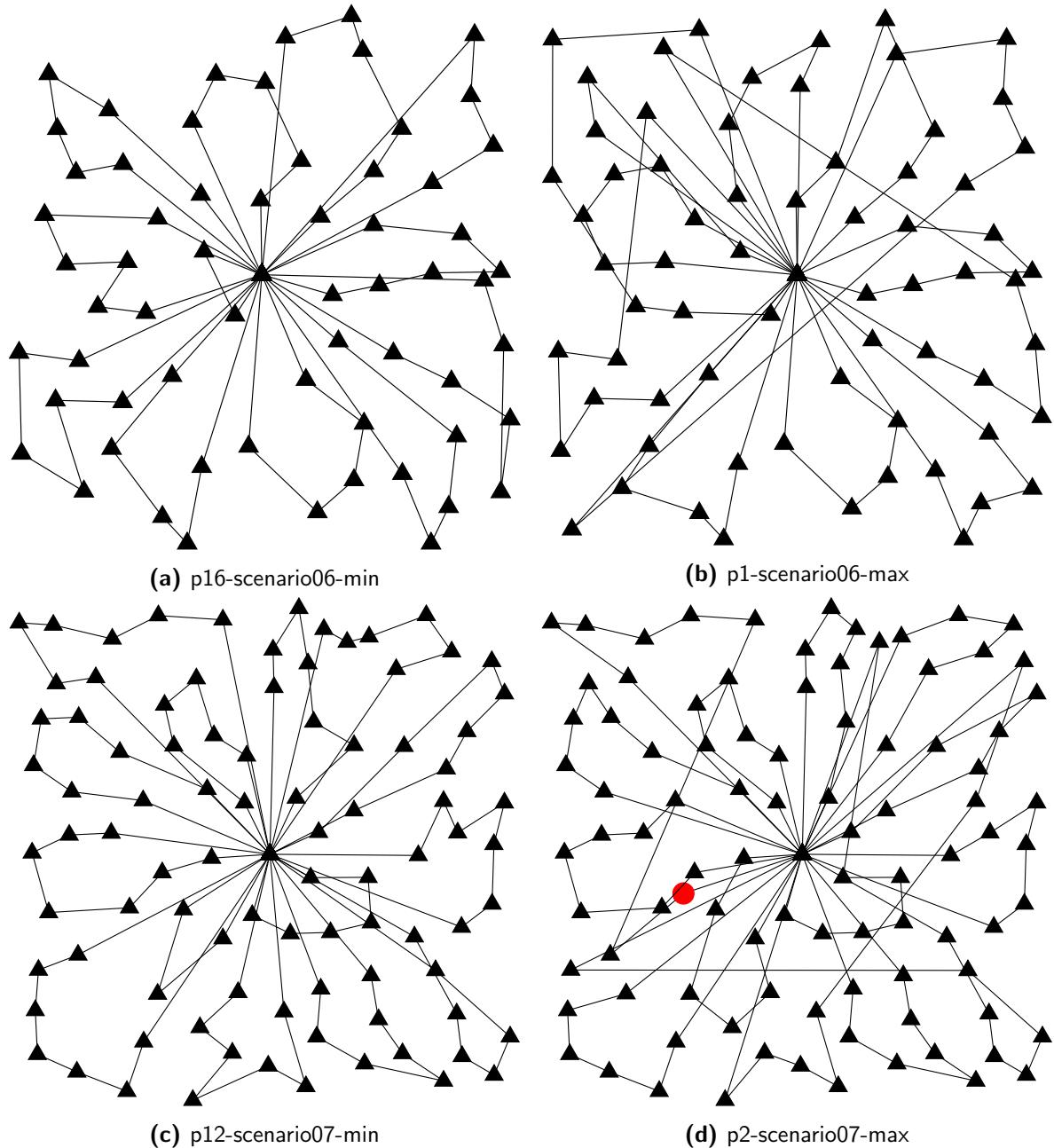
**Figure E-1:** Participant solution



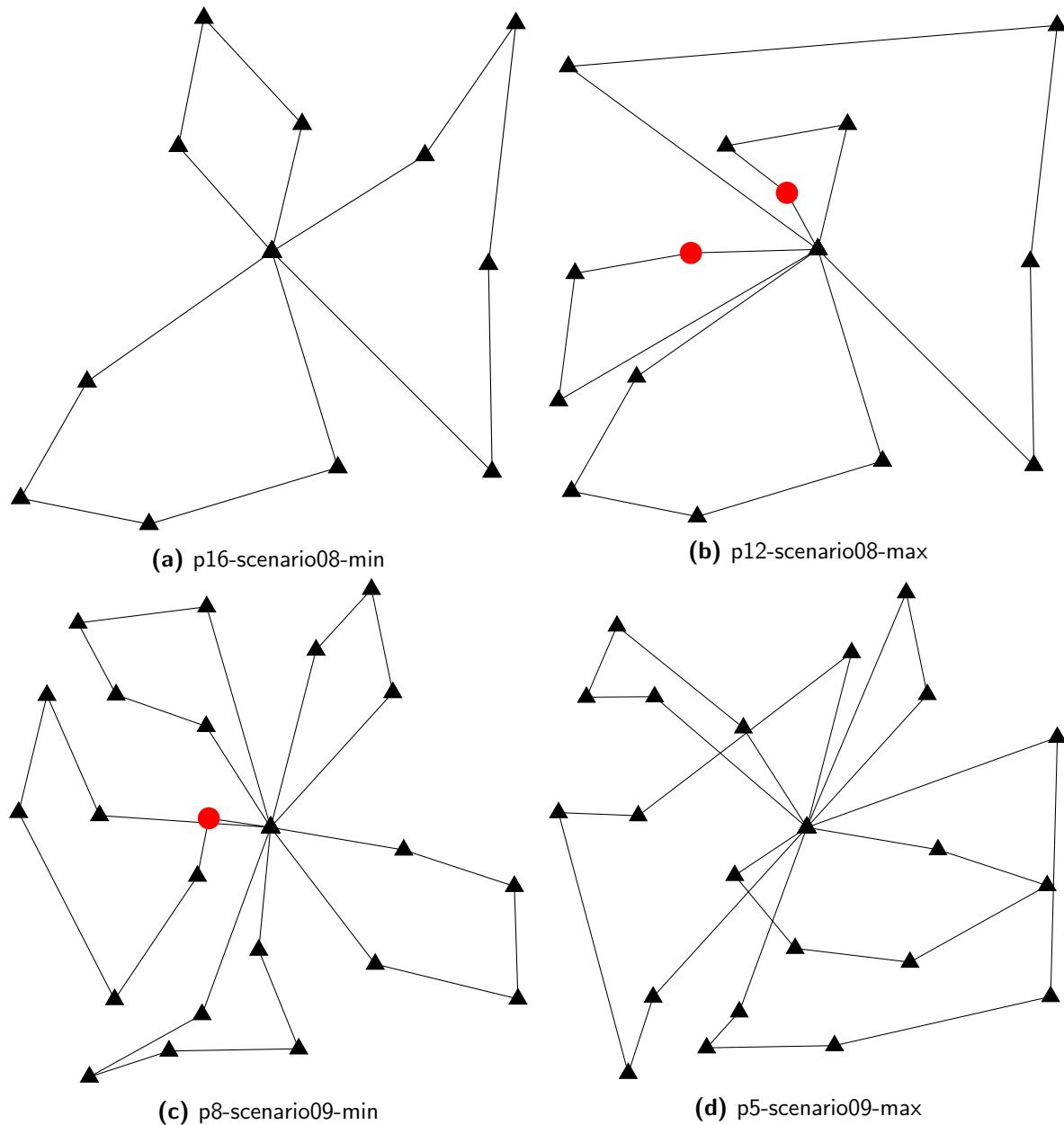
**Figure E-2:** Participant solution (continued)



