MARMARA UNIVERSITY

FACULTY OF ENGINEERING

COMPUTER ENGINEERING DEPARTMENT

Engineering Project I

CSE4197

Project Specification Document

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"METAHEURISTIC BASED MULTI-OBJECTIVE SCHEDULING OF RESCUE UNITS TO CONTROL WILDFIRES"

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1 Problem Statement

Multiple studies have found that climate change has already led to an increase in wildfire season length, wildfire frequency, and burned area. It is also observed that forest fires in Turkey has been done more harm and damage in the recent years. It is extremely important that forest fires are brought under control quickly and in a timely manner before they spread over kilometers. Efficient and optimal assignment and scheduling of the fire engines in a time of forest fire emergency has a crucial importance to handle these events with minimal loss.

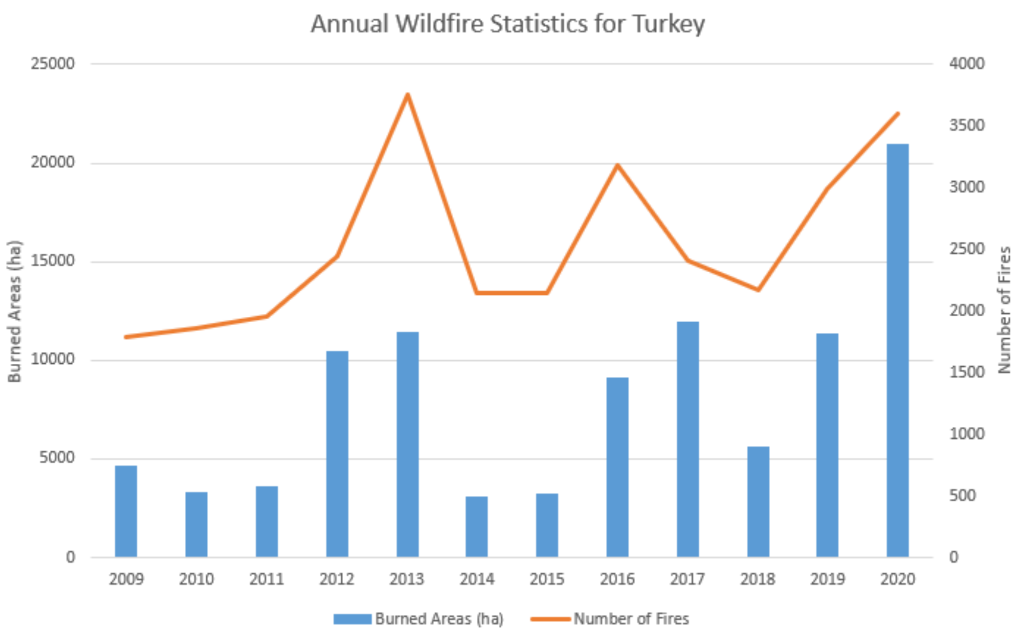

Figure 1: Number of fires and burned areas in Turkey between 2008 and 2020. The data is collected by European Forest Fire Information System [18].

2 Problem Description and Motivation

In times of forest fire emergency, decision makers often make poor decisions or they use weak decision-making algorithms. As a result, rescue vehicles are assigned and scheduled to multiple fire points in a not optimal manner. It is known that in the forest fire emergency situations, the affected areas may lack enough and necessary resources and fires would have to be extinguished with limited resources. In our case the resources are fire fighting vehicles and they need to be assigned to the fire points/areas in a most optimal way so that the fire propagation can be minimal and the areas can be processed in a fastest way. We believe that our project will benefit this problem in a way that;

- The amount of forest fire spread can be reduced.
- Casualties and injuries can be reduced/prevented.

- Damage and rescuing costs can be reduced.

We think providing a correct and a suitable study to this problem can be a great asset to the forest fire disaster management systems. Today it is an absolute requirement for decision systems to have fast and proper algorithms. Similarly, in the area of forest fighting decisions systems a strong decision maker algorithm can save more than ever.

We want our model to take all the necessary information of a wildfire event into account. For example, rate of spread of the fires in different fire locations, information about area, terrain, weather, available resources, distances of fire locations and fire fighting vehicles etc.

We see that this problem is often studied in the research literature and many algorithms and mathematical models are proposed. We observed that those studies lack some significant aspects of a emergency rescue/fire extinguishing process. Some of those key aspects are; uncertainty of a forest fire emergency situation, non-preemption and preemption scheduling, deterministic and stochastic approaches etc. So, we try to implement a model with those important features and come up with a more realistic approach to this problem by taking real world forest fire emergency events into account.

2.1 Problem Formulation

In this section, we present formal problem definition. We first present terms/notations used in the formulation.

Input Parameters	
$G = \{V, E\}$	an undirected graph where V and E denote vertices and edges respectively;
V_N	set of fire points;
V_K	set of depots;
N	number of fire points;
K	number of depots;
c_{ij}	cost of sending a rescue unit to fire point i from depot j;
t_{0ij}	elapsed time until rescue units departed from depot j to fire point i;
t_{Aij}	arrival time of rescue units to fire point i from depot j;
v_{si}	fire spread speed of fire point i;
v_{fj}	fire fighting speed of rescue units on the depot j;
M_j	number of rescue units on depot j;
Decision Variables	
t_{Ri}	the time the extinguish fire point i;
y_{ij}	number of rescue units sent to fire point i from depot j;

Figure 2: Notations/terms used in the problem definition

The emergency scheduling of wildfires can be defined over an undirected graph $G = (V', E)$. V' is defined as $V = V_N + V_K$, where V_N represents the set of fire points and V_K represents the set of depots. E represents set of edges between depots and fire points.

2.1.1 Fire Spread Model

Fire spread speed is one of the most important factors of the wildfires. It could significantly affect the rescue work. Fire spread speed depends on many factors. Spread pattern of the fire is dependent on the environment. In our first attempt, we will be using the same model proposed by Guangdong Tian et al[7].

$$v_s = v_0 k_s k_\phi k_\omega = v_0 k_s k_\phi e^{0.1783 v_\omega} \tag{1}$$

where v_s and v_0 represent the fire spread speed and initial spread speed, respectively; k_s, k_ω and k_ϕ are correction factors of fuel types, wind force and terrain slope, respectively. As part of this project, we will be planning to consider adding different forms of uncertainty in the spread model.

$$v_0 = aT + b\omega + c \tag{2}$$

Also, where T is the temperature; ω is the wind force; a, b and c are factors related with the terrain and they are determined by the actual location of wildfire.

2.1.2 Mathematical Model

In this model, there are two objectives and five constraints which are;

$$Min \quad f1 = \sum_{i=1}^{N} t_{Ri} \tag{3}$$

$$Min \quad f2 = \sum_{i=1}^{N} \sum_{j=1}^{K} y_{ij} \cdot c_{ij} \tag{4}$$

$$t_{Ri} = \frac{\sum_{j=1}^{S} (t_{0ij} + t_{Aij}) \cdot y_{ij} \cdot v_{fj}}{\sum_{j=1}^{S} y_{ij} \cdot v_{fj} - v_{si}} \tag{5}$$

$$M_j \geq \sum_{i=1}^{N} y_{ij}, \quad \forall_j \in V_K \tag{6}$$

$$v_{si} \leq \sum_{j=1}^{S} y_{ij} \cdot v_{fj}, \quad \forall_i \in V_N \tag{7}$$

$$t_{Ri} \geq 0, \quad \forall_i \in V_N \tag{8}$$

$$y_{ij} \in \mathbb{N}, \quad \forall_i \in V_N, \quad \forall_j \in V_K \tag{9}$$

Objective (3) is to minimize the total fire-extinguishing time. Objective (4) is to minimize the cost of the used rescue units. Cost variable (c_{ij}) could be anything depending on what is wanted. e.g. If we want to minimize the total travel distance we could replace it with the distance between fire points and depots. Or if we want to minimize the total number of rescue units used on the rescue we could simply set it to 1. Constraint (5) defines the extinguishing time of the fire point i. Constraint (6) defines that rescue unit(s) sent from depots cannot exceed its own capacity. Constraint (7) defines the required minimum fire fighting speed on fire point i. Constraint (8) defines that extinguishing time of the fire point must be positive. Constraint (9) defines that the number of rescue units sent to fire point i must be a natural number. Also note that the arrival time of rescue units (t_{Aij}) calculated by dividing length between fire point i and depot j by the travel speed of rescue units on depot j. Due to distance and speed being a constant implies that arrival time is also a constant and can be calculated before hand.

