# A greedy heuristic algorithm to solve a VRP-based model for planning and coordinating multiple resources in emergency response to bushfires

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## Abstract

Uncoordinated responses are problematic in various operations, especially in crucial circumstances such as bushfires, where they are associated with decreased efficiency, effectiveness, and safety. This paper presents a new VRP (Vehicle Routing Problem) model for routing, scheduling, and coordinating bushfire-related resources including Ground Resources (GR) and Aerial Resources (AR) in the suppression phase of a bushfire event. The coordination must be in a way that ARs' operations are allowed prior to GRs' operations, otherwise, aerial interference is unhelpful. The problem is NP-hard (Non-deterministic Polynomial-time) and cannot be solved in a Polynomial-time using exact methods, but due to the crucial circumstances of bushfires, it should be solved in a reasonable time. Therefore, we proposed a greedy heuristic algorithm to solve it. Dividing bushfires' area into a set of fire sites, we solved instances with different numbers of fire sites using both CPLEX and the greedy algorithm and compared the results. CPLEX fails to solve the instances having more than three fire sites, but the greedy algorithm solves the largest instance having 9 fire sites in less than 1 minute. The ignorable Relative Percent Difference (RPD) of the greedy algorithm in the first five instances indicates that our proposed algorithm is reliable.

*Keywords:* Coordination, Vehicle routing problem, Scheduling, Bushfire suppression, Greedy heuristic algorithm

## 1. Introduction

Disasters have always affected humans' life and the environment by stopping people from doing their routine [1], and bushfires (wildfires) are one of them. Bushfires are uncontrollable fires occurring in weed, forest, grassland, or plantation or nursery stock [2]. Each year, we witness bushfires' effects on our assets and natural resources. Recently, affected by global warming, an increasing number of bushfire incidents are happening in many countries such as Brazil and Australia. In 2019, Brazil experienced more than 74,000 fires within the first eight months, while 2018's total was about 40,000 [3]. Therefore, efficient plans in order to mitigate severe bushfires' impacts on all living creatures' lives and our properties are vital.

The statistics show how many resources and lives have been destroyed during bushfire incidents. One of the worst bushfires experienced by Victoria, Australia was in 2009 and was known as ' Black Saturday',

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which resulted in many homes being destroyed, and 173 people losing their lives [4]. Moreover, in the 2019-20 Australian bushfire season, three main areas, including New South Wales, Victoria, and Queensland, were affected by bushfires. The number of these incidents were higher than or almost consistent with that of previous years in these areas [5].

To tackle this very issue, it should be taken into account that, in situations like bushfire incidents where several organizations are working together to achieve the same overarching goal, their operations should be coordinated [6]. Bodaghi et al. [7] also stated that uncoordinated responses have always caused significant problems, considering this, they coordinated Victorian emergency response teams in their research. A real event caused by such a problem is the one mentioned by Brewer [8], which is based on a true story of a group of American firefighters who lost their lives in the Yarnell Hill fire, Arizona. This event was reported due to uncoordinated responses. Considering this coordination, when a fire incident occurs, Ground Resources (GRs) must arrive after Aerial Resources (ARs) having finished their operations. In other words, ARs are allowed prior to GRs' operations otherwise, aerial interference is unhelpful, and it is highly likely to interrupt GRs and deteriorate the conditions. However, if they are properly planed, they play a pivotal role in extinguishing bushfire. Teague et al. [4] showed that ARs played an important role in suppressing fires for the period January–February 2009, they declared that ARs had to finish their fire suppression operations before the GRs arriving there. Despite the fact that climate limits made flying unsafe, and other policy barriers delayed the ARs, they played a very important role in that incident.

These statistics indicate that suppressing fire is problematic worldwide. However, a vast majority of the failures are controllable by planning and coordinating GRs and ARs to reach an optimal utilization. In this study, we consider homogeneous GRs and heterogeneous ARs having different water carrying capacity. Since bushfires burn freely and controlling them is difficult, they simply can be extended if they are not extinguished by a proper plan. Therefore, presenting an efficient algorithm that can solve large-size problems in a reasonable time is necessary.

This paper focuses on proposing a mathematical formulation model for planning and coordinating the available resources at a single depot for an efficient fire suppression, referred to as the Coordination in Emergency Operation Response (CEOR). The problem seeks routing both GRs and ARs and assigning them to the fire sites in an incident according to their demands. In other words, once an incident is detected, the whole incident is divided into possible fire sites by Fire Management, which is not in the area of this paper. Then, using our model, they can plan available resources in the right priority, which was mentioned in the previous paragraphs, in order to give services to the fire sites to control them as soon as possible. The model gives an optimal plan for both ARs and GRs simultaneously. Moreover, since the problem refers to a crucial situation we minimize suppression time as an objective function.

The main contributions of this paper are as follows:

a) To coordinate homogeneous GR and heterogeneous AR for responding to a bushfire event.
b) A new VRP-based mathematical coordination model for planning fire suppression operations in a bushfire event.
c) To propose a greedy heuristic algorithm to solve this problem.

The remainder of this paper is arranged as follows:

– Section 2 reviews the related literature.
– Section 3 describes the problem and the presented model.
– Section 4 presents the mathematical formulation.
– Section 5 introduces the applied solution.
– Section 6 examines test cases.
– Sections 7 investigates the results.
– Section 8 & 9 describe managerial insights and conclusions.

## 2. Literature review

Most of the papers in the response phase of disasters tried to model their problems using the Operation Research (OR) methods. OR is a significant method that has been used to model and solve disaster problems, for instance, earthquakes, floods, and hurricanes. There is also a substantive usage of OR methods to solve bushfire problems in the literature review [9].

Bodaghi and Palaneeswaran [10] proposed a MILP project-scheduling-based model for scheduling and assigning various teams of non-expendable resources to emergency operations. The emergency operations require the synchronization of multiple teams. Although they applied their model to a hypothetically simulated case study, they do not develop an algorithm to solve test cases. Rodríguez-Veiga et al. [11] used ARs for bushfire suppression and then they proposed two MILP models for two tasks assigned to coordinator: The allocation of ARs to flight routes and refueling points. In their study, aerial coordination provides flight safety as well as the effectiveness of the mission. Their study gap is that they did not pay attention to GRs' activities. Yang et al. [12] proposed an emergency logistics system for bushfire suppression with VRP modeling. They considered a priority for servicing the fire sites by dedicated vehicles and then analyzed two case studies at a bushfire in the Daxingan mountains. The necessity of the ARs is ignored in this model.