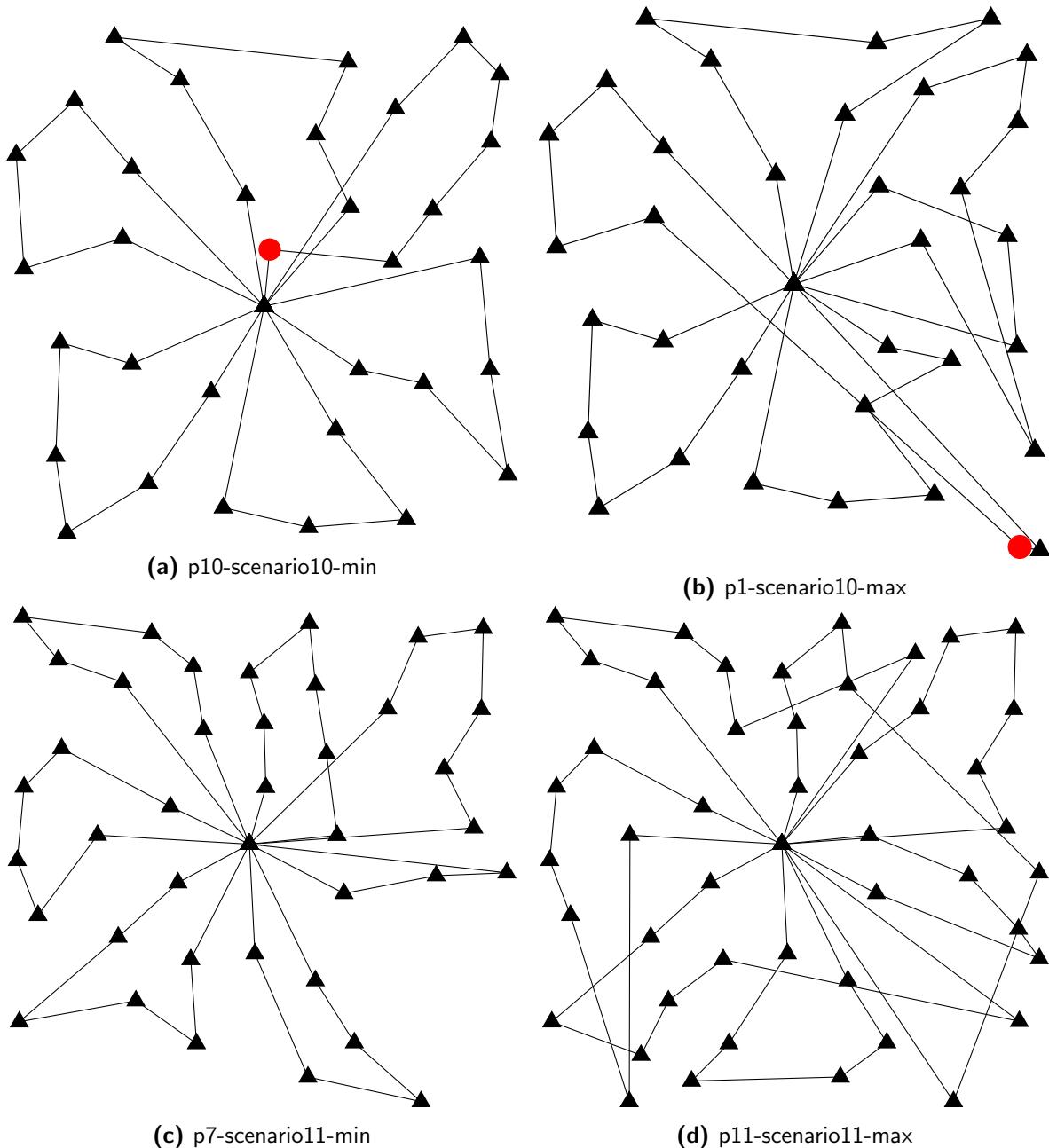
**Figure E-3:** Participant solution (continued)