This model is taken from the paper Peng Wu et al[8] proposed. Their extension to multi-depot case has taken and some changes have been made. Differences between this model and the model they are proposed are below;

On objective (4) the old model [8] was only considering the number rescue units used on the rescue. This models adds a cost constant for handling different type of minimization approaches (e.g. minimizing total travel distance). On constraint (5) old model assumes that fire started just before rescue units departed from depots. In the new model (t_{0ij}) is added for handling the case that rescue units do not leave the depots immediately. On constraint (7) old model does not consider the case that rescue units could be distinct and have different capabilities of fighting fire. In the new model the constraint is checking for fire fighting speed of rescue units instead of number of rescue units.

3 Main Goal and Objectives

We aim to to propose a meta-heuristic multi-objective evolutionary algorithm to solve this problem efficiently and optimally to overcome the issues of this problem. We are planning to implement a multi-objective genetic algorithm which we think will be the most suitable for our model. We aim to propose the most suitable mathematical model according to our requirements in this study and try to solve the model with many different possible parameters. We are also planning to generate sufficiently enough and precise terrain data to test our algorithm and compare it with other proposed algorithms.

For our genetic algorithm implementation, we need to handle the components of the meta-heuristic correctly. Moreover, we need to understand the requirements of the problem by observing other studies in the literature so that we can alter our algorithm in a appropriate way. We can also program tuning methods to improve the success rate of the genetic algorithm. Consequently, developed programs and mathematical models must be provided correctly.

We want to observe a certain size of improvement with our algorithm over other proposed algorithms in the literature. For example, our measures may be timing, factor of destruction, casualties, cost and so on. We will measure these metrics to observe how well our approach works against other approaches (bench-marking our work with other suggested algorithms) and what improvements we can apply to our study.

Our main objectives are:

(i) Minimize the response time of rescue vehicles by minimizing total travel time of rescue vehicles and the time it takes for the rescue vehicles to extinguish fires totally.

(ii) Decrease the time it takes for the fire fighting vehicles to arrive to the one or multiple fire locations. Therefore minimizing the number of dispatched rescue vehicles by an optimal scheduling.

(iii) Generate quite precise terrain data or collect real data (if possible) to benchmark the algorithms truly.

(iv) To be able to be ready for uncertain events during a fire emergency so that the fire fighting vehicles can adapt to changes rapidly.

(v) To be able to minimize the total damage and destruction to reduce overall costs during a forest fire emergency situation.

4 Related Work

Over the past decades, a number of studies concentrated on emergency planning and scheduling for various natural disasters and catastrophic events. Researchers have addressed many problems and their variants, including earthquake relief, traffic incident response, personal evacuation, flood emergency, and wildfires. Many different models has been developed, e.g. integer linear programming models, dynamic programming models, goal programming models, genetic algorithm models, immune algorithms and many other meta-heuristic models. In our research, we examined in detail the articles aiming to solve wildfire problems with meta-heuristic methods. Now, we share the important ones of these articles together with their approaches to the problems. We have also included a summary table to classify articles.

Model Classifications

Paper	Objectives	Rescue Resources	Multiple Vehicles	Method
1	Multi-objective	Single-depot	Yes	Genetic Algorithm
2	Single-objective	Multi-depot	Yes	Heuristics
3	Single-objective	Multi-depot	Yes	Mixed Integer Programming
4	Single-objective	Single-depot	No	Various Heuristics
5	Single-objective	Single-depot	Yes	Integer Linear Programming
6	Single-objective	Single-depot	Yes	Genetic Algorithms and PSO
7	Multi-objective	Single-depot	Yes	PSO and DE combined
8	Multi-objective	Single-depot	Yes	Both Genetic Algorithm and DP
9	Multi-objective	Single-depot	Yes	E-constraint method

Figure 3: Classification of the proposed models.

Emergency Logistics for Wildfire Suppression Based on Forecasted Disaster Evolution [1]

Yang, Z. et al proposed a study about the trend of wildfire spread. In their study, it is aimed to rank the emergency levels of fire points and determine the emergency priorities of the fire sites. The model then aims to extinguish all fires at the most satisfactory times by making use of these priority levels. Like many articles in the literature, this article deals with wild fires with a single depot and multiple fire sites. Also, the paper considers the real data from wild fires that occurred in the Daxingan Mountains on March 19th, 2003 and on June29th, 2010. The Wangzhengfei method was used to predict fire spread which is claimed to be suitable for the Daxingan mountains terrain. The article considers the problem in two different scenarios. In the first scenario, forest fires spread slowly and therefore the number of rescue units sent is less than the total number of fire points. In the second scenario, forest fires spread rapidly and the number of rescue units sent is greater than the number of fire points. The first scenario solves the problem in multi-objectives: F_1, minimizing the total travel time of the emergency vehicles and F_2, minimizing the total cost of the emergency vehicles. The proposed model combines these to objectives into a single objective by $F = aF_1 + (1-a)F_2$. It then uses the ICA, which is an kind of a genetic algorithm. The second scenario solves the problem by creating functions of B(t) total area burned at time t and C(Xi) total cost from a fire site i. It then finds Xi* optimal number of rescue units to be sent fire point i which is corresponding extremum point of total cost function. The first scenario given in this article is quite similar to the approach we are aiming for. The proposed model is using evolutionary algorithms to solve the problem. Here, the small difference is that we aim to solve multi-depot cases.

Emergency Response in Natural Disaster Management: Allocation and Scheduling of Rescue Units [2]

Felix Wex et al constructed an optimization model for Rescue Unit Scheduling and Assignment Problem (RUASP) for Natural Disaster Management and Decision support systems. They generated data based on the interviews with associates of the THW who were direct contact to first search and rescue teams after the major earthquake in Japan in 2011. They proposed a single objective mathematical model aims to minimize the weighted sum of completion times over all incidents by the rescue vehicles. They proved that their problem is NP-Hard and implemented various heuristics for the problem. They tested each heuristic and compared the performances of them with each other. They observed RUASP problem can be solved in less than a second for the instances up to 40 incidents with the solution values being at most 10.9. The study suggests a improved version of multiple Traveling Salesman Problem (mTSP). This study builds a single objective model for routing and scheduling of rescue vehicles during the response phase to a disaster. The proposed model suggests a deterministic approach and does not take uncertainty of a disaster situation into account. Author also addresses some future research directions about preemptive scheduling, collaboration between rescue units, stochastically modeling of disaster information by fuzzy set theory to solve the problem of uncertainty.

