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**GENETIC ALGORITHM BASED SIMULATION-OPTIMIZATION FOR FIGHTING
WILDFIRES**

A thesis presented to
the faculty of
the Engineering & Applied Science

In partial fulfillment
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Master of Science

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Wildfire is one of the most significant disturbances responsible for reshaping the terrain and changing the ecosystem of a particular region. Detrimental effects of wildfires on environment as well as human lives and properties, and the growing trend in terms of frequency and intensity over the last decade have necessitated the development of efficient forest fire management techniques. During the last three decades, Forest Fire Decision Support Systems (FFDSS) have been developed to help in the decision-making processes during forest fires by providing necessary information on fire detection, their status and behavior, and other aspects of forest fires. However, most of these decision support systems lack the capability of developing intelligent fire suppression strategies based upon current status and predicted behavior of forest fire. This thesis presents an approach for construction of efficient fireline via intelligent resource allocation. A Genetic Algorithm based approach has been proposed in this thesis for resource allocation and optimum fireline building that minimizes the total damage due to wildland fires. The approach is based on a simulation-optimization technique in which the Genetic Algorithm uses advanced forest fire propagation models based upon Huygens principles for evaluation of performance index of its solutions. Both homogeneous and heterogeneous scenarios have been considered. Uncertainties in weather conditions as well as imperfect knowledge about exact vegetation and topographical conditions make exact prediction of wildfires very difficult. The thesis presents Monte-Carlo simulations to develop robust strategies in uncertain conditions. Extensive simulations demonstrate the effectiveness of the proposed approach in efficient resource allocation for fighting complex wildfires in

uncertain and dynamic conditions. Application of Parallel Genetic Algorithm has also been shown that reduces computation time without compromising the optimality of solution.

Approved: _____

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Fire is a natural component of many forest ecosystems, but forest or wildland fires can and often do pose significant threats to public safety, property and forest resources. Wildland fires can be considered to be one of the dominant disturbances in the forests of United States. Fire has a profound effect on the forest ecosystem. Short-term or immediate effects of fire are annihilation of forest vegetation and animals, change of soil composition and it jeopardizes human safety. These and other immediate effects of fire affect the overall ecosystem of the forest even long after the suppression of the forest fire. Apart from its threat to forest flora and fauna, wildfire made changes in soil composition is responsible for change in future vegetation of a particular region and can cause soil loss to soil erosion. Forest fire caused changes in water temperature and composition directly influences aquatic life forms. It is considered as one of the primary processes that influence the vegetation composition and structure of any given location; it helps shape the landscape mosaic and influence bio-geochemical cycles such as carbon cycles.

In recent years, in spite of large expenditures and substantial infrastructure dedicated to wild-land fire-fighting, the damage done in terms of acres burnt has risen dramatically and has reached record highs during the last couple of years. Data provided by National Interagency Fire Center (works with National Fire and Aviation Executive Board and provides unified guidance for fire

agencies in the United States) suggests that during 2005-2009 wildland fires have consumed on an average, approximately 782,1086 acres of land per year. The severity of the wildland fires can be judged from the fact that during just a period of two weeks, the October 2007 California wildland fires resulted into approximately 0.5 million acres of burnt land, evacuation of a million people, and had a price tag of over 1 billion dollars. Apart from these short term socio-economic impacts, large wildland fires have smoke-related health impacts, and huge long-term environmental impacts. Mega wildland fires pump a large amount of carbon-dioxide very quickly into the environment which can have tremendous impact on climate. Wildfire emissions contain greenhouse gases and a number of critical pollutants which can have a substantial impact on human health and welfare. In a study carried out to estimate carbon dioxide (CO_2) emissions using computer models [1] for October 2007 California fires, it was found that the fires produced 7.9 metric tons of CO_2 in just one week which was equivalent to 25% of monthly CO_2 emissions due to burning of fossil fuels in California. Similarly, forest fires in Indonesia in 1997 were estimated to have released between 0.81 and 2.57 giga tonnes (0.89 and 2.83 billion short tones) of carbon dioxide into the atmosphere, which is between 13%–40% of the annual carbon dioxide emissions from burning fossil fuels [2].