Rodríguez-Veiga et al. [13] proposed a MILP (Mix Integer Linear Programming) model that optimally selects resources (ARs, brigades, and engines) for extinguishing a fire in different time periods during the planning period. They carried out a simulation study to obtain the optimal solution. Wei et al. [14] and Wei et al. [15] focused on optimizing the daily responses to demands for fire suppression over a fire season for efficient initial attacks. In the former paper, the authors used a chance-constrained two-stage stochastic programming model to determine how many resources need to be hired and where they should be located. They considered three types of resources including hand crews, fire engines, and water tenders in their study. The latter paper optimizes the daily responses to demands for engine and crews by moving resources between stations. In the model, they preferred to send an engine to fill a crew request instead of sending no resources at all. In another related work, Lee et al. [16] developed a scenario-based standard-response optimization model to deploy and then dispatch initial attack resources to fire sites in bushfires suppression. Their model minimizes the number of fire sites that are not serviced by standard-response. They do not take into account coordinated activities between resources, although they considered both GRs and ARs in a firefighting operation. The above mentioned studies are summarized in Table 1.

Cerna et al. [17] also developed a methodology to calculate the fire brigades operational breakdowns and predict disruptions with machine learning techniques. Their focus was on failurs due to human and vehicular materials and applied it on a real fire department in France. In terms of methodologies used to solve VRP models, which are in the NP-hard problem categories, we investigated following papers, all of which have presented (meta)heuristic methods. Galindres-Guancha et al. [18] presented a multi-objective capacitated VRP model considering drivers' workload balance as well as cost of routs as two practical objectives in the real world. To solve the model, they decomposed it into single sub-problems, which were solved using Iterated Local Search method. They concluded that this method was a practical method for multi-objective VRPs. Mutar et al. [19] proposed a single objective capacitated VRP model, which were solved using the improvement of Ant Colony System, which offered a better solution in comparison with some other methods. Ouaddi et al. [20] presented a multi-tours dynamic VRP with overtime considering two objectives, and they solved it using an approach based on memetic algorithm. Their results showed a better solution compared to the Ant Colony System implemented on the same problem in a previous study. Londono et al. [21] implemented an iterated local search method in three stages on a green VRP with three objective functions. Their methodology was quite novel in the related literature. Suksee et al. [22] applied a Greedy Randomized Adaptive Large Neighborhood Search Procedure on a problem of Location Selection and Vehicle Routing. They compared the result with the exact solution calculated by

A Mathematical Programming Language (AMPL) program, which showed that in small-scale cases the heuristic method could find the optimal solution within less process time, and it could find a better solution in larger-scale cases. While AMPL could not find the optimal solution in larger-scale cases in a limited process time, the heuristic method could find the better solution in a few seconds. The problem solved in this paper has a similar scale and complexity to that of Suksee et al. [22]. As the heuristic method has worked for their problem, for our model, we decided to employ a Greedy Heuristic Method, in which we have used Local Search Method, too. The detailed methodology will be discussed in Section 5. Moreover, Shu [23] and Hojati [24] overcame the challenge of solving NP-hard problems in large size instances using a greedy heuristic algorithm. The former studied a warehouse-retailer network design model, and the latter considered a Shift Minimization Personnel Task Scheduling Problem, which schedules ground crews of a large airline in a large airport. They concluded that the greedy heuristic algorithm works well in comparison with the current solution approaches, and its important advantage is being able to solve very large instances fast.

*Gaps and contribution*

The literature indicated a lack of coordinated activities between GRs and ARs. We proposed a new VRP-based mathematical coordination model for IMTs' (Incident Management Team) response fire suppression operations to a bushfire event. The innovations are mentioned clearly as follow:

- Considering coordinated activities between the GRs and ARs.
- Considering specific water sites for ARs to reload at.
- Proposing a new VRP-based mathematical model by taking into account these gaps.
- Solving test cases using a greedy heuristic algorithm.

## 3. Problem Statement

As mentioned in the introduction, a bushfire is an uncontrollable fire occurring in forests, and FM (Fire Management) is a procedure that incorporates a range of intersessions to monitor, use, and reestablish fire-prone forest ecosystems [25]. Fire suppression is one of these efforts that aim to extinguish or prevent the spread of fire in forests. According to the reports of the previous real-world cases, FM uses two main types of resources including ARs and GRs in order to control bushfires. As it is clear in the related literature, aerial support in bushfire suppression plays a key role, and ARs' attacks and GRs' activities are complementary to each other. National Aerial Firefighting Center (NAFC), in Australia, highlights that 18 million liters of fire suppressant and retardant by 23 aircraft in 2005 grew to more than 29,500 firebombing drops by 123 aircraft in 2016 [26]. In Section 1, we showed that lack of coordination between ARs and GRs cause significant problems. Considering this issue, in this paper, we propose a mathematical model, which schedules and routes both ARs and GRs.

The pattern of our proposed model is illustrated in Figure 1. In this Figure, GRs are considered homogeneous and ARs are considered heterogeneous with their own water carrying capacity. Fire sites are shown by F1, F2, and F3 as the important sites determined by the FM in the detection phase of a bushfire. Three water sites are shown as L1, L2, and L3, on which ARs can load water. Water sites can be any reservoir of natural or artificial water such as lakes, rivers, reservoirs behind the dam, artificial lake, etc, which are considered to have infinite capacity. It should be noted that the ARs are capable of loading at both airports and water reservoirs as shown in Figure 1. To fully suppress the fire sites, special demands of fire sites should be satisfied. For instance, suppression of a fire site may need initial attack by ARs, followed by GRs' operations to prevent backfires. In the meantime, another fire site could well require GRs' operations without aerial suppresion. Since each AR is allowed to unload and reload for each fire site several times, it may visit each arc several times. We consider each visit in different trips in the mathematical modeling.

## 4. Formulation

In this section, we present an effective network for the CEOR problem by considering coordination between the resources. To formulate the mathematical model, the following characteristics are considered:

- The speed of each AR and GR is given, and then travel time is calculated.
- The water capacity of each AR is known.
- The fire sites' demands for GRs, which are considered as process time, and their demands for ARs, which are calculated by the volume of water that is needed according to their areas, are known.
- Loading time of ARs at loading sites including water sites and airports is known.
- The service time spent on fire sites by ARs is considered in their travel time from one site to another one, but, for GRs, it is a decision variable, which is determined in the model according to the total demand of a fire site for GRs, which is a known parameter.
- The water capacity of loading sites is considered infinite.
- Each fire site can be served by one type or more types of coordinated resources.
- We use $r$ to show different trips of ARs, and all ARs start their trip from a single depot, which is an

airport.