Probabilistic Allocation and Scheduling of Multiple Resources for Emergency Operations; a Victorian Bushfire Case Study [3]

Behrooz Bodaghi et al constructed a framework to facilitate the scheduling and sequencing resources using multiple stochastic scenarios. The proposed model integrates GIS and Mixed Integer Programming (MIP) approaches. They applied their model to data from the Black Saturday bushfires in 7 February 2009 in Victoria, Australia. They proposed a single objective mathematical model that has goals of determining the sequence of demand points visited by chosen vehicle(s) to deliver requisite resources and minimizing the completion times of relief operations at individual demand points. the proposed model The multi resource scheduling model under uncertainty (MRSU) solves the deterministic MIP many times using parameters that are varied stochastically. The objective function of the model is to minimize the weighted sum of completion times over all demand points. The weighted factor depends on the severity level of each demand point. Authors point out that utilizing simple decision heuristics does not result any optimal outcome, also other emergency relief papers often fail to consider the multiple resources required in times of emergency as well as they rather assume the input information will be static. They suggest a model which takes vehicles with varying capacities for both expendable and non-expendable resources into account. Their results concluded that their model can generate plans to schedule multiple resources. (on optimizing scheduling and sequencing). For future research studies, they explain that their problem can be improved with meta-heuristics and hybrid methods especially because of the fact that MIP is quite erratic.

The Disaster Emergency Unit Scheduling Problem to Control Wildfires [4]

P.J. Araya-Cordova et al proposed a single objective mathematical model to determine a schedule and the working times of the disaster emergency unit (DEU). Their objective is to minimize the sum of the total damage and the total waiting cost of the forestry companies. The authors build an isoelastic damage function to calculate each forest locations damage cost. they proposed a centralized and a decentralized approach for the problem. The algorithm focuses on minimizing the sum of the total damage and the total waiting cost of the forest areas. It can be integrated in a management decision support system where the total cost/utility is distributed among firms according to the order/sequence of formation (scheduling and minimizing damage function). They run their algorithm using a relatively small instance (4 forestry companies) with optimization tools provided by MATLAB. They also suggested truthful mechanism for decentralized approach where DEU does not know the real waiting costs of the forestry companies. They observed increasing a damage cost of a town increases the waiting costs of other towns. In other words, working time of DEU affects the total damage outcomes of each town. Authors suggest that future research can be about solving the problem of sequential use of a resource with uncertainty.

Resource-Constrained Emergency Scheduling for Forest Fires with Priority Areas: An Efficient Integer-Programming Approach [5]

P. Wu et al proposed a model unlike many other articles, their study is aimed to find an optimal solution to the proposed problem. An integer linear-programming (ILP) model is developed to generate its optimal schedule scheme, which is exactly solved by commercial software CPLEX. The proposed model has a single objective, to minimize the total travel distance of all fire-fighting teams. Also, the priority levels of the fire points are assumed to be known. In the article, the model was first given in a nonlinear form and converted to linear form step by step. Then, the obtained model was transformed into a TSP problem and it was proved that the problem is an NP-hard problem. It is stated that the optimal solutions of large-sized samples with up to 100 fire points and 30 firefighting teams can be found in about 1 minute with the proposed approach.

Emergency Scheduling for Forest Fires Subject to Limited Rescue Team Resources and Priority Disaster Areas [6]

Y. Ren et al proposed a extremely simple article. Unfortunately, the propagation rate of fires is not taken into account in this model. Instead, the whole idea is to send rescue units to different fire points, with the single objective of minimizing the overall travel distance. It is assumed that the priority levels of the fire points are known. In addition, a fire point must be covered only once by a fire fighting team, and after the fire is extinguished, rescue vehicles can go to other fire points. In the paper, it is stated that the problem is NP-hard and a hybrid algorithm integrating genetic algorithm (GA) and particle swarm optimization (PSO) is adopted to solve the proposed model. Although the heuristic algorithm approaches presented in this article are well explained, the presented model is rather simple compared to our work, since the presented problem does not have fire propagation rate and the model is single objective.

Dual-Objective Scheduling of Rescue Vehicles to Distinguish Forest Fires via Differential Evolution and Particle Swarm Optimization Combined Algorithm [7]

Guangdong Tian et al proposed a dual-objective optimization model for forest fires in order to minimize the extinguishing time of fire points and the number of rescue vehicles used. They have implemented their version of partical swarm optimization. They introduced differential evolution operators into PSO. They applied this approach to real-world emergency scheduling problem of the forest fire in Mt. Daxing'anling, China. They verified the effectiveness of their approach by comparing it with genetic algorithm and PSO. Their model consists of single host for rescue vehicles. There are multiple fire points and multiple rescue units can work in a single fire point. They have also proposed an elaborate fire spread model. They indicated that their method works better compared with NSGA-II and MOPSO. For future work they suggested an user interface that help decision-makers to choose a suitable scheduling solution.

Bi-Objective Scheduling of Fire Engines for Fighting Forest Fires: New Optimization Approach [8]

Peng Wu et al proposed and dual objective optimization model for forest fires by optimizing the work done by Guangdong Tian et al [7]. They changed some of the constraints using the fact that the rescue units are identical. They managed to decrease the number of variables and constraints that used in the model. In order to find a scheduling solution from this model, they proposed a dynamic programming algorithm and a greedy algorithm. Greedy algorithm cannot guarantee the solution optimality but it is time complexity is lower than dynamic programming algorithm. Beside of the single-depot model, they also proposed an extension the multi-depot case. Unfortunately their methods for solving single-depot case does not work on multi-depot model. They indicated that their improved outperforms the existing model. For future work they pointed out that their model could not address the case with distinct rescue units. They also stated that, in real life the time for the rescue units to reach the destination varies. They suggested that extending the model in this way would be an important direction.

A Multi-objective Emergency Scheduling Model for Forest Fires with Priority Areas [9]

Lubing Wang et al proposed a multi-objective rescue unit scheduling model for minimizing the extinguishing time of forest fires and minimizing the total travel distance of rescue units. To solve this model, they implemented an iterative and fuzzy logic decision-making based on e-constraint method. Their model is for single-depot case and there can only one rescue unit on each fire point simultaneously. The number of fire points is larger than number of available rescue units. In their model, they assign priority to fire points by their severity and extinguish fire points those with higher priority at once. Rescue units must return after completing their work. They indicated that this problem is NP-Hard. They suggested that their model and the method they are proposed are effective and has practical importance. For future work they remarked that they will also consider the case that a fire point is rescued by multiple rescue units.

5 Scope

In our project we are going to propose a multi objective fire scheduling model and propose some ways to solve it efficiently. Our objective is using minimal number rescue units to effectively extinguish fire points. Our first objective is the minimize the total time to extinguish all fire points. Our second objective is to use minimum number of rescue units. Due to nature of our two objectives they are in conflict. Therefore, we will be finding Pareto solutions for the decision-makers to choose from. Below, we share some of the key points in our project scope.

- Since the problem is NP-hard, we will not be using Dynamic Programming and Integer Programming methods which have exponentially running times. Instead, we aim to use heuristics to approximate Pareto front solutions.
- In our model, we will fully know the shortest distances between all fire points and fire stations. Therefore, we certainly do not address issues such as path finding for rescue units. Instead, we will already know the shortest paths between the points.
- At the start of the project, we will first consider non-stochastic environments. After creating the relevant models, we are now ready for stochastic events. The rate of fire spread, distances between fire points and fire stations, ignition times of fires and many other parameters will be completely stochastic.
- We will use the fire spread model that is proposed by Guangdong Tian et al [7]. In our model there will be multiple fire stations (i.e., multi depot) and rescue units on different fire stations will be distinct. Multiple rescue units will be able to rescue same fire point.
- In the proposed problem, it is always guaranteed that resources are sufficient to extinguish all fire points. So, it is guaranteed that there will be a scheduling of rescue units to extinguish all fire points.