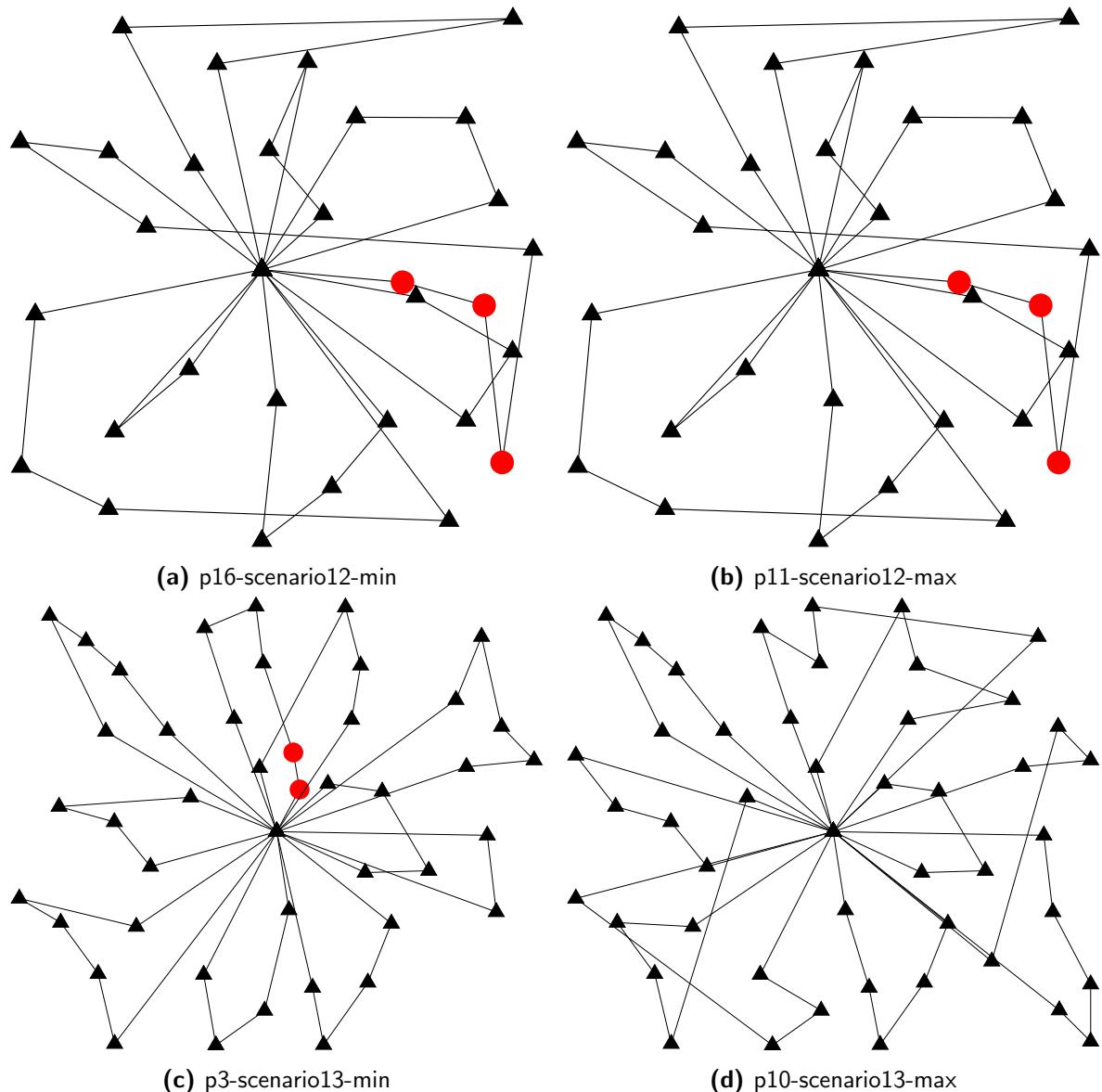
**Figure E-4:** Participant solution (continued)



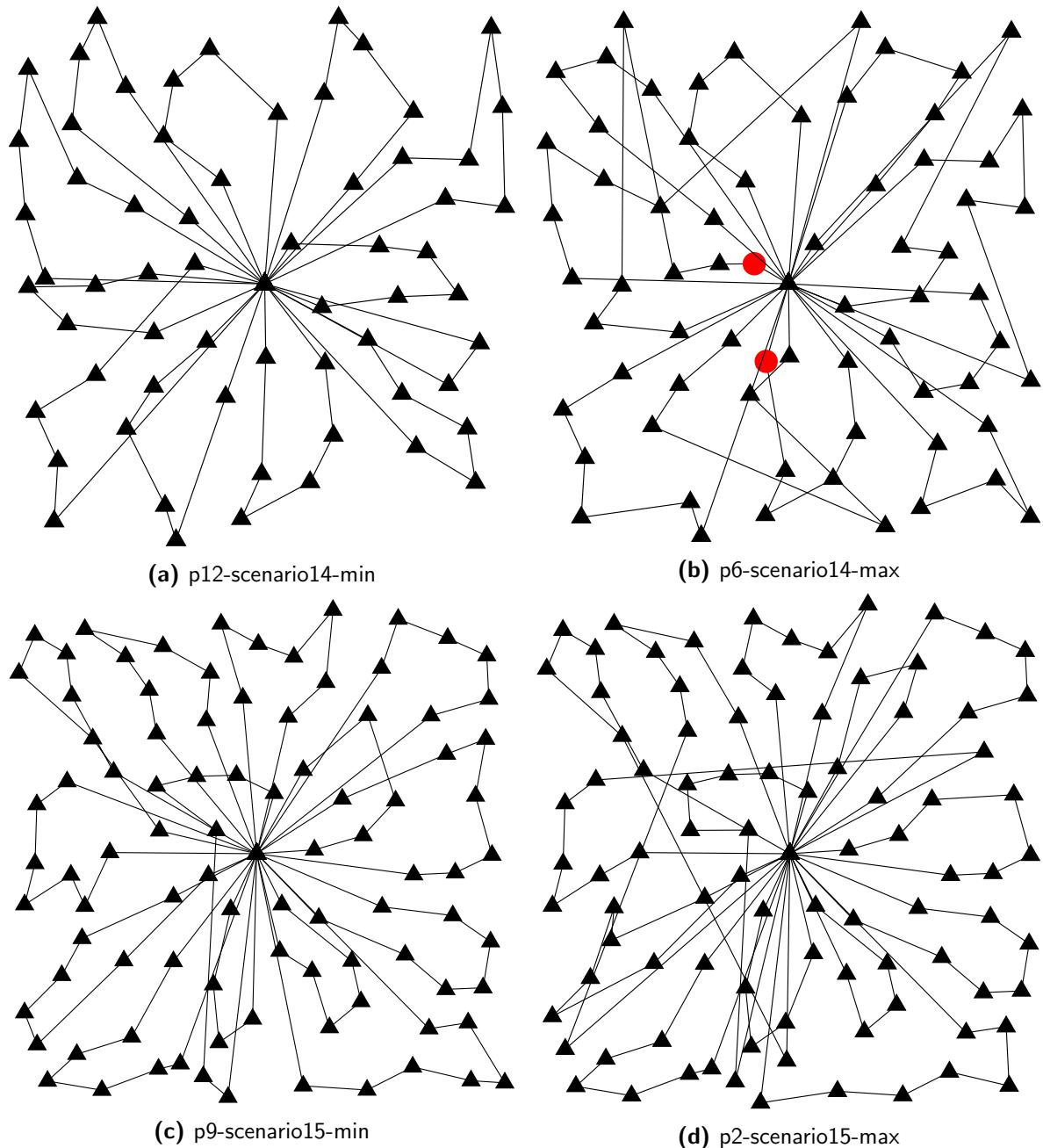
**Figure E-5:** Participant solution (continued)



**Figure E-6:** Participant solution (continued)



**Figure E-7:** Participant solution (continued)



**Figure E-8:** Participant solution (continued)

### E-3 Post-Survey Participant Feedback

This section lists all comments obtained from participants in the post-survey. The following questions were asked:

1. How do you assess the usefulness and the functionality of the map view? Please provide examples in your elaboration.
2. How do you assess the usefulness and the functionality of the timeline view? Please provide examples in your elaboration.
3. How do you assess the usefulness and the functionality of the payload view? Please provide examples in your elaboration.
4. How do you assess the usefulness and the functionality of the battery view? Please provide examples in your elaboration.
5. How do you assess the usefulness and clarity of the color use in the display? Please provide examples in your elaboration.
6. How do you assess the usefulness and clarity of the use of different icons to signify the different UAV type in the display? Please provide examples in your elaboration.
7. Do you have any other comments or suggestions with respect to the interface or the experiment?