Impact of forest fires on human lives and properties as well on environment makes it necessary to effectively manage forest fires. There are overall three aspects of forest fire management; **fire use**, **fire prevention** and **fire suppression** [3].

Fire use is the process in which a naturally or artificially generated forest fire is utilized to manage fuel distribution in the forest by removal of wooden debris and vegetation. Fire use is a major program of Fire and Aviation Management (a part of the US Forest Service) that includes

the combination of **Wildland fire** use and **Prescribed Fire** applications to meet natural resource objectives. Fire prevention includes taking different steps for the prevention of wildfires such as removal of hazardous fuels and generating wide spread consciousness about forest fires. Prediction of forest fires is an important part of fire prevention and is itself a big challenge. Forest fires can be caused by human sources or can be a natural phenomenon. Some forest-fires can be predicted beforehand with prior knowledge of the region and climatic conditions but majority of fire occurrence is stochastic in nature. Fire prevention also includes reduction of hazardous fuel that catalyzes fire growth rate. Although forest fire preventive measures help in damage reduction and in some cases prevention of forest fires (mostly human generated fires), fire suppression is considered as the most important aspect of forest fire management. Lack of total control over removal of hazardous fuels and most of the forest fires being originated through sources (such as lightning) which are essentially stochastic in nature, fire suppression aspect of forest fire management requires special attention.

Even with large expenditure and substantial infrastructure solely dedicated for the prevention and suppression of wildfires, the damage due to wildland fire shows an increasing trend over the years and in the last decade itself, on an average 62,862 wildland fires have been reported with a total burned area of 6,931,3271 acres according to National Interagency Fire Center. Such a situation demands changes in fire management policies and incorporation of more scientific approach to the overall problem. Federal fire policy has been significantly modified since 1995 to recognize and comprehend the role of fire as an essential ecological process (fire-use) [3]. One of the main objectives of the 1995 fire-policy revision was to reduce fire damage annually to 1,200,000 hectares (2,965,264 acres) of forests using mechanical and prescribed fire treatments [3]. The basic idea

behind fire treatment in a controlled manner is to reduce hazardous fuels that accelerates forest fire propagation, before any forest fire. Review reports reflect that the progress towards that goal has been considerably slower due to constraints on smoke production; difficulties in plan preparation and execution; potential impacts on different species[3]. Progress has also been hampered because of the risk involved in the activity for both fire crews and the nature. Different initiatives have been taken since then for the betterment of forest fire management such as the Health Forest Initiative (HFI is a law proposed in response to the widespread forest fires during the summer of 2002). In spite of these policies, a comprehensive development in forest fire management has not been very noticeable. The primary goal of forest fire management is to reduce the total damage due to forest fire. The damages not only include the total land burned but also protection of valuable materials such as human lives and properties if the wildland fire threatens human habitats.

To help the incident managers in making decisions, Forest Fire Decision Support Systems (FFDSSs) have been developed by the science community during the last thirty years which provide valuable information on forest fire behavior, fire detection, and risk assessment. The main categories of FFDSS systems and fire management tools correspond to the following functions of forest fire management:

- Pre-suppression planning
- Fire danger assessment
- Fire detection
- Fire behavior prediction

- Operational fire suppression (including dispatching)
- Fire effects assessment and mitigation

Examples of FFDSS include LANIK [4], Spatial Fire Management System (SFMS) of Canada [5], and FOMFIS [6] and DEDICS [7] of Europe. Each of these systems has its own merits and demerits and some were specially developed for some particular scenarios. FFDSSs provide the necessary information for the fire fighting incident managers to take appropriate actions for forest fire containment. Recently FAM (Fire and Aviation Management) have developed WFDSS (Wildland Fire Decision Support System) tools [8] to help fire managers and agency administrators make decisions regarding strategies and tactics on wildland fires. FFDSS and WFDSS have improved with time in fire detection, fire behavior prediction and other areas but development of intelligent strategies for the suppression of forest fires and efficient resource allocation to minimize damage and cost is still lacking in such systems. For fire suppression strategies, these systems are mostly used to evaluate certain strategies generated by the fire managers in charge of the area. The strategies generated are mostly based on thumb rules and experience of the fire managers in charge. Incorporation of intelligent strategy making capability and efficient resource allocation into the FFDSS is expected to minimize the damage and cost of forest fire fighting.