6 Methodology and Technical Approach

The main purpose of our study is to find a scheduling of rescue units that will extinguish the fires in the minimum time. However, since the problem is an NP-Hard problem, we have to find methods and approaches that will enable us to reach satisfactory results in a short time. Under these time constraints, the proposed models for this problem have to be based on heuristics and some artificial methods. In this section, we list these technical approaches that can benefit us in solving this difficult scheduling problem.

6.1 Multi-objective Evolutionary Algorithms (MOEAs)

An evolutionary algorithm is a meta-heuristic optimization algorithm which is inspired by the evolutionary biological mechanisms. The general methods of an EA are reproduction, recombination, mutation and selection. EAs work by composing the methods above between generations. In a usual EA, in every generation, some particular individuals will be selected and some others will be eliminated based on a fitness function. Since selected individuals are fitter, they will be able to reproduce fitter breeds. Evolutionary algorithms can be used not only to optimize single objective problems, but also to optimize problems with multi-objectives. However, in these cases, the methods applied in various phases such as mutation and parent selection show great differences. In multi-objective cases, we talk about non-dominated solutions (i.e., Pareto Front solutions) rather than a single optimal solution. In this section, we share two very powerful multi-objective evolutionary algorithms that we plan to use in this research.

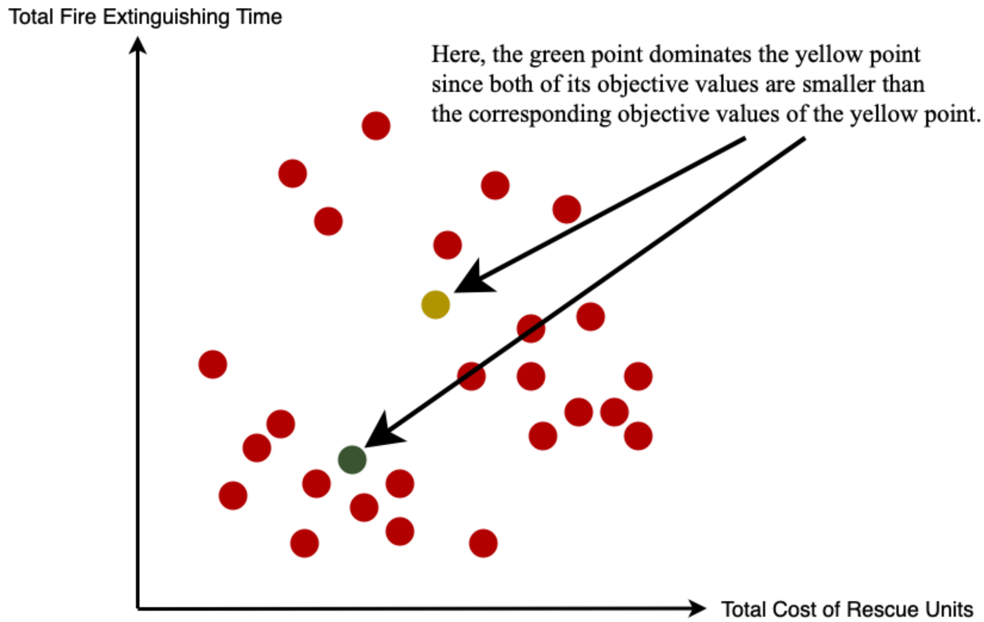

Figure 4: The main purpose of multi-objective evolutionary algorithms is to find satisfactory solutions that no other solution can dominate. A solution S1 dominates the other solution S2 if all of the objective values of S1 are better than the corresponding objective values of S2. Here, both objective values of the green point are less than those of the yellow point. Therefore, the green point dominates the yellow point.

6.1.1 Non-dominated Sorting Genetic Algorithm II (NSGA II)

Non-dominated Sorting Genetic Algorithm II (NSGA II), is one of the most popular multi-objective optimization algorithms [11]. It has fast non-dominated sorting approach, and fast crowded distance (i.e., average distance of two neighboring solutions) estimation procedure. It uses an elitist principle where the best solutions called elites, in each generation, are inserted into the next. We plan to mostly use the NSGA II algorithm to obtain satisfactory results in our study. Below, we share the high-level procedure for the NSGA II algorithm.

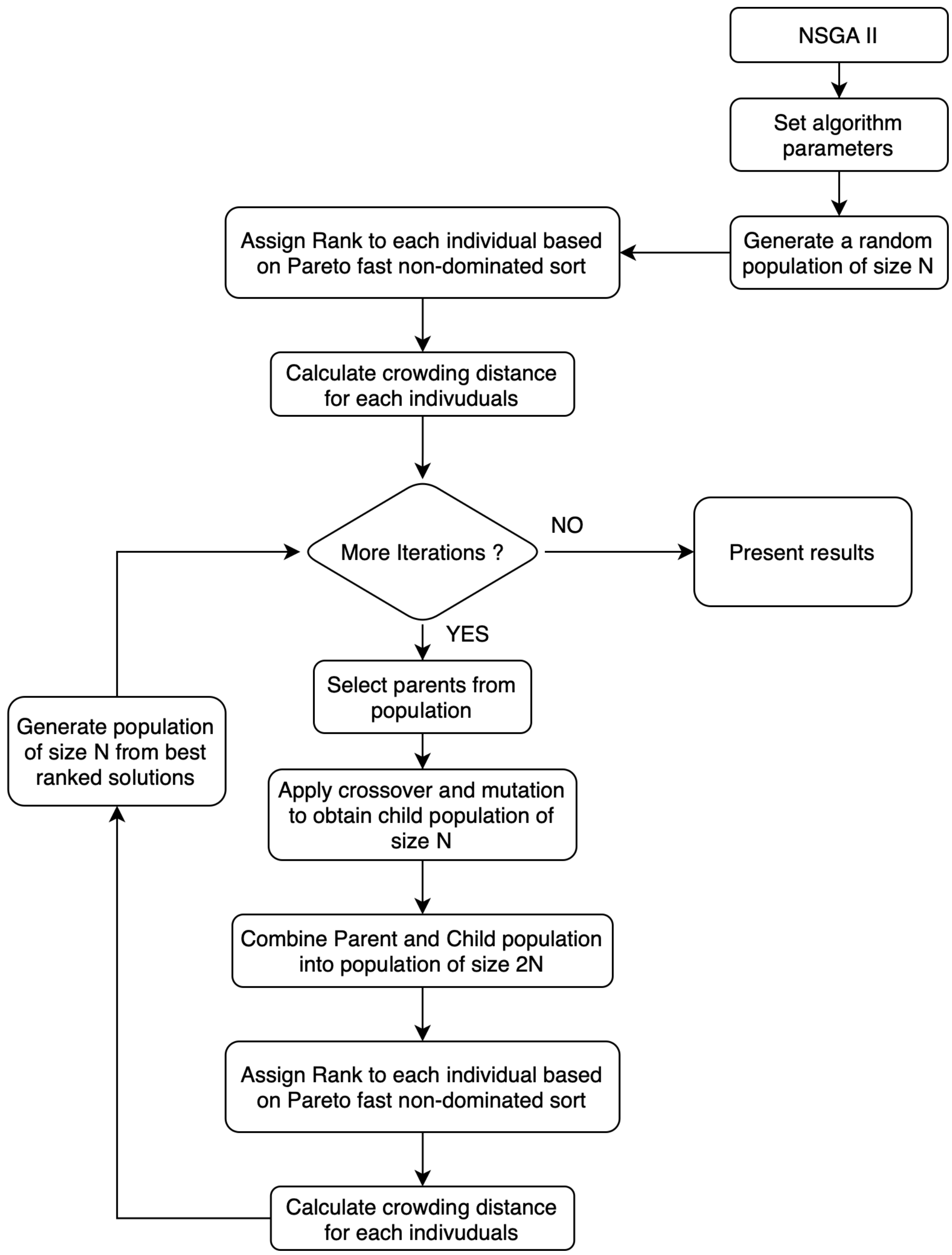

Figure 5: Flowchart for NSGA II algorithm [10].