### 4.1. Notations and sets

The sets and indexes used to formulate the problem mathematically are described as follows:

$\mathscr{N}$ Set of all sites $i, j \in \{\mathscr{A} \cup \mathscr{E} \cup \mathscr{L} \cup \mathscr{F} \cup \hat{\mathscr{A}} \cup \hat{\mathscr{E}}\}$;

$\mathscr{A}$,$\hat{\mathscr{A}}$ Single starting depot and hypothetical ending depot for ARs, respectively;

$\mathscr{E}$,$\hat{\mathscr{E}}$ Single starting depot and hypothetical ending depot for GRs, respectively;

$\mathscr{L}$ Set of all water sites, that $l \in \{1, 2, \dots, \mathscr{L}\}$;

$\mathscr{F}$ Set of all fire sites, that $f \in \{1, 2, \dots, \mathscr{F}\}$;

$\mathscr{Q}$ Set of all GRs and ARs, that $q, q^{'} \in \{\mathscr{V} \cup \mathscr{D}\}$;

$\mathscr{D}$ Set of all ARs, that $d \in \{1, 2, \dots, \mathscr{D}\}$;

$\mathscr{V}$ Set of all GRs, that $v \in \{1, 2, \dots, \mathscr{V}\}$;

$\mathscr{R}$ Set of all trips of ARs, that $r \in \{1, 2, \dots, \mathscr{R}\}$;

### 4.2. Parameters

Parameters and the values that are calculated are as follows:

$cap^d$ Capacity of ARs, that $d \in \mathscr{D}$ (Liter);

$ds_i$ Total demand of fire site $i \in \mathscr{F}$ for GRs (Hour);

$h^q$ Start time of $q \in \mathscr{Q}$ to be dispatched from its depot;

$lt^d$ Loading time of ARs, that $d \in \mathscr{D}$;

$sf_j$ The area of fire sites, that $j \in \mathscr{F}$;

$vq^q$ Speed of resources, that $q \in \mathscr{Q}$;

$vw$ The volume of water required for firebombing one unit of fire sites' area (Liter);

$dist_{ij}$ Distance from $i \in \mathscr{N}$ to $j \in \mathscr{N}$;

$t_{ij}^{q}$ Travel time of resource $q \in \mathscr{Q}$ from $i \in \mathscr{N}$ to $j \in \mathscr{N}$, that $t_{ij}^{q}$=$dist_{ij}$ / $vq^{q}$;

$M$ Big positive number;

### *4.3. Decision variables*

The following decision variables are defined to discover the configuration of the emergency response in bushfires:

$Ab_{i}^{v}$ Service time spent on fire site $i \in \mathscr{F}$ by GR $v \in \mathscr{V}$;

$W_{j}^{rd}$ Arrival time of AR $d \in \mathscr{D}$ at fire site $j \in \mathscr{F}$ in trip $r \in \mathscr{R}$ after loading from loading site;

$W_{j}^{\prime v}$ Arrival time of GR $v \in \mathscr{V}$ at fire site $j \in \mathscr{F}$ after AR leaving there there;

$U_{i}^{rd}$ Arrival time of AR $d \in \mathscr{D}$ at loading sites $i \in \{\mathscr{A} \cup \mathscr{L}\}$ in trip $r \in \mathscr{R}$;

$X_{ij}^{rd}$ 1 if AR $d \in \mathscr{D}$ travels from $i \in \mathscr{N}$ to $j \in \mathscr{N}$ in trip $r \in \mathscr{R}$, and 0 otherwise;

$X_{ij}^{\prime v}$ 1 if GR $v \in \mathscr{V}$ travels from $i \in \mathscr{N}$ to $j \in \mathscr{N}$, and 0 otherwise;

$Y^{d}$ 1 if AR $d \in \mathscr{D}$ is used for firebombing, and 0 otherwise;

$Y^{\prime v}$ 1 if GR $v \in \mathscr{V}$ is used for supporting operations, and 0 otherwise;

### *4.4. Mathematical formulation*

We present the following mathematical model for the CEOR problem mentioned in this paper. For a better illustration, the constraints are classified in two classes named AR routing and GR routing, which route and schedule the related resources. Then, at the end of the model, the coordination constraint is presented.

*Objective function:*

$$Min \qquad Z = \sum_{r \in \mathscr{R}} \sum_{d \in \mathscr{D}} \sum_{j \in \mathscr{F}} W_{j}^{rd} + \sum_{v \in \mathscr{V}} \sum_{j \in \mathscr{F}} W_{j}^{\prime v} \tag{1}$$

*s.t*

*AR routing:*

$$\sum_{j \in \mathscr{F}} X_{ij}^{rd} = \sum_{j \in \{\mathscr{F} \cup \mathscr{A}\}, i \neq j} X_{ji}^{r-1d} \qquad \forall r > 1,\ d \in \mathscr{D},\ i \in \{\mathscr{A} \cup \mathscr{L}\} \tag{2}$$

$$\sum_{i\in\{\mathscr{A}\cup\hat{\mathscr{A}}\cup\mathscr{L}\}} X_{ji}^{rd} = \sum_{i\in\{\mathscr{A}\cup\mathscr{L}\}} X_{ij}^{r-1d} \qquad \forall r>1,\ d\in\mathscr{D},\ j\in\mathscr{F} \tag{3}$$

$$\sum_{r\in\mathscr{R}}\sum_{d\in\mathscr{D}}\sum_{i\in\{\mathscr{L}\cup\mathscr{A}\}} cap^d.X_{ij}^{rd} \geq sf_j.vw \qquad \forall j\in\mathscr{F} \tag{4}$$

$$\sum_{r>1}\sum_{i\in\mathscr{A}}\sum_{j\in\{\mathscr{L}\cup\mathscr{A}\cup\hat{\mathscr{A}}\}} X_{ij}^{rd} \leq 0 \qquad \forall d\in\mathscr{D} \tag{5}$$

$$\sum_{r\in\mathscr{R}}\sum_{i\in\mathscr{F}}\sum_{j\in\hat{\mathscr{A}}} X_{ij}^{rd} \leq 1 \qquad \forall d\in\mathscr{D} \tag{6}$$

$$\sum_{i\in\{\mathscr{A}\cup\mathscr{L}\}}\sum_{j\in\mathscr{F}} X_{ij}^{rd} \leq Y^d \qquad \forall r\in\mathscr{R},\ d\in\mathscr{D} \tag{7}$$

$$\sum_{i\in\mathscr{A}}\sum_{j\in\mathscr{F}} X_{ij}^{1d} = Y^d \qquad \forall d\in\mathscr{D} \tag{8}$$

$$h^d + lt^d + t_{ji}^d \leq W_i^{1d} + M.\left(1 - X_{ji}^{1d}\right) \qquad \forall d\in\mathscr{D},\ j\in\mathscr{A},\ i\in\mathscr{F} \tag{9}$$

$$U_i^{r-1d} + lt^d + t_{ij}^d \leq W_j^{rd} + M.\left(1 - X_{ij}^{rd}\right) \qquad \forall r>1,\ d\in\mathscr{D},\ i\in\{\mathscr{A}\cup\mathscr{L}\},\ j\in\mathscr{F} \tag{10}$$

$$W_j^{r-1d} + t_{ji}^d \leq U_i^{rd} + M.\left(1 - X_{ji}^{rd}\right) \qquad \forall r>1,\ d\in\mathscr{D},\ i\in\{\mathscr{A}\cup\mathscr{L}\},\ j\in\mathscr{F} \tag{11}$$