1.2 Research Summary

Fighting a large active fire is a very challenging task primarily because of the complexity and uncertainties involved in the task. Complexity arises due to a large number of firefighting resources, heterogeneity in types and capabilities of the resources, growing number of homes in

proximity to forests, limited logistical access of the fire sites using roads, spatial distribution of the fire, and occurrence of fires simultaneously at multiple locations during high seasons. All the fire-fighting assets, with their diverse capabilities and constraints, must be managed in real-time so that the entire set of heterogeneous systems operates at the highest possible level of synergy and effectiveness. To compound the complexity, wildland fire-fighting is of a time critical nature and decisions need to be made in an uncertain environment with incomplete/inaccurate information. Uncertainties arise due to dynamic nature of the task, changing weather conditions, and lack of complete knowledge of fuel and ground conditions. Both the complexity and uncertainty affect the ability to accurately predict the fire growth and use the available resources in an optimal and timely manner. With the advances in the capability to accurately predict fire propagation, the ability to gather and process information for obtaining accurate situational awareness, and the computational optimization methods, it is believed that paradigm shifting methods can be developed to help incident managers in generating strategies for effective wildfire fighting. Firefighting efforts in wildland areas require different techniques, equipment, and training from the more familiar structure fire fighting found in populated areas. Broadly speaking, there are two kinds of strategies used by the fire crews, direct attack and indirect attack.

Direct attack is any treatment applied directly to burning fuel such as wetting, smothering, or quenching the fire chemically or by physically separating the burning from unburned fuel. This strategy includes the utilization of urban and wildland fire engines, aircrafts and helicopters for applying retardants directly to the burning fuel. In most of the cases, the objective is to build firelines around the fire for suppression.

Indirect attack associates with the preparatory suppression tactics used at a distance from the burning fuels. This strategy also involves building firelines via methods such as fuel reduction, backfire generation, and wetting unburned fuels. A fireline is a strip of land cleared of flammable materials like plants and shrubs. After the initial firefighting crews mitigate wildfire propagation rate with the help of fire retardants, firelines are required to be built that can actually contain the forest fire. These may be constructed by physically removing combustible material with tools and equipment. Firelines may also be created by a method called backfire generation which involves creating small, low-intensity fires using drip-torches or flares. When the firefront reaches the fireline it stops propagating further due to the lack of additional flammable materials. Thus, fireline building strategy is considered to be one of the most basic strategies for the containment of wildland fires.

In real life wildfire fighting scenarios, a limited number of resources are available and the goal is to use the resources in the best possible manner so that the total damage due to the forest fire is minimized. Optimum resource utilization and allocation is an important part of forest fire fighting. In this thesis, an effort has been made to incorporate search and optimization techniques of Artificial Intelligence for making strategies for Forest Fire Fighting strategy. Search and optimization techniques can be broadly categorized into [9]:

- Calculus Based Techniques
- Enumerative Techniques
- Random Search

Calculus based methods depend on the existence of derivatives and has a high tendency to provide local optimum solutions or sub-optimal solutions for multimodal search spaces. For the mentioned firefighting strategy building problem, expressing the total damage in terms of a parametric function is very hard and hence existence of derivatives is out of question. Addition of randomness into problems with vast multimodal, discontinuous and noisy search spaces is essential to find the global optimum solution. Exhaustive search and total random search though guarantees the global solution, but requires very high computational time for medium or large search spaces. Guided Random Search techniques such as the Evolutionary Algorithms are **random** yet **directed** search methods that possess the capability of obtaining the global solution for a multimodal, discontinuous and noisy search spaces. Considering these conditions, the **Genetic Algorithm**, a family of computational models inspired by evolution, is chosen for this research. In this thesis, the Genetic Algorithm (GA) is used to generate the optimum fireline that minimizes the damage due to forest fire and determines the location of the firefighting crews on the landscape from which fire suppression should start so that the fire doesn't escape and the total damage is minimized at the same time. Fire escape is a phenomenon when the firefront reaches the fireline sites before they are built and hence the fireline becomes incapable of containing the wildfire.