6.1.2 Strength Pareto Evolutionary Algorithm (SPEA)

Implemented by Zitzler and Thiele et al. According to the comparative case study written by Zitzler and Thiele, Strength Pareto EA (SPEA) can be very effective in sampling from along the entire Pareto-optimal front and distributing the generated solutions over the trade off surface. Like NSGA II, the SPEA algorithm follows an elitist approach [10]. SPEA introduces an external population which stores all non-dominated solutions discovered so far beginning from the initial population. It is a popular algorithm that we are likely to use in this study due to its elitist nature.

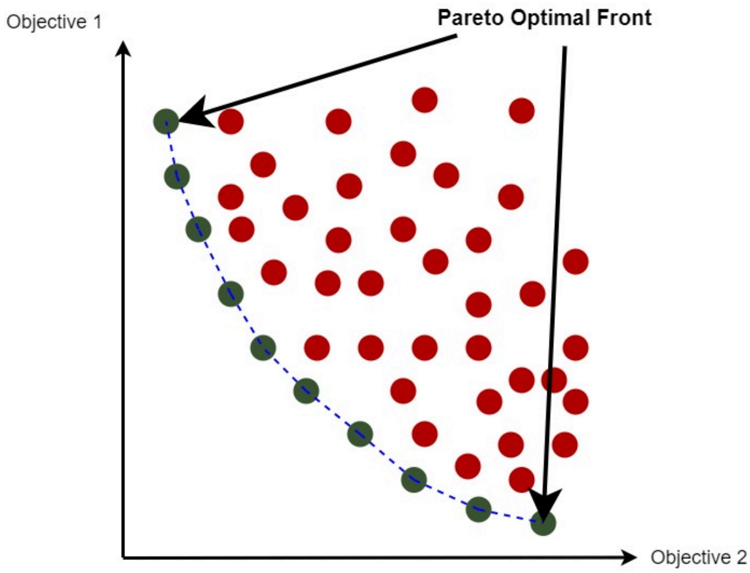

Figure 6: Pareto optimal front on a multi-objective minimization problem. Green points represent Pareto optimal solutions and red points represent dominated solutions. The blue line between green points is Pareto optimal front.

6.2 Stochastically Generating Test Environment

Due to the scarcity of real data on the propagation rates and locations of fire points in wildfire disasters, we plan to generate our own test data. We aim to determine various parameters such as ignition times, propagation rates and coordinates of fires with randomness. For example, initially the simulation may start with a few fire points with varying propagation rates. Over time these fires can lead to other fire points with different propagation rates and coordinates. The model may adopt a new schedule of rescue units to solve this new environment. Below, we share the way we prepare test environments for the models we will implement.

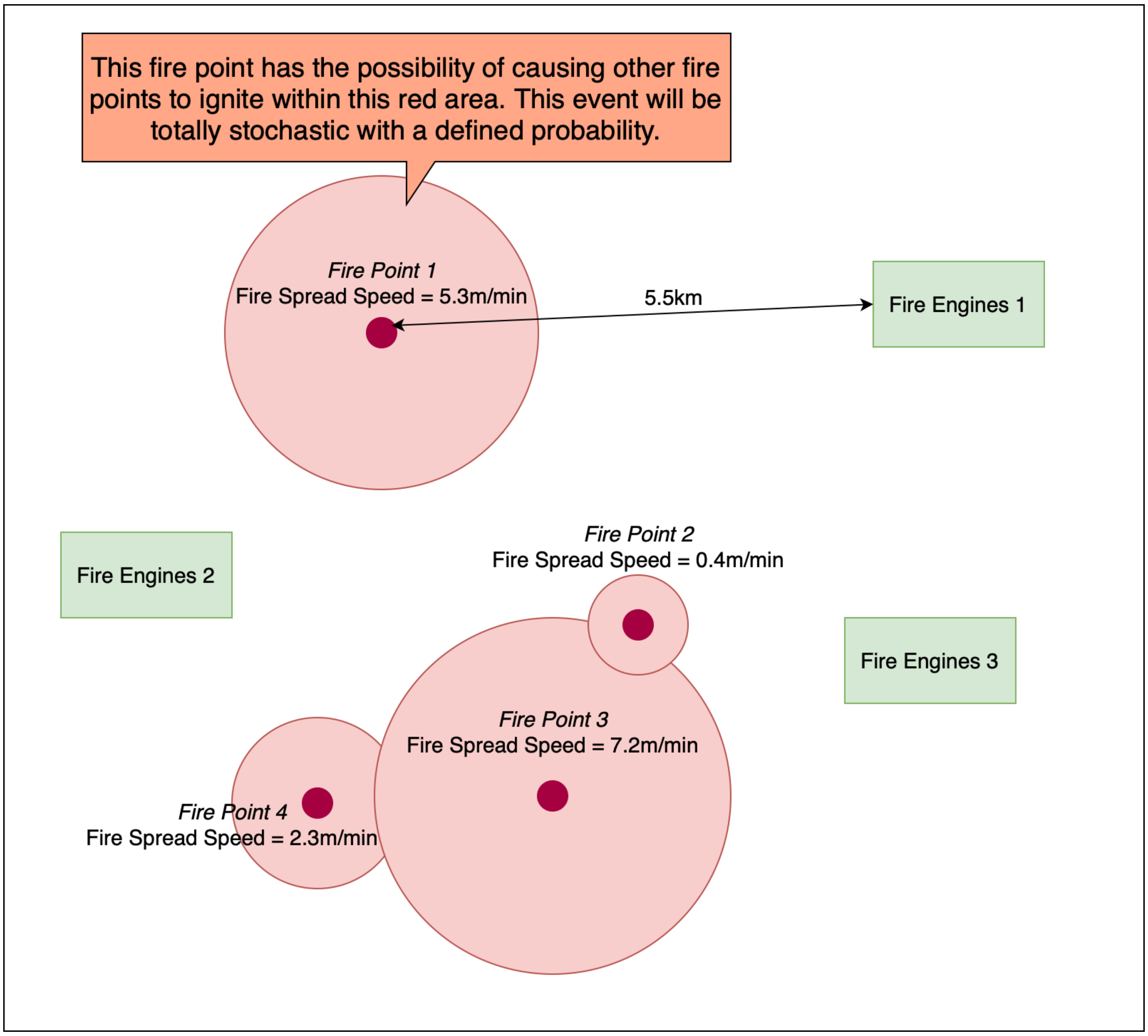

Figure 7: The test environment to provide stochastic events. Some fire points may cause other fire points to ignite with some random probability. There are distances between fire points and fire Stations. For example, there is 5.5km between Fire Point 1 and Fire Engines 1.

To create realistic tests, we will develop a Machine Learning model that offers a similar fire spread to past forest fires. We could determine the number of fire points, ignition times of fires etc. with the help of previously obtained data. In the future, we will search for data sets containing sample fires and use them when creating a stochastic environment in our machine learning model.