*GR routing:*

$$\sum_{i\in\{\hat{\mathscr{E}}\cup\mathscr{F}\},i\neq j} X_{ji}'^{v} = \sum_{i\in\{\mathscr{F}\cup\mathscr{E}\},i\neq j} X_{ij}'^{v} \qquad \forall v\in\mathscr{V},\ j\in\mathscr{F} \tag{12}$$

$$\sum_{v\in\mathscr{V}}\sum_{j\in\{\mathscr{E}\cup\mathscr{F}\},i\neq j} X_{ji}'^{v}.Ab_i^v \geq ds_i \qquad \forall i\in\mathscr{F} \tag{13}$$

$$\sum_{j\in\mathscr{F}} X_{ij}'^{v} \leq 1 \qquad \forall v\in\mathscr{V},\ i\in\mathscr{E} \tag{14}$$

$$\sum_{i\in\mathscr{F}} X_{ij}'^{v} \leq 1 \qquad \forall v\in\mathscr{V},\ j\in\hat{\mathscr{E}} \tag{15}$$

$$\sum_{i\in\mathscr{E}}\sum_{j\in\mathscr{F}} X_{ij}'^{v} = Y'^{v} \qquad \forall v\in\mathscr{V} \tag{16}$$

$$h^v + t_{ij}^v \leq W_j'^{v} + M.\left(1 - X_{ij}'^{v}\right) \qquad \forall v\in\mathscr{V},\ i\in\mathscr{E},\ j\in\mathscr{F} \tag{17}$$

$$W_j'^{v} + Ab_j^v + t_{ji}^v \leq W_i'^{v} + M.\left(1 - X_{ji}'^{v}\right) \qquad \forall v\in\mathscr{V},\ i\in\mathscr{F},\ j\in\mathscr{F},\ i\neq j \tag{18}$$

*AR and GR coordination constraint:*

$$M\left(1 - X_{ij}'^{v}\right) + W_j'^{v} \geq W_j^{rd} \qquad \forall r\in\mathscr{R},\ v\in\mathscr{V},\ d\in\mathscr{D},\ i\in\{\mathscr{E}\cup\mathscr{F}\},\ j\in\mathscr{F},\ i\neq j \tag{19}$$

*Variables:*

$$X_{ij}^{rd},\ X_{ij}'^{v},\ Y^d,\ Y'^{v} \in \{0,1\} \qquad \forall r\in\mathscr{R},\ d\in\mathscr{D},\ v\in\mathscr{V},\ i,j\in\mathscr{N} \tag{20}$$

$$W_j^{rd},\ U_i^{rd},\ W_j'^{v},\ Ab_j^{v} \in \Re^{+} \qquad \forall r \in \mathscr{R},\ d \in \mathscr{D},\ v \in \mathscr{V},\ j \in \mathscr{F},\ i \in \{\mathscr{L} \cup \mathscr{A}\} \tag{21}$$

The objective function (1) minimizes suppression total time. Constraints (2)−(11) are related to AR routing. Constraints (2) and (3) maintain ARs flow balance at loading sites and fire sites, respectively. Constraint (4) is ARs' assignment constraint. Constraints (5) and (6) indicate that each AR can leave its depot utmost once in its trip and then if it leaves, it must enter the hypothetical depot only once. Constraint (7) states if an AR is dispatched, binary variable $Y^d = 1$ (i.e. resource $d$ is used). Constraint (8) ensures that an AR starts its trip at depot, if it is used. Constraints (9)−(11) maintain time between sites $i$ and $j$, if $x_{ij}^{rd} = 1$. In addition, these equations and $t_{ij}^{d} \geq 0$ eliminate any sub-tours in AR routing. Constraints (12)−(18) are related to GR routing. All these constraints are equivalent to similar constraints in the AR routing except constraint (13), which is fire sites' demands for GRs' operations. Finally, constraint (19) coordinates GRs with ARs. Constraints (20) and (21) define the decision variables of the problem.

### 4.5. Linearizing non-linear constraints

To linearize the presented model, the non-linear constraints are replaced by their equivalent linear ones. Base on the method offered by Chen et al. [27], constraints (22)−(25) are presented instead of non-linear constraint (13) using an auxiliary variable, $Abb_i^v$, and $\sum_{j \in \{\mathscr{E} \cup \mathscr{F}\}, i \neq j} X_{ji}'^{v}.Ab_i^v = Abb_i^v$ , $\forall v \in \mathscr{V},\ i \in \mathscr{F}$.

$$\sum_{v \in \mathscr{V}} Abb_i^v \geq ds_i \qquad \forall i \in \mathscr{F} \tag{22}$$

$$Abb_i^v \leq M. \sum_{j \in \{\mathscr{E} \cup \mathscr{F}\}, i \neq j} X_{ji}'^{v} \qquad \forall v \in \mathscr{V},\ i \in \mathscr{F} \tag{23}$$

$$Ab_i^v - Abb_i^v \leq M. \left(1 - \sum_{j \in \{\mathscr{E} \cup \mathscr{F}\}, i \neq j} X_{ji}'^{v}\right) \qquad \forall v \in \mathscr{V},\ i \in \mathscr{F} \tag{24}$$

$$Ab_i^v - Abb_i^v \geq 0 \qquad \forall v \in \mathscr{V},\ i \in \mathscr{F} \tag{25}$$

## 5. Solution approach

We generated an optimization model for the CEOR problem in Section 4. This section represents the applied approach to solve the proposed model. We know that VRP models such as ours are in NP-hard class problems. Therefore, in our model, as the number of resources and fire sites increase, exact algorithms can not solve it in polynomial time [28]. These problems should be solved with heuristics or approximation algorithms [29]. Moreover, the problem is in the crisis area, and it should be solved in a reasonable time.

According to the related literature, in the previous sections, we showed that Greedy methods are practical for problems which have a similar complexity and scale to ours. Therefore, We decided to designed an efficient Greedy heuristic algorithm in the Section 5 to solve our problem. Algorithm 1 illustrates the procedure of our greedy algorithm.