The importance of fireline building strategy in wildland fire containment provides the major motivation for using fireline construction as a fire-fighting strategy in this research. The major contribution of this thesis is the development of the GA based simulation-optimization framework that can utilize advanced fire propagation models for optimal resource allocation for fighting complex wildfires. Another significant contribution of this thesis is that it considers both homogenous terrain with constant wind velocity, and heterogeneous terrain (e.g., hilly terrain with slopes) with

added uncertainty in wind speed and direction. Uncertainty in weather conditions is an important factor for fighting a large wildfire that influences its own weather in a very unpredictable manner. This uncertainty in weather provides a major challenge in decision making. The incorporation of uncertainty in wind velocity as well as in both fire propagation rate and direction and usage of Monte Carlo simulation lead to a more realistic implementation of the proposed GA based approach and the solutions are expected to be more robust to uncertainties in weather conditions.

The thesis is organized as follows: First, a background survey on related works is presented followed by a brief discussion on forest fire propagation model for both homogenous and heterogeneous conditions. The problem formulation is discussed in the following chapter which is followed by a brief explanation of Genetic Algorithm and Parallel Genetic Algorithm. Simulation results are shown in the following chapter followed by Conclusions and Future Works.

CHAPTER 2

BACKGROUND SURVEY ON RELATED WORKS

Over the years, researches have been performed in different aspects of wildland fires such as forest fire modeling, fire prediction, fire detection, and risk evaluation. A good amount of research has been performed in the area of forest fire suppression strategies. There are a wide range of ways in which the forest fire suppression strategies and their goals can be formulated. In this Chapter, a survey of related works available in the literature are presented.

In order to understand the importance of developing more efficient fire suppression strategies, it is required to understand the different aspects of forest fire management. As mentioned in Chapter 1, there are overall three different aspects of forest fire management, **fire use**, **fire prevention** and **fire suppression**. Wildfire use is the management of naturally ignited fire to achieve resource benefits, where fire is a natural component of ecosystem. By allowing the fire to play its natural role many natural resources can be enhanced and private property and social values can be protected. It has been observed that naturally caused fire have caused diversity in vegetation and have eliminated heavy hazardous fuel accumulations. Prescribed Fires are any set of fires ignited by the fire-fighters to meet specific objectives. Prescribed Fires are controlled fires ignited in a very planned way to eliminate hazardous fuels and to control the heading direction of the propagating wildfire to achieve some objectives. Without fire, forests become overcrowded and vulnerable to attacks by insects and

disease and heavy buildups of dead vegetation accumulate. Forests and rangelands can become crowded with plants, bushes, and trees which are not adapted to fire. These ecological changes put the forests and rangelands at high risk. For centuries, naturally caused fires have created vegetative diversity, such as a mixture of wildlife habitats, changed terrain while eliminating heavy fuel accumulation at the same time.

Fire prevention includes taking different steps for the prevention of wildfires such as removal of hazardous fuels and generating wide spread consciousness about forest fires and also prediction of forest fires to some extent. Generally the source of forest fires are human faults or a natural phenomenon. Some forest-fires can be predicted beforehand with prior knowledge of the region and climatic conditions but majority of fire occurrence is stochastic in nature. Wildfires are common in climates that are sufficiently moist to allow the growth of vegetation, that act as the fuel during forest fire, but feature extended dry, hot periods. Such places include the vegetated areas of Australia and Southeast Asia, the open rural places in the interior and the Fynbos in the Western Cape of South Africa, and the forested areas of the United States and Canada. Fire can be particularly intense during the period of strong wind and even in drought. The four major natural causes of wildfire ignitions are lightning, volcanic eruption, sparks from rock falls, and spontaneous combustion. The thousands of coal seam fires that are burning around the world can also flare up and ignite nearby flammable material such as those in Centralia, Pennsylvania, Burning Mountain, Australia and several coal-sustained fires in China. Coal seam fires, that can be an effect of forest fires, have substantial socio-economic and ecological effects. They continue to smolder the underground surface even when the surface fire has stopped. Fire prevention, as mentioned earlier is a very important element of fire management that incorporates preventive measures in