6.3 Hybrid Algorithms and Other Multi-objective Genetic Algorithms

During the research, we can also use various single objective algorithms such as Differential Evolution Algorithm, Particle Swarm Optimization in a hybrid way with multi-objective algorithms such as NSGA II. Apart from NSGA II and SPEA, we may also benefit from other multi-objective genetic algorithms such as MOGA, PAES, NPGA, although this is not in our plans at the moment. NPGA and MOGA does not introduce any elitism strategy. Therefore, a number of researchers claim that they are still needed to be improved in the sense of obtaining better Pareto solutions.

6.4 Differences Between Previous Year's Research

A similar project was carried out by Marmara University Computer Engineering Department graduates Eymen, Melik and Rıdvan last year. They worked on the wildfire disaster models having multiple objective functions and multiple resource points as well. However, their aim was to unify the objective functions and convert the multi-objective problem into a single-objective one. They proposed:

$$F_4 = \alpha N(F_1) + \beta N(F_2) + \gamma N(F_3) \tag{10}$$

Where F_4 is the unified objective function of the problem and F_1, F_2, F_3 are the previous objectives of the model. Here,
F_1: Minimizing the extinguishing time of all fire points.
F_2: Minimizing the total travel time of the emergency vehicles.
F_3: Minimizing the total number of emergency vehicles used.
$N(F)$: Normalization function of F.

$$N(F) = \frac{F - min(F)}{max(F) - min(F)} \tag{11}$$

Unfortunately, Pareto solutions cannot be mentioned in this approach. In addition, determining the values of weights in the formula is an another problem. In our approach, instead of combining these objectives, we aim to find Pareto front solutions that optimize these objectives at certain levels. The biggest advantage of Pareto front solutions is that it gives decision makers a choice among hundreds of successful solutions.

The differences are not limited to the algorithm we use. The way we generate the test environment also greatly differs from the previous year's research. We aim to introduce a new graph generators for testing, and we use new methods to provide a stochastic test environment. As we stated in section 6.2, we will be using machine learning models to provide a stochastic test environment which is completely new approach. As in the Figure-7, we will provide graph generators where the spread of fire points and their severity can clearly be observed.

7 Professional Considerations

7.1 Methodological Considerations/Engineering Standards

In this section, we share the methodologies we used in the background to carry out this important project.

Tools and Software	
Project Management	• *Git&Github:* Source code control • *Jira:* Task management • *Telegram:* Communication, planning etc. • *Dropbox:* Keeping Resources
Literature Survey	• Google Schoolar • Marmara University VETİS System • IEEE Xplore • ELSEVIER - Science Direct
Algorithm Implementations	• *Python:* Visualizing Algorithms, Implementing Algorithms, Libraries • *C++:* Implementing Algorithms, Building Stochastic Events
Designing Charts, Graphs, Tables, Figures	• *Python:* Visualizing Large Data • *Microsoft Excel:* Visualizing Small Data • *Draw.io:* Sketching Tables, Figures and Diagrams

Figure 8: Project tools and software.

7.2 Realistic Constraints

7.2.1 Economic

With the spread of Industry 4.0, countries have increased the measures aimed at protecting the environment in an extraordinary way. Thanks to these environmental measures, the tourism revenues of the countries increase and gain a reputation among other countries. This project aims to minimize the areas burned in forest fires and the cost of rescue resources used. Therefore, this research will directly have a positive impact on the country's economy. On the other hand, the execution of this project is extremely cheap. Let's consider a software running the algorithms we've developed and creating a schedule for firefighters on the map. Its design and all testing phases will take a maximum of 3 or 4 months. Considering today's engineer salaries, the realization of this project is quite possible with small figures such as 60 thousand Turkish Liras.

7.2.2 Environmental

Due to the subject of this project, it directly concerns the environment we live in. We shared that one of the objectives in this project is to minimize the total burnt area. Therefore, this project definitely has the potential to contribute to the protection of forests that supply oxygen to big cities. If this research is successful, it could be a model that could benefit decision makers charged with protecting forests.

7.2.3 Ethical

When we look at the objectives in this project, we see that it aims to minimize the resources to be used in responding to forest fires. However, it should not be forgotten that reducing the resources to be used will extend the extinguishing time of the fire and cause more area to be ash. Therefore, decision makers should not use this project only to target minimal resource use.

7.2.4 Health and Safety

This research cannot harm human life. On the contrary, considering that some large-scale forest fires may cause loss of life, it is a fact that this research will reduce the loss of life and property. At the same time, the ideas and methods in this research can be used in other natural disaster problems. This being the case, it is clear that this research aims to protect human life in many aspects.

7.2.5 Sustainability

We shared that if our research was successful, the costs of implementing this research would be extremely low. When we leave aside the cost of the project and look at its usability, we can imagine a very powerful system that facilitates the work of firefighters. This system can be integrated into all fire stations in the country and the planning phase can be optimized in case of forest fires.

7.2.6 Social

In an extremely critical event where forest fires occur at multiple locations, it may seem unreasonable to leave the planning to a software program. Therefore, it will not be possible at first to gain the trust of the people in the Disaster and Emergency Management. If not for now, maybe this trust can be gained with the development of technology in the future.

7.3 Legal Constraints

Currently, this research aims to serve as an idea for response planning in times of disaster and relief. Considering the current plan, the only condition for publishing this research is that our original methods solve the problem with satisfactory results.

8 Management Plan

We first specify the Phases we will follow during our research. Then share the responsibilities among team members with the help of GANTT charts etc.

8.1 Description of Task Phases

- **Phase 1:** Making in-depth literature survey.
- **Phase 2:** Preparation of PSD document.
- **Phase 3:** Preparation of the multi-objective mathematical model of the problem from the general point of view.
- **Phase 4:** Implementing multi-objective algorithms that solve the created model.
- **Phase 5:** Designing animation environments to monitor the operation of algorithms, and visualizing the results.
- **Phase 6:** Preparation of ADD document.
- **Phase 7:** Designing the stochastic test environment to be used while testing algorithms.
- **Phase 8:** Development of new models that reflect the created stochastic environment.
- **Phase 9:** Development of new algorithms that solve the new stochastic model.
- **Phase 10:** Preparation of poster presentations with the obtained images and charts.
- **Phase 11:** Writing the thesis report of the research.

8.2 Division of Responsibilities

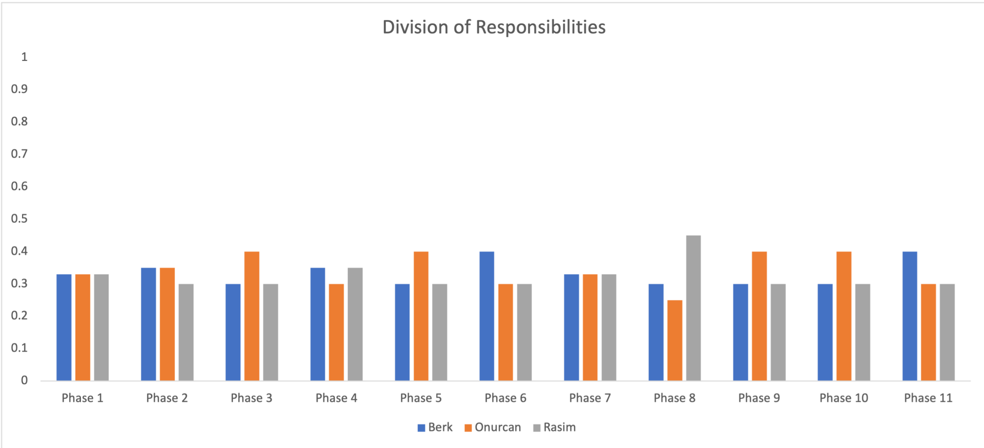

Figure 9: Responsibility sharing among group members.