The comments of the participants can be found in Table E-2, Table E-3, Table E-4, Table E-5, Table E-6, Table E-7 and Table E-8.

**Table E-2:** Q1: How do you assess the usefulness and the functionality of the map view? Please provide examples in your elaboration.

Participant	Comment
P1	The map view is useful in rerouting the drone/flight path in terms of payload and battery. So for instance the payload and the battery helps one in selecting destinations close or far away from the depot. Could do with more screen area.
P2	The map view was clear enough for the task. The colors used (indicating the payload left and the possibility to return to the depot) were very useful.
P3	map view was useful in providing me with an overview of all the UAV's and all the points of delivery. Could quickly devise a plan based on where everything was located
P4	The map view shows a good overview of the airspace through the use of a dark neutral background and bright highlight colors.
P5	The colours in the map view made it easy to distinct when aircraft were out of battery.
P6	Useful - hints displays waypoint constraints
P7	The map view is the most useful area of the interface. The color codes are well planned and hence I did not have to refer to the other areas of the interface often and the problems could be solved using only the map view.

P8	Very useful, for almost all the experiments, it was the one I relied on the most. Most of the information needed is inferred from the map view. The only vague aspect is when it comes to the warnings/conflicts. The other views help clarify what conflict occurred.
P9	Map view is the most important of the four. So much attention / eye-focus is needed on the vehicles and routes themselves that there is no time for the attention to wander away from the map view.
P10	Map is probably the most important view. I used this to try and optimize the flight path.
P11	Map is extremely important as it gives you the picture in terms of distances to fly. This allows you to go back and forth solutions to see if you can further improve on the chosen solutions. Without this display the task would be impossible.
P12	really nice, can see information on all the parts (payload, battery etc) in it. With one look you could get info on all the systems, so helps to keep the focus in one spot instead of having to look around at 4 different displays
P13	Extremely useful once you get the hang of it, all other views become secondary and are used only to confirm the FP you set in the map view.
P14	Very Useful
P15	very useful
P16	The map is useful and gives a general overview of the scenario being studied, however, the selection of waypoints could be more easier instead of selecting and deselecting each UAV.

**Table E-3:** Q2: How do you assess the usefulness and the functionality of the timeline view?  
Please provide examples in your elaboration.

Participant	Comment
P1	The timeline view is good but could take a lesser area of the screen. I feel the user would mostly choose between payload and battery. So even though it is an essential view to the practicality of the problem it is less relevant.
P2	The timeline view was good enough and useful to check the arrival time at the depot
P3	Timeline was useful in seeing where the time conflicts were and being able to see which UAV's were contributing to the problem.
P4	The timeline view serves its purpose in indicating conflicts at the depot. A clearer representation of time allocation of aircraft being serviced would be to have hangars. Aircraft would be assigned to any free hangar for the duration of their service, and in such way depot availability would be more easily distinguishable.
P5	I rarely used it. It was only useful when all other constraints were met.
P6	Did not really look at it, used the map instead to create diversions/waypoints.
P7	I think after the map view the timeline view is quite useful. The fact that I could click a landing block and get to the corresponding aircraft makes using this area quite easy.

P8	Timeline view was useful for avoiding crashes at the depot. This is more important for the "deliver coffee bean problem". The time till arrival at the depot is not very helpful, as it is not very intuitive to look at the time. Rather, it is more useful to look at the number of legs and the length of each leg. However, the colors yellow and orange are sometimes hard to distinguish, especially when the aircraft are of small size.
P9	It is great when arriving at a solution and then checking for depot conflicts. During the actual reorganization of the routes, however there wasn't a lot of need for it.
P10	This view is useful only once the flight plan is already chosen. I used it at the end just to minimize conflicts.
P11	Map is extremely important as it gives you the picture in terms of distances to fly. This allows you to go back and forth solutions to see if you can further improve on the chosen solutions. Without this display the task would be impossible.
P12	I only used it when there was a conflict at the arrival. So useful when that happens, otherwise i didnt look at it
P13	Rather useful, only for when assessing whether two drones will collide. Apart from that, they do not play at all any importance to someone who prioritizes the payload over time.
P14	slightly useful
P15	It's clear
P16	I haven't used it that much in most experiments but maybe some changes can be done. If the experiments take into account the total time to reach the depot, refuel the uavs and depart, perhaps this functionality could be expanded in that sense.

**Table E-4:** Q3: How do you assess the usefulness and the functionality of the payload view?  
Please provide examples in your elaboration.

Participant	Comment
P1	The payload view is really useful and is handy in terms of functionality. It is easy to read when the clock is ticking.
P2	It was useful to assess quickly if there was enough payload to make another delivery before returning back to the depot
P3	Payload view was useful to determine how many points could be traveled to.
P4	The payload view works fine by given a good indication of the unused payload at a glance. Even though it's situated in the lower left corner, the gauge is large and clear enough to allow swift reading of the data.
P5	The payload view was good. However, I used the map view more often. Payload view was mainly used when i could not directly distinguish from the colours in the map what the payload was.
P6	Preferred to use the map instead to tell me whether a drone has spare payload or not.
P7	Well understanding the color codes, the remaining payload number per aircraft can be estimated, thus I did not have to look at this area of the interface quite often.