areas where fire is likely to occur. Forest fire generated through human source such as in areas like recreational and camping areas can be predicted beforehand and preventive measures can be taken likewise. Fire prevention also includes reduction of hazardous fuel that catalyzes fire growth rate. The primary objective of fuel-management projects are the reduction of potential hazardous fuels, not the overall fuel distribution of a region. Researchers [3] have claimed that recent federal fire policies and initiatives all seek to reduce fire hazards by reducing forest fuels without distinguishing hazardous and non hazardous fuels. This strategy of reduction of hazardous forest fuels though possesses an intuitive appeal but application of this strategy only is not expected to alter fire hazards significantly. Forest fire propagation is not simply a function of forest fuels but also of weather, wind and topography. Local climate conditions can also be influenced by fire treatments resulting in increased complexity in predicting fire behavior. With the change of global climatic conditions, prediction of wildland fire occurrence is expected to become more complex according to the scientists.

Recent changes in fire management policies have made resource allocation more flexible that have helped more efficient suppression of forest fires [8]. Flexibility have been added by treating the national shared resources such as aircrafts, equipments, Type 1 crews (hand crews), etc as national agency assets and are managed in centralized fashion. They are moved to areas and incidents based on Predictive Services and planning levels. The goals of such actions are to enhance the responsiveness of the assigned resources and elimination of high concentration of resources in a particular geographic area to avoid redundancy.

The third aspect of forest fire management is the **forest fire** prevention. In forest fire management, Forest Fire Decision Support Systems (FFDSS) plays a very important role in pre-

suppression planning, fire danger assessment, fire detection, fire behavior prediction, operational fire suppression that includes dispatching, fire effect assessment and mitigation.

Pre-suppression planning

A Decision Support System (DSS) for pre-suppression planning is an off-line tool able to facilitate decisions that have to be made during the planning process and to aid in the physical production of the plan. Pre-suppression planning is used before the onset of an emergency that includes collection and presentation, in a readily accessible form, of all relevant data and information (spatial, statistical, managerial and operational); analysis of data and information for recognizing dangers, priorities, needed works and actions; determination of the role and the way in which stakeholders are to become involved and to function; specification of actions to do, responsible persons, ways of communication, conditions for involvement and the level of involvement.

Fire danger assessment

The main functionality of a fire danger system is to obtain and manage data on the factors that contribute to fire danger, weigh them according to a predetermined methodology (fire danger model) and produce outputs in the most desirable form. Different sensors and software are used for the detection of fire. Initial Attack Fuzzy System (IAFS) developed by the GRVC-USE-P007 group, as part of its contribution to EUFIRELAB [10], computes a danger index of initial attack by taking inputs as, visual images, meteorological conditions and characteristics of the terrain.

Fire detection

The fire detection activities are an important aspect that concerns all the institutions with responsibilities in fire detection and fire monitoring activities. There are two basic components of fire detection plan: one based on aerial means and the other on ground means. Automated or semi

automated land based systems are available that either replace a person in a watchtower or assist the person. Aerial means include utilization of aerial vehicles supported with enough technology to detect forest fires. Forward looking Infrared (FLIR) is a kind of camera used by the pilots /observer to detect the temperature difference that aids detecting wildfires.

Fire behavior prediction

Fire behavior prediction systems can give outputs that describe not only the spatial behavior of forest fires, direction and rate of spread, but also quantifies and most often display different variables which can be very useful when analyzing fire effects: intensity, flame length, energy release. Some notable fire behavior predicting software are BEHAVE[11] and FARSITE [12]. Although both systems are based on the same fire spread model (ROTHERMEL's (1972) mathematical fire spread model [13]), they function quite differently as the former produces fire behavior predictions related to variables such as fire spread rate, fire line intensity and flame length, in the form of numbers and (when examining ranges of inputs) tables and graphs, while the latter uses terrain and spatial wind and fuel distribution information to develop spatial fire spread simulations.