### 5.1. Greedy heuristic algorithm

First of all, we need to sort the fire sites to satisfy their demands for ARs. As shown in Algorithm 1,in the first $for$ loop, different sorts of fire sites are considered based on $sf_f.vw$ and $ds_f$ in the first *iter*, and randomly in others. This is because, in the first *iter*, we try to satisfy the demands in a greedy way, in which the fire sites with lower demand for ARs and higher demands for GRs should be serviced earlier than others in order to reach the minimum total suppression time. However, in the remained iterations, we check randomly sorted fire sites to make sure that there is not a better solution.In the second $for$ loop, the sorted fire sites demands for ARs are satisfied. In the third $for$ loop, with the same pattern of sorting, the fire sites' demands for GRs are satisfied. This way of sorting, force the algorithm to minimize the arrival time (objective function) of each resource at each fire site greedily. This description and the pseudo-code show how the mentioned coordination between ARs and GRs in the mathematical model is considered in our greedy algorithm as well.

In the first *while* loop, at first, based on a local search method, we greedily choose which AR should be selected and which loading site is better to load at (if the fire site needs ARs). Then, in this loop, we update the value of the objective function (time) of ARs after each service. This loop is very decisive because it considerably reduces the complexity of the model by eliminating the main cause of its complexity, which is the index $r$, and automatically indicates the index by its iterations. In the second *while* loop, at first, we choose which GR should be selected (if the fire site needs GRs). Then we calculate the value of the objective function (time) of GRs. At the end of the first $for$ loop which sorts fire sites in different iterations, the objective functions of *iter*s are reported. Finally, the best iteration, whose objective function is minimum, is reported as the best *iter*.

**Algorithm 1** Greedy heuristic algorithm

**Begin**

$list_q \leftarrow \{\varnothing\}$; Initialize the current path list of all AR $d \in \mathscr{D}$ and GR $v \in \mathscr{V}$
$arr_q \leftarrow 0$; Initialize the current arrival time of all AR $d \in \mathscr{D}$ and GR $v \in \mathscr{V}$
$\hat{w}$; Index for all depots and water reservoirs that each AR reload at; $\hat{w} \in \{L \cup A\}$
*time* ; The arrival time summation of all resource to fire sites
**for** $iter \in T$ **do**
  $time = 0$
  In first iteration sort all $f$ based on $sf_f.vw$ and $ds_f$ and in remained iterations sort them randomly
  **for** *all sorted f* **do**
    $f' \leftarrow$ current fire site
    **while** $sf_{f'}.vw > 0$ **do**
      $i \leftarrow$ current position for $q'$
      $\hat{w}' \leftarrow$ depot or water reservoirs that cause to minimize route $i\hat{w}'f'$
      $arr_{q'} = Min_{q \in D}[arr_q + (t^{q'}_{i\hat{w}'} + t^{q'}_{\hat{w}'f'})]$
      $X^{rq'}_{i\hat{w}'} = 1$ and $list_{q'} \leftarrow \hat{w}'$
      $X^{rq'}_{\hat{w}'f'} = 1$ and $list_{q'} \leftarrow f'$
      Update $arr_{q'} \leftarrow arr_{q'} + (t^{q'}_{i\hat{w}'} + t^{q'}_{\hat{w}'f'})$ and update $time \leftarrow time + arr_{q'}$
    **end**
  **end**
  In first iteration sort all $f$ based on time that final AR has already left $f$ and in remained iterations sort them randomly
  **for** *all sorted f* **do**
    $f'' \leftarrow$ current fire site
    **while** $ds_{f''} > 0$ **do**
      $i \leftarrow$ current position for $q'$
      $arr_{q''} = \mathrm{Min}_{q \in V} \mathrm{arr}_q$
      $X'^{q''}_{if''} = 1$, $list_{q''} \leftarrow f''$
      Update $arr_{q''} \leftarrow arr_{q''} + Ab^{q''}_i + t^{q''}_{if''}$ and update $time \leftarrow time + arr_{q''}$
    **end**
  **end**
**end**
*best time* = Min time
report *iter* that provides the *best time* and report $list_q$ and $arr_q$

## 6. Test cases

This section assesses the computational performance of the greedy heuristic algorithm that is implemented on the platform of Python 2019.3. We solved each optimization problem using GAMS, CPLEX 12.8 with a 5000 seconds time limit, and the best feasible solution is reported. We conducted the results on a desktop computer equipped with Intel(R) Core(TM) i5 CPU @ 4.00 GHz and 16 GB of RAM.

We randomly generated the test cases to evaluate our proposed greedy algorithm and show how execution time is affected by different sizes of the test cases. We reported CPU time ("CPU.t"), objective value ("Obj"), and relative percent difference ("RPD") in Table 2. We also illustrate the test cases' size by the total number of ARs plus GRs ("AG (Aerial and Ground resources)"), reloading sites ("$\hat{W}$"), and fire sites ("F"). RPD is calculated as below:

$$RPD(\%) = \frac{Obj - minObj}{minObj} \tag{26}$$

For example, in the first test case and the column of CPLEX, $Obj$ is the optimal solution obtained by CPLEX, and $minObj$ is the minimum value between obj of CPLEX and Obj of the greedy heuristic algorithm.

For better analyses, we considered specific features for the generated test cases. The number of resources varies between 2 and 16. We used an AR and a GR in the first test case, but others are different. The ARs are heterogeneous, and we considered three ARs with specific capacities (680, 1200, 15142 liters) in the test cases. Inspired by Rodríguez-Veiga et al. [11], we used the same number for each of them in different test cases. The number of fire sites and water sites, inspired by Rodríguez-Veiga et al. [11], varies between 2 and 9, and between 2 and 6, respectively. We calculated the volume of water needed for each fire site using Gill [30], which showed that 12 megalitres water were used for Mt Lubra bushfire case in the Grampians, where 120,000 hectares burnt in January 2006 (i.e. 0.001 litre water was dropped on per square meter surface). Each fire site's demand for GRs' services is generated randomly between 0 and 1 hour. We allow the fire sites' demand for GRs or/and ARs to be zero due to the specific demand for each fire site mentioned in Section 3. The distance in the network is generated randomly between 0 and 15 $km$. The rest of the parameters are in Table 3.