P8	Payload view was more important in the scenarios when there were many customers. In simpler situations, just monitoring the color of the aircraft sufficed, as there was not much pressure to make urgent decisions.
P9	It is great for checking which flight I have to focus on, but the information that is contained could be shown in the map view, without having to select each vehicle to check for the amount of payload, e.g. showing the number of un-allocated payloads next to the vehicle.
P10	This view was probably equally as important as the battery view however I found myself looking at the battery view more than this one.
P11	It is useful, but I only used it at the end of the scenarios to see if, after trying to optimize the use of the swarm of UAVs for the purpose set, there were any conflicts. Then simply extending the path of one or more UAVs would solve it.
P12	good, I used it to see if I could divert smaller planes that had payload left to closer locations such that a big plane got a payload back to bring to a more distant location. Very useful if you want to get to all locations
P13	Very useful when trading off between dropping off drones at points other than the depot, and along the way. They also have the tendency of influencing the decision, i.e. a drone with more payload is more likely to be sacrificed by taking as many points as possible.
P14	not at all useful
P15	Clear
P16	Useful, easy to interface with.

**Table E-5:** Q4: How do you assess the usefulness and clarity of the battery view in the display?  
Please provide examples in your elaboration.

Participant	Comment
P1	The battery view is really clear and easy to use. The demarcations (dotted lines) allowed me to understand what percentage of the battery is being consumed for which path. Though ideally I would place it next to the payload view (towards the bottom panel).
P2	Useful to check whether the UAV was capable of delivering more before returning back to the depot.
P3	Battery view was useful to determine the remaining battery life
P4	Personally I barely used the battery view itself, as the projected range on the map view is more indicative of the aircraft capabilities. It helps in seeing how much battery is missing to perform a certain route, but the range indication on the map is a lot more practical.
P5	Battery view was good, as it showed when the battery was depleted. The additional colours in the map were an added benefit.
P6	Again, preferred the map as it directly gave me hints on action.
P7	This area of the interface is the one that I use the least. I felt that the representation of the problem in the map view is quite apt.

P8	I did not make much use of the battery view. Whenever I encountered a conflict for an aircraft, the red color on the leg as well as the green bubbles helped me get the information needed about battery level.
P9	Never looked at it, as most of the battery limitations were very nicely displayed in the map view.
P10	I used this a lot to make sure the routes were possible.
P11	Very important as well, as you are looking for UAVs that can still deliver something, if they cannot then you can see whether another UAV can do part of the delivery such that the UAV you are considering may do another path. So you are iterating on delivering the packages in the best way you can see.
P12	I rarely looked at, cause on the map view you can also see if it will make it or not and what areas could still be reached
P13	Very little usefulness, as the information is already provided within the map view, with regards to how you can create a new route. Have used it very little along the whole experiment.
P14	Not at all useful
P15	Clear
P16	Easy to interface to select and deselect the paths.

**Table E-6:** Q5: How do you assess the usefulness and clarity of the color use in the display?  
Please provide examples in your elaboration.

Participant	Comment
P1	The colours are clear. They are bright and thus are easily identifiable, which is useful in terms of clarity. Even though it might not be aesthetically pleasing but the colours prevented confusion while rerouting.
P2	Good, enough for a good understanding
P3	Colors are always useful. Could quickly identify where the problems lied.
P4	The color scheme used in general is very user friendly. The dark background reduces eye strain/fatigue and allows more focus on the highlighted items in the FOV, as these draw more attention.
P5	The colours were really chosen good! Good to easily distinguishable when doing the experiment.
P6	Good, colors are intuitive, red and green occur in bad and good situations respectively.
P7	The colors in the display are very useful.
P8	Timeline view was useful for avoiding crashes at the depot. This is more important for the deliver coffee bean problem . The time till arrival at the depot is not very helpful, as it is not very intuitive to look at the time. Rather, it is more useful to look at the number of legs and the length of each leg.
P9	It takes a lot of time to: select the vehicle and look at the bottom left. It is a necessary information though.
P10	Very useful, the colors helped to give me an overview of the status of each UAV.
P11	It was useful as it connected some of the 'dots' in understanding the relations between the various constraints.

P12	Usefulness was good, could see from the map view if there was payload left, or too little payload, if areas can be reached or not. Maybe for the color of the plane the three colors indicating payload left over can be more clear instead of yellow, orange and red, maybe green orange and red or so. The red color really help to check if there was a probem somewhere
P13	Extremely useful, as it eases the cognitive process. The difference between amber and yellow for example helped a lot to reroute drones without looking in the payload view. In some cases a collision color between two drones appeared, even though one of them would have no reached the depot, which was a little bit misleading. It would be nice to show the color of the drop off zones that are not in the flight plan in a blinking way to make sure you do not miss anything.
P14	some other color should e used instead of orange cz sometimes it is difficult to differentiate from yellow specially when there are too many veicles.
P15	It's clear
P16	Quite usefull, however, in some cases I did not distinguish the UAVs from the color. When that happened was when it couldn't reach the depot.

**Table E-7:** Q6: How do you assess the usefulness and clarity of the use of different icons to signify the different UAV type in the display? Please provide examples in your elaboration.

Participant	Comment
P1	Yeah the icons are extremely clear and it is good that the locations are just diamonds and nothing more. The icon selections keeps the screen neat and prevents chaos.
P2	Not useful. The size of the UAV was not important for the task. In the end, it only matters the battery capacity and payload.
P3	It was highly useful as then when clicking on a UAV i already had a plan in mind for the strategy i was going to use. For the smaller UAV's i knew they had a high capacity but low battery, whereas with a large UAV it had low capacity but a large battery capacity. Therefore with the small uav i already planned to make it take over points in the area which were going to be delivered to by the big uav, and then i could make the big uav travel points far away.
P4	I didn't take UAV size or speed into account, as to me other parameters had a higher importance: range and payload.
P5	UAV types could be just the same size. Did not pay attention to the UAV types.
P6	It's okey for me, I imagine some people would have issues with discerning as the shape size difference is quite small.
P7	The icon sizes make the use of the interface quite intuitive.
P8	It was a good indicator for speed. However, often times there were slower UAVs that had quite a bit of battery life. I think it biases the user to check for the larger UAVs first, when sometimes a smaller UAV has the capability of traversing large distances.
P9	Never looked at it, as most of the battery limitations were very nicely displayed in the map view.

P10	Useful: I was able to - at a glance - know whether a UAV was going to have enough battery to take on a longer route.
P11	That was sufficient for its purpose. Larger symbols mean extended range. These were the guys you were hoping for to get during the scenarios as they could be used to deliver at more remote places.
P12	Good, I really could see which planes I wanted to go long distances and which the shorter ones.
P13	Quite useful, generally the bigger drones had more battery and that played an important part in the overall optimization strategy.
P14	well different icons were useful but I would suggest to use different shapes instead different sizes.
P15	It's useful
P16	Easy to interface, the problem seems well represented.