Operational fire suppression

FFDSS is built to aid the fire managers take decisions on fire suppression and evaluate their strategies.

Fire effect assessment

The main objective of a DSS of this category is to help post-fire decision-making. Alternatively, emphasis is given on providing support for fire management decisions and actions, by analyzing potential fire effects in case of a fire and suggesting measures to take in order to avoid undesirable outcomes.

Some available FFDSS were discussed in the previous Chapter. LANIK [4] includes an initial attack simulation model that predicts the impact of ground and aerial resources. SFMS [5] incorporates a full implementation of the Canadian Forest Fire Danger Rating System, providing assessments of fire ignition and growth potential and predicted fire behavior. FOMFIS [6] is aimed at the definition, design, and implementation of a computer based system giving support to the process of planning activities and resource distribution for the preventive operations carried out by the forest fire fighting services. The DEDICS [7] system emphasizes more on detection, situation awareness, database management, and communication which can support decision making and management. FFDSSs provide the necessary information for the fire fighting incident managers to take appropriate actions for forest fire containment. A recently developed system, WFDSS (Wildland Fire Decision Support System) helps to improve the understanding of wildland fire decisions and the rationale behind them. Forest fire behavior estimation software like FARSITE and BEHAVE and others are deterministic systems but WFDSS-Fire Spread Probability Model (FSPro) is probabilistic in nature. It is a spatial model that calculates and maps the probability of fire spread, in the absence of suppression, from a given fire perimeter or ignition point for a specified time period. WFDSS-FSPro helps managers prioritize firefighting resources based on probabilities of fire spread. The model helps to assess a fire's growth potential. Managers can then match appropriate strategies, tactics, and resource allocations. The program can also aid in communication with affected partners and the public. A detailed background of forest fire propagation models are presented in Chapter 3.

Technically, the different Forest Fire Decision Support Systems are systems integrating the different technical aspects of forest fire pre-suppression planning, fire danger assessment, fire de-

tection, fire behavior prediction, operational fire suppression that includes dispatching, fire effect assessment and mitigation. Resource management is a very important part of both Forest fire management and FFDSS and its goal is optimal utilization of the resources. Dynamic programming technique has been utilized in optimization of resources for forest fire suppression. In [14] a mathematical model for dynamic programming was developed for the economic analysis of forest management operations. The developed model determined the optimal size of firefighting team for handling fire problems. Using cost of access for different locations, the coverage of the land based fire fighting agents was analyzed. A dynamic programming model was introduced that determined the different combinations of locations according to the coverage of fire fighting agents maximizing the coverage area. This technique is applied to Forest Fire Protection System in Chile. Budget constraints has always necessitated the development of techniques for the measurement of effectiveness of initial attack on forest fires of different sizes. This motivated research in the direction of optimal initial attack usage for fire containment. By using the operational research technique of dynamic programming, researchers [15] developed a mathematical model representing the most economically efficient initial attack team (from the available resources) for forest fire suppression ([15]). The costs considered in their work included the cost of transportation and use, rate of fire spread, damage due to fire, line construction productivity, size of fire detected and other factors. Considering the mentioned costs, a cost function was formulated and optimization was performed accordingly ([15]). Earlier works on this field was by [16], where cost effective dispatching of water bombers and crew delivering helicopters was evaluated using dynamic programming but only transportation cost was considered. Usage of Genetic Algorithm is found in [17] where Chi et al.

have used the Genetic Algorithm to construct the best combination of available resources for forest fire fighting but optimal fireline building and realistic fire growth models have not been used.

In two recent papers, HomChaudhuri et al. [18] and HomChaudhuri et al. [19] proposed a Genetic Algorithm based framework for resource allocation and optimal fireline building for wildfire propagation in homogenous terrain with constant weather and wind conditions and heterogeneous terrain with added uncertainty in weather and wind conditions.