In Table 3, we show how each element affects the test cases' size and how efficiently our proposed algorithm works. In the mathematical model, one of the effective factors is $r$ index, which indicates ARs' trips and is affected by the amount of fire sites' demands for ARs. The whole number of trips is calculated as below:

$$r = \sum_{f \in \mathscr{F}} \left\lceil \frac{sf_f.vw}{\min_{d \in \mathscr{D}}(cap^d)} \right\rceil \times 2 + 1 \tag{27}$$

In Equation (27),based on an AR having the lowest capacity, the number of times that it must unload to fully satisfy each fire site's demand is calculated. Then, this value is doubled due to the fact that it has to unload and reload in two different trips for its each service. Finally, one number is added to the total value because of the index $r-1$ in the mathematical model. As shown in Table 3, another effective factor on the test cases' size is the number of fire sites, "F". In addition to its effect on the mathematical model as an index ($f$), it causes the $r$ index to be larger. The number of $r$ increases extremely as the number of fire sites increase even if the fire sites have the least amount of demands because ARs must reload for each fire site at least once, which needs at least two trips of ARs. In other words, for each fire site, it must unload and reload and use two trips. Since $r$ is an index in the mathematical model, it has a serious effect on the test cases' size. For instance, in test cases 3 and 4 in Table 3, as the number of fire sites ("F") increases from 2 to 3, the CPU time for the CPLEX processor becomes almost 80 times higher, while other elements stay the same or even decrease. However, changing the number of water sites ("$\hat{W}$") is not as effective as the number of fire sites ("F") on the size of the test cases (see test cases 2 and 3 in Table 3). The CPLEX can find optimal solution of the test cases 1-5, but it can not solve the rest of them in the 5000 seconds time limitation. Our proposed greedy heuristic algorithm can solve them in less than one minute for the worst case. For a better illustrate, in Figure 2, We drew the 1-5 test cases on the left axis and the 6-10 test cases on the right axis. Considering the test cases solved optimally by CPLEX, our proposed algorithm can solve the first three of them optimally and the rest of them with ignorable RPD. It indicates that our proposed algorithm is reliable.

In the previous explanations, it turned out that a small increase in the number of fire sites ("F") causes a big jump in the computational time of the test cases solved by CPLEX. In this paragraph, we illustrate how the computational time of the test cases solved by the greedy heuristic algorithm is affected. As the test cases' size increase, the computational time of them solved by the greedy heuristic algorithm grows extremely (see Figure 2). Table 3 shows all the significant changes in the computational times of the test cases when solved by the greedy heuristic algorithm are due to the rise in the number of both ARs and GRs ("AG") and fire sites ("F"). For instance, in test cases 5 and 6, or 8 and 9, the CPU.t increases significantly when three number is added to the number of the fire sites ("F"), despite the fact that other features stay the same. (To see the effects of "AG", see test cases 7 and 8.) Therefore, a small increase in the number of fire sites and the number of resources affects the complexity of the problem considerably. However, the proposed algorithm can solve the test cases in a reasonable time.

## 7. Results and discussion

In this section, we discuss the parameters of GRs and ARs that affect the objective function in order to determine the ideal features for them. As it is mentioned above, ARs are heterogeneous, and we use three types of them, in the test cases, including large-sized, (Coulson B737 air tanker – “Bomber”), medium-sized (Bell 204B – “Helitak”), and small-sized (Eurocopter AS355F1 Twin Squirrel – “Firebird”) aircraft with 1 to 4 units available. For GRs, we use homogeneous vehicles, $V$, with 1 to 4 units being available. Table 2 shows more details about the resources.

### 7.1. Sensitivity analysis

According to the mathematical model, the value of the objective function drops down if the fire sites are extinguished in less time. The features of the resources influencing this are their speed, capacity, and loading time. Here, we considered a test case with nine fire sites, three water sites, and four available resources (one GR and 3 ARs of each type). Investigating ARs’ features, in tables 4, 5 and 6, we show the impacts of some changes in their loading time, capacity, and speed, respectively, on the objective function value in the considered test case. As the objective function value is the summation of all arrival times and does not show the total ”operation time”, we mentioned it in all tables as well. In Table 4, the trend of the $obj$ shows that, for all ARs, the smaller their loading times are, the better the objective function value is. The best value for the $obj$ is resulted in the last row, where the loading times have the minimum values. In Table 5, the trend of $obj$ shows that the higher the capacity of both small and medium ARs are, the better the objective function value is. However, for the large AR, any rise in its capacity has no impact on the $obj$. This is because, in this test case, the total demand of all fire sites are less than the capacity of large ARs, and increasing it does not help to extinguish the bushfire sooner. The best value for the $obj$ is resulted in the last row, where the effective capacities are higher. In Table 6, the trend of $obj$ shows that the higher the speed of all ARs are, the better the objective function value is. The best value for the obj is resulted in the fourth row, where the speed of meduim-sized AR is more than doubled, and that of both small and large-sized ones stayed unchanged. All Tables 4, 5, and 6 show that the ”operation time” is not affected as much as the ”$obj$”. This is due to the coordination between ARs and GRs, in which GRs operate as the final supportive resources on fire sites, and the ”operation time” more depends on their arrival time than that of ARs. We will discuss it more in the following paragraphs.

Here we show how the ”operation time” is affected. In Table 7, the influences of changes in the GRs’ speed are shown, and compared to Table 6, here, more betterment (decline) can be seen in ”operation time”.

Moreover, according to table 8, the main effective parameter on ”operation time” is the number of resources. One may expect a decline in ”operation time” when increasing the number of resources. However, in this case, our results show that it behaves differently in various situations. For example, affected by the coordination constraint, adding to the number of ARs without any change in the number of GRs has only a little impact on ”operation time”. However, adding only one number to GRs haves the ”operation time”. After this, an addition to the number of ARs are more effective on ”operation time”.

## 8. Managerial insights

Managers always look for the best decision, especially in crisis circumstances, where they have to make serious decisions under a time pressure. We presented an optimisation tool that helps them in these situations. Although the proposed tool is presented in bushfire situations, they are useable in other relief operations such as earth quick, flood, etc. According to the historical data, when a bushfire occurs, suppressing it in a minimum time is very important. Moreover, the proper usage of available resources over the time limitation has a pervasive influence on preventing the fire from expanding and burning more areas and properties. Our tool prepares these possibilities. According to the results in Section 7, managers are advised to adapt the tool for specific bushfires' situations to take the advantage of the tool in order to control them successfully. For this purpose, there are some relevant management tips here about both available resources and the areas of bushfires.