**Table E-8:** Q7: Do you have any other comments or suggestions with respect to the interface or the experiment?

Participant	Comment
P1	The experiment was fun to execute. There is of course a learning curve that one goes through in using the tool but that becomes clearer with every tutorial and definitely every exercise. So the first few experiments/scenarios might not be performed best, as the user is still getting used to the tool, however by the 3rd the user is completely aware and used to the controls and thus can focus more on the problem at hand.
P2	In the coffee beans scenario it should be made clear what is more important for the company (economically, or in terms of image etc.). It could be added something like: If the coffee beans are not delivered, the costumers will have a bad image of the company and possibly stop buying product (future economic damage to the company). On the other hand, if the UAV does not return to the depot, there is an economic impact since it will need rescue later on and it can be very expensive.
P3	Controls can be a bit finicky thus preventing actions from sometimes being done correctly, thus wasting time. Could maybe have some data being displayed over the uav icon so one wouldn't have to press the drone icon to get battery and capacity details.
P4	Very well designed experiment. Some levels were overwhelmingly difficult, give me a break. Well done!
P5	Yeah, please add the escape button to the experiment. (makes it easier for gamers). Also try to limit the amount of clicks per action.
P6	Control was not always very intuitive, left click should also deselect when not clicking on anything.
P7	I experienced a few glitches during the experiment runs, other than that I don't think any suggestions.
P8	However, the colors yellow and orange are sometimes hard to distinguish, especially when the aircraft are of small size.

P9	The difference between 0 payload (orange) some payload (yellow) was sometimes not too clear.
P10	Knowing which drone will be dispatched to take on a specific route before it leaves the depot might be useful. At the very least it may alter the approach in deciding the solution.
P11	Very important because it allows you to see whether the UAV will survive. Basically in the S&Rescue scenarios you did not care much for the UAVs but just the payload delivery. In the Coffee scenarios it was the opposite.
P12	No
P13	A one button control Z, to cycle multiple attempts at rerouting one drone would be nice.
P14	Well, it would be nice to if operator knows the path a particular type of UAV will follow, it would help more in optimizing the rerouting strategy. Different delivery points should have different weights as that would help in prioritizing the delivery points and accordingly rerouting the routes.
P15	Unselect could be done by clicking somewhere else
P16	Just one: the dynamical behaviour makes the experiments quite interesting. Depending on the scenario, the ATM manager choose whether he/she will risk the uavs to save people or deliver any materialistic good. Thence, one way to improve would consider including refueling at the depot or other stations located in the map.

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## Appendix F

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# Code Architecture

### F-1 Vehicle Routing Problem Optimisation

The Vehicle Routing Problem optimisation is used to be able to create the scenarios for the experiment which is then given to the participants and also used to test if the problem was solvable with the addition of the dynamic element. As the addition of the new customers and the battery defect was defined right at the beginning of the experiment, the problem was considered a static problem to test if the problem was solvable. The algorithm is based on the **Google Optimization Tools** or the **Google OR Tools** which is a library designed to generate the best solution for a problem, out of a large number of possible solutions. Figure F-1 displays the functions used to generate the solution. The algorithm was able to adjust the velocities and maximum horizon battery for the vehicles to see the effect of these variables on the scenarios. The algorithm was able to adjust the payload capacity, velocities and maximum horizon battery for the vehicles to see the effect of these variables on the scenarios. This was crucial for the design of the scenarios. The tool was integral in providing a quick approach as when a problem was taking too much time, there was a time limit set, and also a *Search Control* was used occasionally to provide a *first solution strategy*.

After the solution is produced, the result is then used by **PlotScenario** which makes the plot to be able to visualise the problem.

### F-2 Multi-UAV Simulator

The multi-UAV simulator is based on JAVA, and it was extended from Koerkamp et al. The code was based on the MUFASA editor (MEDIT). To develop the interface, the Eclipse Luna Version 4.4.2 and Java version 1.6 was used. The simulator made use of the scenario files from the **scenarios** folder that was generated by the VRP optimisation code. The sequence of the scenario given to the participants was based on the number given to them, and outputted through **setup.txt** file in the **experiment-design** folder. When the interface was started,

the simulator inquired about the participant ID and then based on this, displays the scenario. At each run, the interface creates a log file in the **logs** directory. There is also a **logs-click** folder, which contains the click logs. The **logs** directory helped to show the routes which were taken by the participants at all time, and the **logs-click** shows the clicks that were done by the user.

The architecture of the multi-UAV simulator is displayed in Figure F-2. the main frame is in the package **+atclib.ssd.main**. The **SSDFrame** is the main executable in the code. The **Mission** object defines the scenario. The fleet of the UAV is defined in **UAV** objects. This also contains the **Flightplan**, and additionally contains the **waypoint** objects.