8.3 Time Line with Milestones

- **Milestone 1:** Time to implement the model and the algorithms.
- **Milestone 2:** Generating the test environment for the stochastic events.
- **Milestone 3:** Preparation of poster presentations and introduction video.

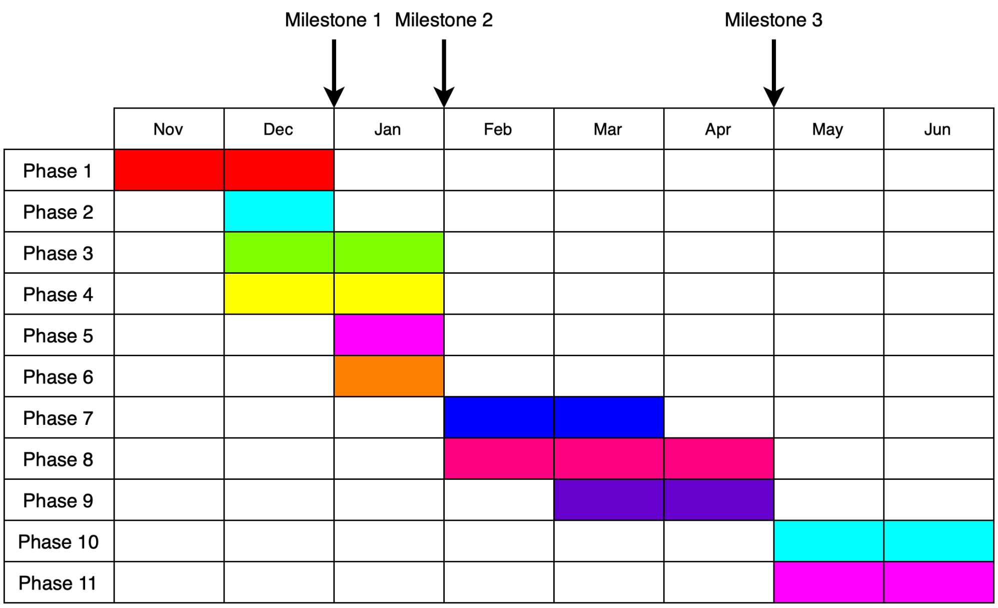

Figure 10: Time line with milestones.

9 Success Factors and Risk Management

9.1 Measurability/Measuring Success

We will use the following performance evaluators to measure the successes of our objectives:

I. **Hyper-volume Indicator:** This indicator is being used for performance evaluation in Multi Objective Evolutionary Algorithms (MOEA). It basically measures the volume of the dominated portion of the objective space by calculating the area of the solution set. For example, to compare two different MOEAs, both algorithms must be run with same objectives and parameters and area of both solution sets must be calculated. After the measures, the solution set with the bigger result will show a higher performance.

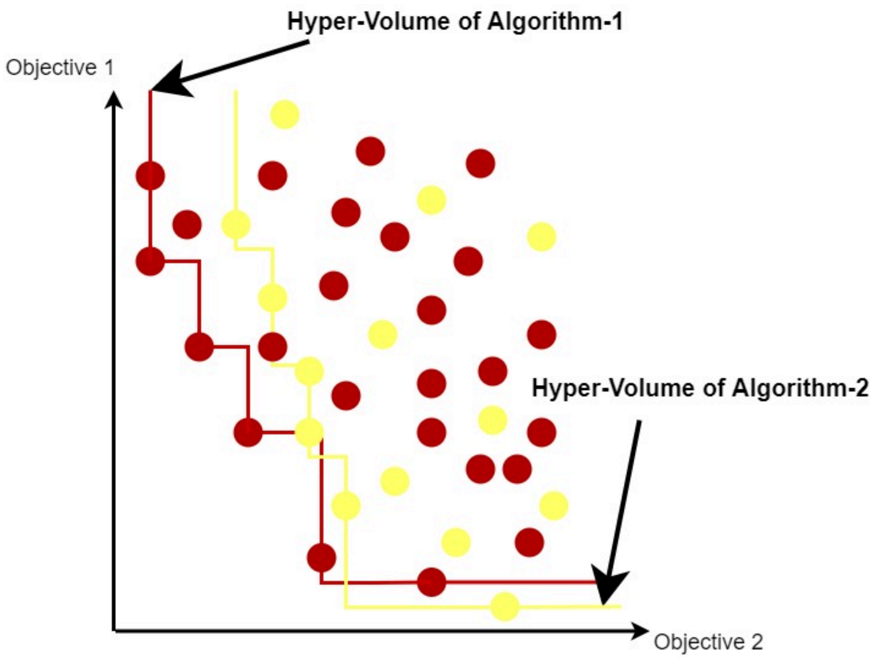

Figure 11: Hyper-volume comparison between two multi objective algorithms.

In Figure-11, Algorithm-1 (red solution set) shows a higher performance against Algorithm-2 (yellow solution set) since covered area of the best solutions of Algorithm-1 is bigger than the covered area of other algorithm. This means that the points of Algorithm-1 are closer to Pareto optimal front.

II. **Inverted Generational Distance Indicator (IGD):** IGD is being used to measure the convergence of a solutions set to the Pareto optimal front. This metric is highly effective for MOEAs and is used widely for quality assessments of proposed algorithms. IGD is calculated by summing the distances between best solutions and their closest point in the Pareto optimal front. The distances are in Euclidean distance form and summation of the distances show the performance of the algorithms. Two different MOEAs can be compared by using this indicator.

Basic Mathematical Notation of IGD:

$$IGD(A,P) = \sum_{a \in A} min\, \forall_p \in P\; d(a,p) \tag{12}$$

$$d = \sqrt{\sum_{k=1}^{N} (a_k - p_k)^2} \tag{13}$$

(12) Calculates the summation of the distances between best solutions and their closest point in the Pareto optimal front. A is the group of best solutions and P is the group of Pareto solutions. (13) d is the Euclidean distance between N points by Pythagorean theorem.

III. Spread Space: Spread space indicator is used to measure how well Pareto optimal front is covered by the solution set. This indicator takes diversity of the solutions into account. More overlapping solutions means better performance.
E. Zitzler et al proposed a solution named Maximum Spread(MS) [17]:

$$MS = \left[\frac{1}{m} \sum_{i=1}^{m} \left[\frac{\min\left(f_i^{max}, F_i^{max}\right) - \max\left(f_i^{min}, F_i^{min}\right)}{F_i^{max} - F_i^{min}} \right]^2 \right]^{\frac{1}{2}} \tag{14}$$

(14) Where f_i^{max} and f_i^{min} are the maximum and minimum values of the ith objective in PF_g, respectively, and F_i^{max} and F_i^{min} are the maximum and minimum values of the ith objective in $PF_{optimal}$, respectively. m is the number of objectives. Bigger MS means better performance.

IV. Cost: Cost factor explains the general time complexity of our algorithm. This complexity depends on algorithm run time, number of fitness function evaluations, stopping criterion and so on. We aim to see at least 10% improvement at this indicator against the proposed works in the literature.

The performance evaluators I., II. and III. are related to MOEAs. Our success factors for objectives are in the following:

(i) **Success Factors for Objective 1:** This objective creates a conflict between objectives and therefore results in a multi-objective optimization problem. Our algorithm should be able to minimize the given result variables considerably. We will evaluate the performance of our algorithm by benchmarking with other famous MOEAs. To compare the algorithms, we will use the performance evaluators I., II. and III. We expect to see at least 15% improvement against other proposed algorithms.