It turned out that ”operation time” does not decline by increasing the number of ARs without any change in the number of GRs. Apparently, it seems that due to the sufficient number of ARs to do their task on time, the GRs do not need to wait to do their supportive operations on fire sites, which could reduce total ”operation time”. However, as fire site's demands for GRs is as an effective factor, it should be noted that GRs may not need to wait, but there should be a sufficient number of them to satisfy the demands in less time, otherwise, they have to service fire sites in sequence, which takes a great deal of time, especially in large-scale bushfires. Thus, in such situations, increasing the number of ARs only increase the suppression cost, and managers should choose a proper number of both ARs and GRs. Moreover, when the duration time between ARs' operations and GRs' supportive operations on fire sites increase, the efficiency of their coordination decrease because the longer it is, the more possible the bushfire is to accelerate again and expand. We have two pieces of advice for this problem. Firstly, it is a good idea to divide a bushfire area into more fire sites because it makes each fire site has lower demand for GRs, which can reduce GRs' service time on the fire sites and cause the fire sites to be serviced sooner. Secondly, increasing the number of GRs according to the fire sites' demands for GRs is another practical approach. Furthermore, about ARs, according to Section 7, managers should employ ARs with higher capacity, higher speed, and lower loading time.

## 9. Conclusion

We have witnessed the destruction of natural resources and humans' funds and lives due to fires such as recent bushfires burning in the forests of Amazon and Australia. In practice, To prevent the spread of such bushfires, the managers need to decide about the optimal assignment and routing of ARs and supportive GRs quickly. They also have to coordinate these resources in a proper way, which is described in the previous sections, to enhance the effectiveness of fire suppression operations. Considering these issues, in this paper, we proposed a new VRP-based optimization model for this problem. We know that VRPs are NP-hard problems, and decision-makers need a tool that can solve them in a limited time. Our results show that the CPLEX solver is unable to solve this model in real-world scales. Therefore, we proposed an efficient greedy heuristic algorithm to solve it. To validate the reliability of the greedy algorithm, in the test cases that CPLEX can solve, we compared the optimum solutions with the solutions obtained from our algorithm. The results illustrate that the greedy algorithm also can achieve the optimal solutions of those test cases that CPLEX can solve.

In practice, the proposed model is useable for general relief operations such as coordination between road cleaning resources and supplier resources in events such as floods, earthquakes, and hurricanes. Therefore, the proposed greedy algorithm is also useable for solving the mentioned problems. Moreover, we know that minimizing the time of operation, which is considered as the objective function in our model, leads to saving more properties and lives, which is a considerable objective in all crisis circumstances. An important feature that makes our model a realistic one is coordinating GRs and ARs.

Future work can focus on other useful solution approaches including metaheuristic algorithms such as genetic and ant-colony to solve the mathematical model and compare the results. Moreover, the mathematical model can be developed to make it closer to the real-life cases. For example, considering multiple depots, where the routes of resources can start and end, is a good idea. To further extend the mathematical model, the uncertainty of climate conditions can be taken into account. Considering time windows and blocked roads are also good points to make the model more realistic.

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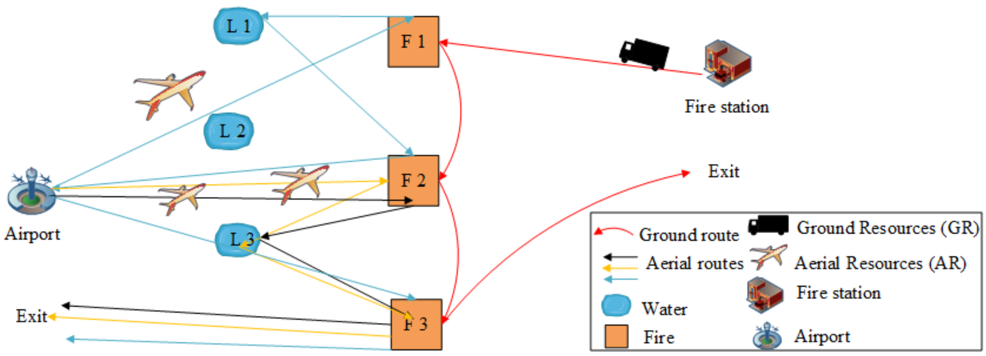
**Figures Captions:**

**Figure 1.** Scheme for Coordination in Emergency Operation Response (CEOR).

**Figure 2.** Computational time of the test cases solved by greedy heuristic algorithm (both vertical axes show CPU.t(s). the one on the left-hand side shows CPU.t of test cases 1-5, and the one on the right-hand side shows that of test cases 6-10.

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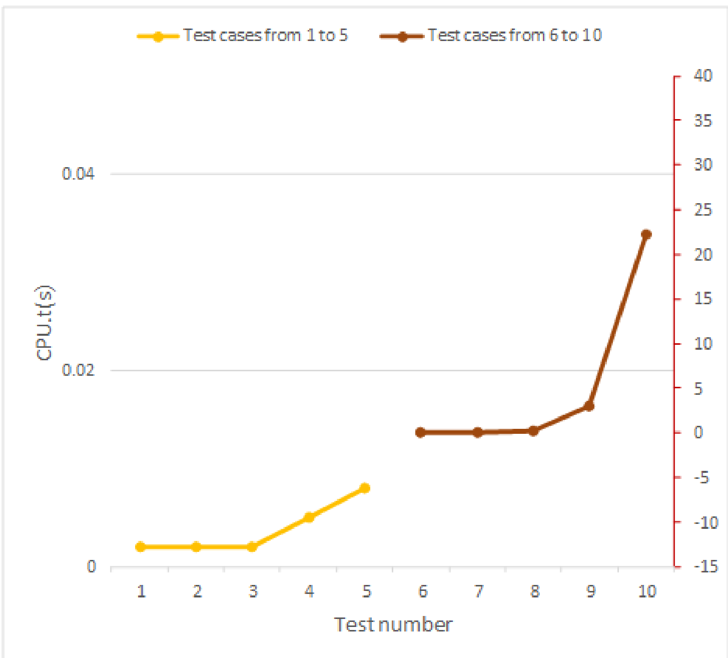


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**Tables Captions:**

**Table 1.** Summary of optimization models for fire management in response phase (VRP-Vehicle Routing Problem, MILP-Mix Integer Linear Programming, MAX-Maximize, MIN-Minimize, PS-Project Scheduling, S-Scheduling, As-Assignment, ARs-Aerial Resources, GRs-Ground Resources).

**Table 2.** Features of the resources (Km-Kilometre, ARs-Aerial Resources, GRs-Ground Resources).

**Table 3.** A summarized results of the test cases.

**Table 4.** Impact of loading time of ARs (shown by D) on the objective function value..

**Table 5.** Impact of capacity of ARs (shown by D) on the objective function value.

**Table 6.** Impact of speed of ARs (shown by D) on the objective function function value(Km-Kilometre).

**Table 7.** Impact of speed of GRs (shown by V) on the objective function value when that of ARs (shown by D) are fixed (Km-Kilometre).

**Table 8.** Impact of number of GRs (shown by V) and ARs (shown by D) on the objective function value while all of them have the best features in the previous tables.