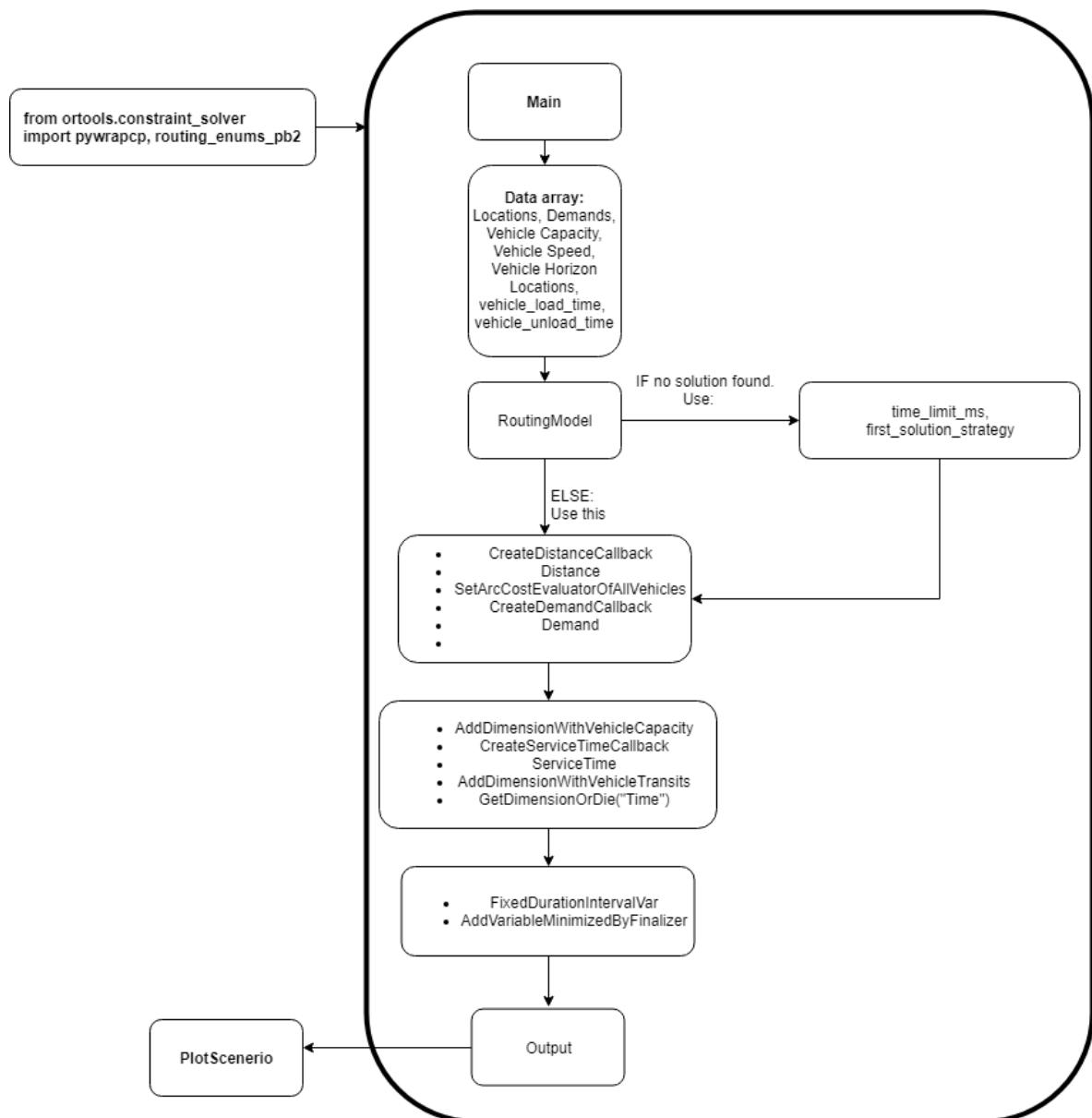
The click log and the data aids in getting the result from the participants and is contained in **+atclib.ssd.main** package under **ClickLogger** and **DataLogger**. For the map view, the **+atclib.ssd.display.elements** package includes the files. There is an additional object for the Battery indicator which is in **GLBatteryIndicator**. For the timeline view, **+atclib.ssd.display.timewindow** package includes the object for it. For the payload view, **+atclib.ssd.display.payloadwindow** package includes the objects for it. The envelope around the UAV are in **PerformanceEnvelope** and **PathStretchEnvelope**, This is used to visualise the constraints to the users. To be able to export the code, a runnable file was created by File > Export > Runnable JAR file.

### F-3 Experiment Survey

For the experiment survey, a web form was created and this was based on PHP and HTML. The way it was presented to the participants can be seen in Figure F-3. To run the survey on the machine, XAMPP is used to run it on the localhost. The results from the survey form will generate a data file for a particular ID that is inputted by the user. Once a participant ID is created, it would not be possible to start the survey with the same ID to avoid repetition of the value.

### F-4 Post Experiment Data Processing

From the data, the results had to be calculated for the dependent variable. The scripts were based on MATLAB. The data is first converted to .mat format, and then the data is then analysed and lastly, the figures are created for the dependent variable. The architecture code for post-processing can be seen in Figure F-4. The three parse files were run to be able to convert the log files. And then the data is processed to calculate the required information for each of the dependent variables and generate the figures, which is automatically saved.