Researches have been performed in the past in making the existing decision support systems more user friendly and interactive. For example, to support the decision making of the forest managers an integrated system based on several Artificial Intelligence techniques have been developed called SIADEx ([20]). It is a complex framework integrating several AI techniques with the capability of design and re-design of firefighting plans. This system is interactive as well as user friendly so that even non technical staff members can handle them. Another system incorporating artificial intelligence is CHARADE (in [21]) used in CIFSC (Centre Inter-regional de Formation de la Securite Civile), a firemen school in the south France region. The system is used in planning first attack on forest fire that is based on case based reasoning and constraint based reasoning. A design of fire suppression simulation by using “a discrete event agent model based on a discrete cellular space” has been presented by Hu and Sun [22]. Modeling of different firefighting agents (direct attack, indirect attack and parallel attack) and a general framework of wildfire suppression simulation using cellular methods are available in the reference [22].

Researches in other aspects of forest fire suppression and management include modeling of firefighting agents, modeling of fireline and evaluation of effectiveness of firelines. Fiorucci et al. [23] have proposed a general framework for the formalization of problems relevant to forest

fire emergency management through real time resource assignment. Finney et al. [24] have performed a “generalized mixed-model analysis” that provides a first step in explaining the relation between suppression efforts and large fire containment. A mathematical model for the probability of the fireline succeeding in containing a fire is available in Mees et al [25] . It is well known that the probability of success of containment increases with the increase in width of the fireline or decrease in flame length. According to Mees et al. [25], uncertainty in fireline and flame length affect the probability of containment and thus affects optimum resource allocation. Deviating from the much on going research on forest fire behavior estimate, their research focused on the uncertainty in the productivity of firefighting agents that incorporates the uncertainty in fireline width. In another study Fried et al [26] described a technique for simulating wildfire containment simulations by considering the interaction between fireline building and fire spread by generalizing and some cases simplifying some methods. By using parametric equations for containment boundary, they added flexibility to the free burning fire boundary shapes and included simulation of parallel and indirect attack. Their method required solutions of first order, non linear and differential equations using numerical methods. Researchers in [27] reported a test of a fire containment model considering a wide range of wildfire suppression units with wide range of productivity’s. It showed the magnitude of the variation of final fire size considering the mentioned units. Two analysis was conducted: The relationship between productivity of fire suppression units, fire propagation rates and final fire size; The sensitivity of final fire size to line construction rates of suppression units in specific situations defined by fuel, weather conditions and other factors.

It is clear from this Chapter that research have been performed in different direction considering different aspects of forest fire management as well as forest fire suppression. As explained in

earlier section, this research focuses on resource allocation and optimal fireline building for the minimization of the damage due to wildland fires. Such research problem is an essential component of forest fire suppression and novel according to the best of our knowledge.

CHAPTER 3

FOREST FIRE PROPAGATION MODELING

In order to develop intelligent resource allocation and optimum fireline building strategies for the minimization of total damage due to wildland fires, a realistic forest fire propagation model is required. It is imperative to model fire growth from a spatio-temporal perspective. Empirical data allow fairly good prediction of wildfire propagation under homogenous conditions but incorporation of factors like wind and fuel variation is a complex problem. Integrating the other aspects of fire behavior (terrain, temperature, humidity, moisture content, etc.) is a more challenging task, and a lot of research has been carried out over the last few decades on this subject. Séro-Guillaumea et al. (2008)[28] have proposed a general framework of forest fire propagation model. There are a couple of basic approaches to fires growth models, namely cellular and the two dimensional deterministic wave approaches.

Researchers have shown special interest over the years in the generation of computerized models of fire growth. Computational methods are used to automate the fire propagation model in nonuniform conditions by considering local uniformity. The most common approaches are the cellular models. The cellular or the grid-based approach for fire growth is simulated in a discrete fashion on a regularly structured grid. A well cited example of this modeling methodology was developed by Kourtz and O'Regan [29] which was based on a Monte Carlo technique. The model enables simulation of a small fire at any time after ignition by predicting the perimeter location and burning area for prescribed fuel and weather conditions. Other cellular techniques also exist. In