**Table 1:** Summary of optimization models for fire management in response phase (VRP-Vehicle Routing Problem, MILP-Mix Integer Linear Programming, MAX-Maximize, MIN-Minimize, PS-Project Scheduling, S-Scheduling, As-Assignment, ARs-Aerial Resources, GRs-Ground Resources).

| Study | Study type | Model type | Objective(s) | Resource type |
|---|---|---|---|---|
| Lee et al. [16] | Bushfire suppression | As MILP | MIN loss | Engines, dozer, hand crews, and helicopters |
| Wei et al. [14] | Bushfire suppression | As MILP | MIN cost | Hand crews, fire engines, and water tenders |
| Bodaghi and pala-Palanesswaran [10] | Emergency operations | PS MILP | MIN time | Multiple teams of non-expendable resources |
| Yang et al. [12] | Bushfire suppression | VRP MILP | MIN time, cost | Emergency vehicles |
| Wei et al. [15] | Bushfire suppression | As MILP | MIN cost | Engines, crews |
| Rodríguez-Veiga et al. [13] | Forest fires suppression | As MILP | MIN cost | ARs, brigades, and engines |
| Rodríguez-Veiga et al. [11] | Bushfire suppression | As MILP | MIN time | ARs |
| Rauchecker and Schryen, [31] | Disaster response | S MILP | MIN time | Rescue units |
| Our study | Bushfire suppression | VRP MILP | MIN time | GRs and ARs |

**Table 2:** Features of the resources (Km-Kilometre, ARs-Aerial Resources, GRs-Ground Resources).

| Resource | Capacity (litr) | Speed (km/hour) | Loading time (minutes) |
|---|---|---|---|
| D (large ARs) | 15142 | 850 | 20 |
| D (medium ARs) | 1290 | 185 | 5 |
| D (small ARs) | 680 | 230 | 2 |
| V (GRs) | – – – | 60 | – – – |

**Table 3:** A summarized results of the test cases.

| Test | Size | CPLEX | | | Greedy algorithm | | |
|---|---|---|---|---|---|---|---|
| | $AG \times \hat{W} \times F$ | Obj | CPU.t (s) | RPD(%) | Obj | CPU.t (s) | RPD(%) |
| 1 | $2 \times 2 \times 2$ | 2.03 | 40 | 00.00% | 2.03 | 0.002 | 00.00% |
| 2 | $4 \times 2 \times 2$ | 1.07 | 8 | 00.00% | 1.07 | 0.002 | 00.00% |
| 3 | $4 \times 4 \times 2$ | 1.42 | 2 | 00.00% | 1.42 | 0.002 | 00.00% |
| 4 | $4 \times 3 \times 3$ | 3.08 | 157 | 00.00% | 3.15 | 0.005 | 02.27% |
| 5 | $8 \times 3 \times 3$ | 0.99 | 5000 | 00.00% | 1.00 | 0.008 | 01.01% |
| 6 | $8 \times 3 \times 6$ | – | – | – | 14.52 | 0.06 | – |
| 7 | $8 \times 6 \times 6$ | – | – | – | 13.90 | 0.06 | – |
| 8 | $12 \times 6 \times 6$ | – | – | – | 6.22 | 0.26 | – |
| 9 | $12 \times 6 \times 9$ | – | – | – | 23.6 | 2.9 | – |
| 10 | $16 \times 6 \times 9$ | – | – | – | 18.21 | 22.30 | – |

**Table 4:** Impact of loading time of ARs (shown by D) on the objective function value.

| Loading time (min) | | | Objective function value | |
|---|---|---|---|---|
| D(small) | D(medium) | D(large) | obj | operation time (hour) |
| 3 | 7 | 30 | 140.6 | 6 |
| 2 | 5 | 20 | 115.6 | 5.9 |
| 1 | 5 | 20 | 105.9 | 5.69 |
| 2 | 2.5 | 20 | 102.3 | 5.37 |
| 2 | 5 | 10 | 70.3 | 6.3 |
| 2 | 2 | 2 | 59.7 | 5.8 |

**Table 5:** Impact of capacity of ARs (shown by D) on the objective function value.

| Capacity (liter) | | | Objective function value | |
|---|---|---|---|---|
| D (small) | D (medium) | D (large) | obj | operation time (hour) |
| 680 | 1290 | 15142 | 115.6 | 5.9 |
| 1300 | 1290 | 15142 | 91 | 5.49 |
| 680 | 2600 | 15142 | 92.5 | 6.55 |
| 680 | 4000 | 15142 | 89 | 6 |
| 680 | 1290 | 30000 | 115.6 | 5.9 |
| 15142 | 15142 | 15142 | 52.7 | 5.8 |

**Table 6:** Impact of speed of ARs (shown by D) on the objective function function value(Km-Kilometre).

| Speed (km/hour) | | | Objective function value | |
|---|---|---|---|---|
| D (small) | D (medium) | D (large) | obj | operation time (hour) |
| 100 | 80 | 500 | 117.5 | 6.8 |
| 230 | 185 | 850 | 115.6 | 5.49 |
| 500 | 185 | 850 | 105 | 5.4 |
| 230 | 400 | 850 | 102.4 | 5.2 |
| 230 | 185 | 1600 | 113.4 | 5.9 |
| 850 | 850 | 850 | 105.6 | 6.2 |

**Table 7:** Impact of speed of GRs (shown by V) on the objective function value when that of ARs (shown by D) are fixed (Km-Kilometre).

| Speed (km/hour) | | | | Objective function value | |
|---|---|---|---|---|---|
| V | D (small) | D (medium) | D (large) | obj | operation time (hour) |
| 30 | 850 | 850 | 850 | 117 | 7.8 |
| 60 | 850 | 850 | 850 | 115.6 | 5.49 |
| 80 | 850 | 850 | 850 | 101.2 | 4.97 |
| 100 | 850 | 850 | 850 | 97.3 | 4.69 |
| 200 | 850 | 850 | 850 | 95 | 4.37 |

**Table 8:** Impact of number of GRs (shown by V) and ARs (shown by D) on the objective function value while all of them have the best features in the previous tables.

| Number | | | | Objective function value | |
|---|---|---|---|---|---|
| V | D (small) | D (medium) | D (large) | obj | operation time (hour) |
| 1 | 1 | 1 | 1 | 37 | 4.9 |
| 1 | 2 | 2 | 2 | 36.8 | 4.37 |
| 2 | 1 | 1 | 1 | 18.7 | 2.49 |
| 3 | 1 | 1 | 1 | 7.6 | 1.7 |
| 3 | 2 | 2 | 2 | 6.5 | 1.4 |

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