**Figure F-1:** Vehicle Routing Problem optimization code architecture.

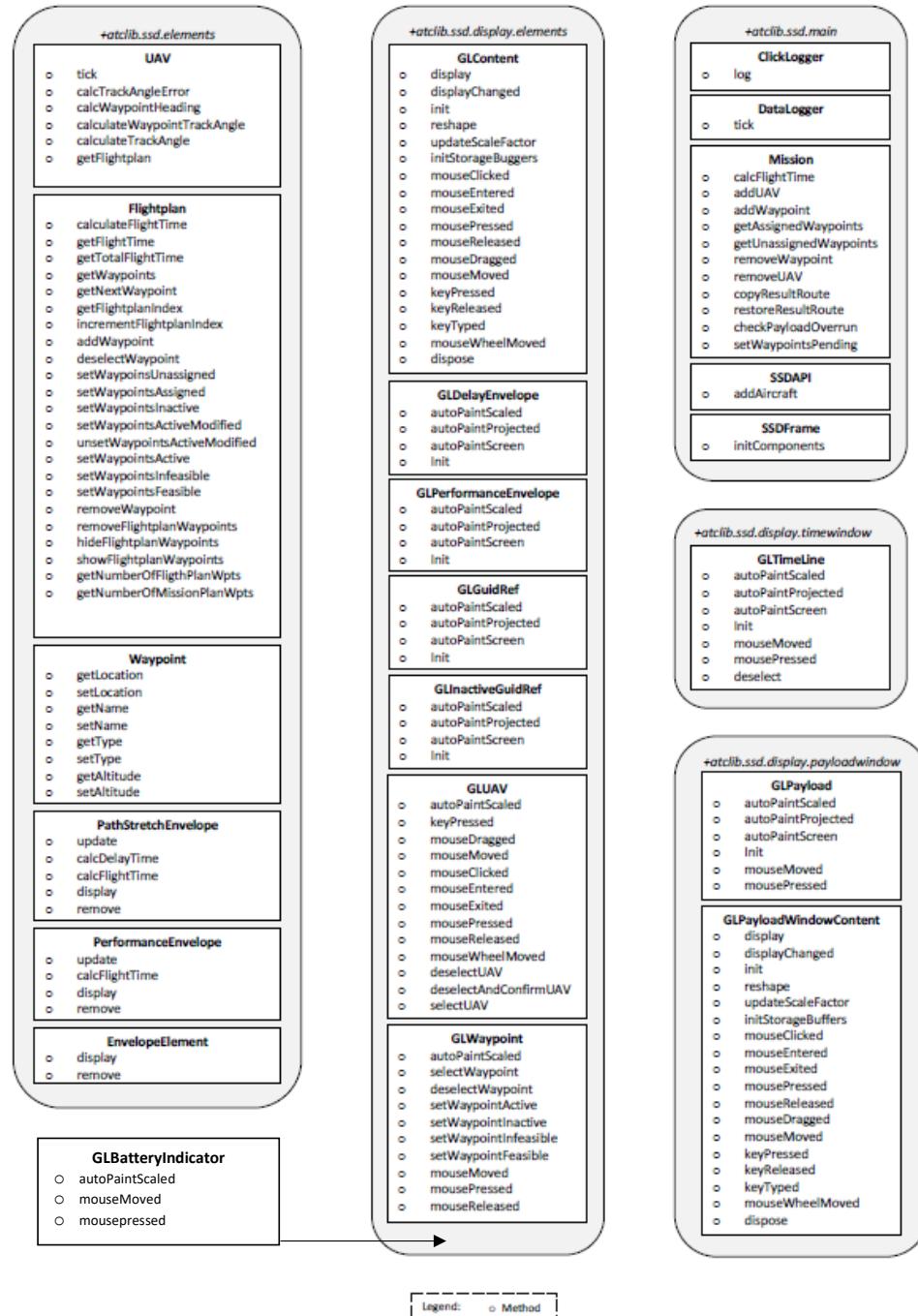
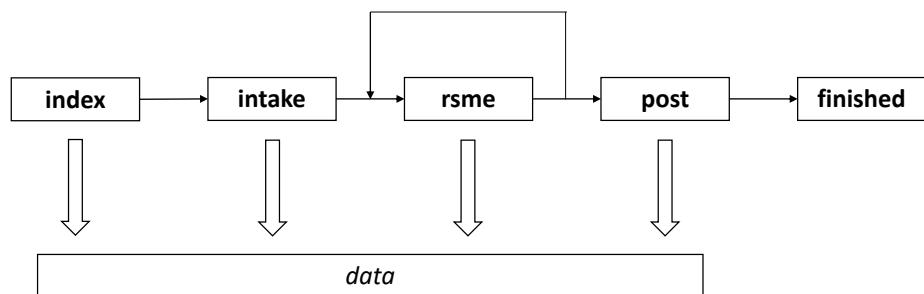
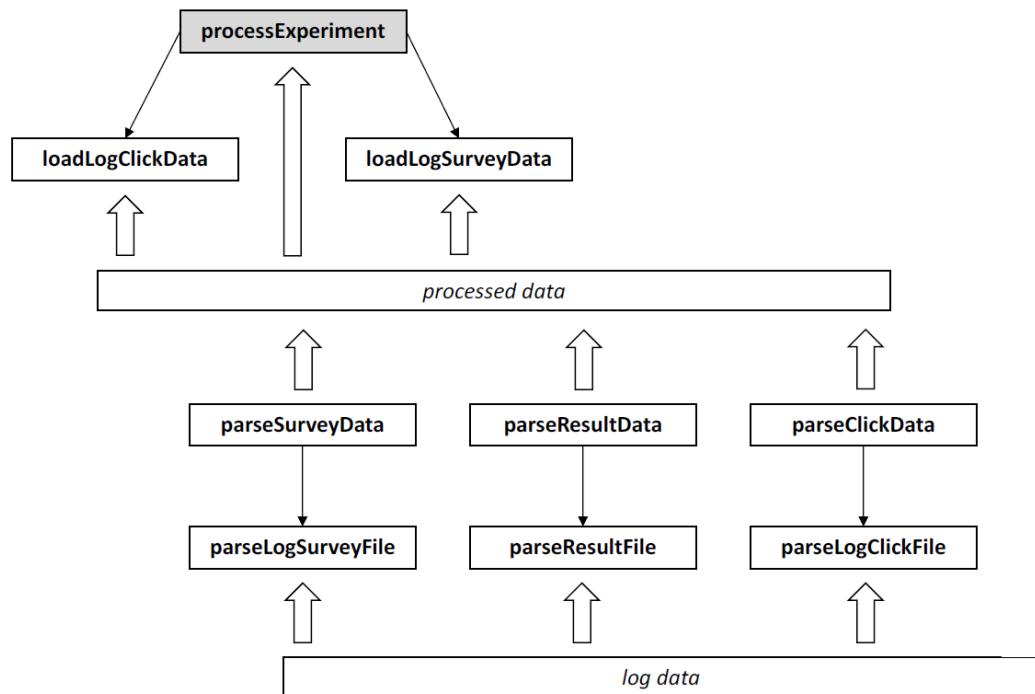


Figure F-2: Multi-UAV simulator code architecture (Koerkamp et al., 2019)



**Figure F-3:** Survey web form code architecture (Koerkamp et al., 2019)



**Figure F-4:** Post processing code architecture (Koerkamp et al., 2019)



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## Appendix G

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# Concluding Remarks and Recommendations

This chapter presents a more elaborate overview of recommendations in addition to the paper. Section G-1 discusses the experiment and interface design, and Section G-2 presents suggestions for future work.

### G-1 Interface and Experiment Design

The interface was effective in use, and the participants used it to a great extent. However, the map view was the most useful one as it provided a summary of most of the information. Some of the participants could not focus on any other view as the map view was enough for them in a limited period. A suggestion for the timeline view is to decrease the area of the screen as it was not used as much. Also, the arrival blocks were confusing for the participants as it was difficult to associate which block was for which vehicle. Thus, it is recommended to add a vehicle number and put it on the block in the timeline view to be able to get a quick grasp on which block is for which vehicle. For the payload view, it provided an initial value for the total number of payloads, but then the colour scheme in the map view provided a clear knowledge about the amount.

In the map view, it would have been more convenient for the participants to be able not to deselect the UAV each time they don't want to make a decision, and rather it deselects on its own when it goes to another vehicle.

To produce an efficient result by the participant, there could be a window in the view which would display the cost of the solution, and so it would provide the user with a better solution rather than only doing it visually. For the experiment, as the participants got used to the controls after doing a few scenarios, thus it is recommended to increase the training volume for future experiments.

There was a lot of colour that is used in the interface, thus it is suggested that the experiment should be screened for colour blind participants.

It is assumed that the user could be able to handle a greater number of payloads, thus in the future, it is recommended to take more customers into account, and also to see how the performance of the participant's changes with more number of mission objectives.

## G-2 Future Work

A few suggestions for future work are as follows. There could be additional of more dynamic scenarios to make the experiment more realistic. Some additional aspects that could be added in the interface are by introducing wind. This would introduce an asymmetry into the system, making it more difficult to solve the problem. More suggestions are: adding a 3D element into the interface, thus considering buildings and their height while making a decision. Also, it is possible to add a time-window for the customers, to provide an estimate to when they will get the payload. Some minor changes that can be added on also are to, consider moving customers and also using multiple depots rather than using a single one.

To make an optimisation code, only the Google OR tools was used for this. There should be more algorithms that could be investigated to possibly asses the scenarios further. Also, to investigate the results of the participants, an algorithm could be created to be able to solve the over-constrained problem and then compare the results of the algorithm with the human to have a better idea on how the human results different with automation.

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