(ii) **Success Factors for Objective 2:** Decreasing the total arrival times of the rescue vehicles requires a good approximated scheduling. We, again, measure the success of this objective by using the performance evaluators I., II. and III. We expect to see at least 15% improvement against other proposed algorithms.

(iii) **Success Factor for Objective 3:** We must generate real-life terrain data or may acquire real terrain data from authorities. Generated data must reflect a natural forest fire situation and performance of algorithm benchmarks on this data must be distinguishable.

(iv) **Success Factor for Objective 4:** Since a forest fire event is stochastic, our algorithm must adapt to changes rapidly. To measure this, we can use stochastically changing forest fire terrain data to test our algorithm and observe how well it performs. The performance of the algorithm between uncertain events should not change more than 10%.

(v) **Success Factor for Objective 5:** Minimizing the total damage and destruction is proportional to the objective 1 and 2. The performance of those objectives will determine the overall costs in a time of forest fire emergency. We can measure the cost factor by comparing different terrain data with our algorithm. The measured costs must be feasible. We expect to observe at least 10% cost reducing.

9.2 Risk Management

- If we cannot obtain real terrain data from authorities, as we mentioned we will use generated terrain data.
- If our algorithm cannot perform better than the other proposed algorithms, then we can implement a hybrid algorithm which can perform better for certain situations. In our case, a hybrid algorithm for forest fires rescue scheduling can be suggested.
- If our study cannot handle uncertainty, then we can suggest different stochastic approaches such as, new statistical distributions for uncertain events, parallel problem instances with different parameters. In the worst case, we can improve our mathematical model or proposed algorithm.

10 Benefits and Impact of the Project

It is an undeniable fact that changes in climate create warmer, drier conditions, leading to longer and more active fire seasons. According to a report by Euronews television news network, an average of 20,760 hectares of land was burned every year in Turkey between 2008 and 2020, and this amount has increased by 755 percent in the same year the report released. In order to solve such a serious problem, various studies should be carried out and the loss of life and property should be minimized. The project we are carrying out will be able to give ideas to the enthusiasts and authorities on issues such as the design of fire detection systems and the design of fire extinguishing management systems. Our study can support decision-makers to handle forest fire emergencies with less losses and less costs. The factor of damage and destruction to living beings, nature, buildings and the number of equipment and rescue vehicles determine the total cost of a forest fire situation. Minimizing this cost can be an enormous improvement in the literature of forest fire studies.

(i) Scientific Impact: We aim to write a scientific paper about our study. If we can provide what we try to accomplish, we will be able to add a significant study to the scientific literature on fores fires. Moreover, since our study is regarding a global problem, researchers all over the world will be able to use our work to extend or build new studies and frameworks.

(ii) Economic/Commercial/Social Impact: Our project aims to contribute to the forest fire fighting management frameworks by improving the action speed of rescue vehicles and providing a better scheduling algorithm. Our study aims to help to minimize the total destruction on nature and reduce emergency costs as much as possible.

(iii) Potential Impact on New Projects: As we think our project will contribute to the forest fire fighting literature, we also assume that our study can be used for future researches. The fact that optimization literature is a constantly growing and forest fire problem is doing more and more harm each day, the researches in this topic will be kept expanding. Consequently, our project can be a significant reference point for many other new projects and studies.

(iv) Impact on National Security: Our project does not interest any security concern.

References

[1] Yang, Z., Guo, L. & Yang, Z., ”Emergency logistics for wildfire suppression based on forecasted disaster evolution”, Ann Oper Res 283, 917–937, 2019.

[2] Wex, F., Schryen, G., Feuerriegel, S., & Neumann, D. (2014). Emergency response in natural disaster management: Allocation and scheduling of rescue units. European Journal of Operational Research, 235, 697–708.

[3] Bodaghi B., Palaneeswaran E., Shahparvari S., Mohammadi M., ”Probabilistic allocation and scheduling of multiple resources for emergency operations; a Victorian bushfire case study”, Comput. Environ. Urban Syst., 81, 2020.

[4] Araya-Córdova, P. J., & Vásquez, Ó. C., ”The disaster emergency unit scheduling problem to control wildfires”, International Journal of Production Economics, 200, 311–317, 2018.

[5] P. Wu, J. Cheng and C. Feng, ”Resource–constrained emergency scheduling for forest fires with priority areas: An efficient integer–programming approach”, IEEJ Trans. Elect. Electron. Eng., vol. 14, no. 2, pp. 261-270, Feb. 2019.

[6] Y. Ren and G. Tian, ”Emergency scheduling for forest fires subject to limited rescue team resources and priority disaster areas”, IEEJ Trans. Electr. Electron. Eng., vol. 11, no. 6, pp. 753-759, Nov. 2016.

[7] G. Tian, Y. Ren and M. Zhou, ”Dual-objective scheduling of rescue vehicles to distinguish forest fires via differential evolution and particle swarm optimization combined algorithm”, IEEE Trans. Intell. Transp. Syst., vol. 17, no. 11, pp. 3009-3021, Nov. 2016.

[8] P. Wu, F. Chu, A. Che and M. Zhou, ”Bi–objective scheduling of fire engines for fighting forest fires: New optimization approaches”, IEEE Trans. Intell. Transp. Syst., vol. 19, no. 4, pp. 1140-1151, Apr. 2018.

[9] L. Wang, P. Wu and F. Chu, ”A Multi-objective Emergency Scheduling Model for Forest Fires with Priority Areas”, 2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), 2020.

[10] E. Zitzler and L. Thiele, ”Multiobjective evolutionary algorithms: a comparative case study and the strength Pareto approach,” in IEEE Transactions on Evolutionary Computation, vol. 3, no. 4, pp. 257-271, Nov. 1999.

[11] K. Deb, A. Pratap, S. Agarwal and T. Meyarivan, ”A fast and elitist multiobjective genetic algorithm: NSGA-II,” in IEEE Transactions on Evolutionary Computation, vol. 6, no. 2, pp. 182-197, April 2002.

[12] Qiang Long, Changzhi Wu, Xiangyu Wang, Lin Jiang, Jueyou Li, ”A Multiobjective Genetic Algorithm Based on a Discrete Selection Procedure”, Mathematical Problems in Engineering, vol. 2015, Article ID 349781, 17 pages, 2015.

[13] Eiben, A. and Smith, J., 2015. Introduction to Evolutionary Computing. 2nd ed. Berlin: Springer.

[14] O. Schutze, X. Esquivel, A. Lara and C. A. C. Coello, ”Using the Averaged Hausdorff Distance as a Performance Measure in Evolutionary Multiobjective Optimization,” in IEEE Transactions on Evolutionary Computation, vol. 16, no. 4, pp. 504-522, Aug. 2012.

[15] K. Shang, H. Ishibuchi, L. He and L. M. Pang, ”A Survey on the Hypervolume Indicator in Evolutionary Multiobjective Optimization,” in IEEE Transactions on Evolutionary Computation, vol. 25, no. 1, pp. 1-20, Feb. 2021.

[16] G. G. Yen and Z. He, ”Performance Metric Ensemble for Multiobjective Evolutionary Algorithms,” in IEEE Transactions on Evolutionary Computation, vol. 18, no. 1, pp. 131-144, Feb. 2014.

[17] E. Zitzler, K. Deb and L. Thiele, ”Comparison of Multiobjective Evolutionary Algo-

rithms: Empirical Results," in Evolutionary Computation, vol. 8, no. 2, pp. 173-195, June 2000.
[18] European Forest Fire Information System (EFFIS), Annual reports on forest fires in Europe https://effis.jrc.ec.europa.eu/reports-and-publications/annual-fire-reports