[30], templates of varying shapes and sizes are used to represent the influence of burning cell on its neighboring cells. Moreover Karafyllidis and Thanailakis [31] have developed a model to predict fire growth using cellular automata that can predict fire growth accurately in homogeneous as well as heterogeneous conditions, and can easily incorporate weather conditions and land topography. Methods like stochastic percolating technique [32] or fracture algorithms [33] are used to incorporate the uncertainty associated with forest fire propagation through a regular landscape matrix. There are other cellular techniques [34][35] that under uniform conditions can represent theoretical ellipsoid fire shapes with minimal distortion. In spite of cellular technique's ability to predict forest fire growth, its drawbacks include diminishing success in reproducing the expected two dimensional shapes and growth pattern as the environmental conditions (temporal changes as shifting wind speed and direction as well as fuel moisture) become more heterogeneous [34].

Some of the problems associated with cellular models are avoided by the vector or wave approach based on Huygens' principle [36] for fire growth modeling. This model has been used in this thesis for fire propagation to test and validate the proposed resource allocation and optimal fireline building strategy. This approach is incorporated into the fire growth model FARSITE (Fire Area Simulator [12]). FARSITE model is widely used by the USDI National Park Service, USDA Forest Service, and other federal and state land management agencies to simulate the spread of wildfires, and it automatically computes wildfire growth and behavior for long time periods under heterogeneous conditions of terrain, fuels, and weather.

The rate of spread and shape of forest firefronts are governed by a lot of factors. The most important factors are [37]:

- Fuel type and moisture
- Wind velocity and variability
- Forest topography (The rate of spread is faster in upslope and slower in downslope)
- Fuel continuity
- The amount of spotting (burning material spread by the wind)

Under uniform conditions, two dimensional fire shapes are considered to be ellipsoid in shape. Constant or uniform conditions occur when factors affecting wildfire propagation (topography, fuel, wind and weather, etc.) are spatially and temporally constant. A large number of data have been collected for both controlled and uncontrolled wildfires with continuous fuels, constant wind velocity, moisture content and slope. The collected data indicate that under the mentioned conditions the wildfire starting from a point reaches a quasi-steady state and propagates as a cigar shape that is biased towards the direction of the wind. The analytical approximation of the firefront most frequently used is that of an ellipse[38][39] while other shapes like tear drops [39], ovoids [40], fan shaped [41]and double ellipses [42] have also been used. Elliptical shape allows the computation of fire perimeter with its simple mathematics. It has been observed that the variation of firefront from the elliptical shape have resulted for sparse fuels, spotting and relative variations from constant conditions inherent in the empirical data. The collected data have also been curve fitted and have been incorporated to some complex devices as in [43]. The curve fitted data though doesn't give correct prediction under variable conditions, however they have been used in past for fire-

fighting. Regardless of the shape of the wildfire, it is observed that the eccentricity of the wildfire increases with wind or slope or both [44].

In this chapter, fire growth model in both homogenous and heterogeneous terrains are discussed.

3.1 Homogenous Model

In this Chapter, the fire growth in homogenous conditions are discussed. Anderson et al. [45] used Huygens Principle of wave propagation to develop a graphical fire prediction method. In their method, in accordance with the Huygens Principle, they assumed each point on the firefront at a certain time “ t ” to act as ignition points for small fires burning for a finite interval of time “ dt ”, that results into small fires of elliptical shape. The shape of each elliptical fire is determined by the conditions at time “ t ” and the interval “ dt ” and the perimeter of the new firefront is defined by the envelop of all ellipses. Richards (1990) [36] derived a system of differential equations using the idea formulated in [45] but using infinitesimal small ellipses and their finite difference equations. The equations derived by Richard’s could handle variations of weather and fuel assuming the eccentricity of the ellipses, given a fuel type, is a function of wind direction only.

Under homogenous fuel and constant weather-wind conditions, it is generally accepted that fire ignited at a point will expand as an ellipse at a constant rate [45]. The ignition point is considered as the rear focus of the ellipse. Firefront at a certain time t is represented parametrically by equation 3.1, where $0 \leq \phi \leq 2\pi$.

$$\begin{aligned}x(\phi, t) &= a(t)\cos(\phi) \\ y(\phi, t) &= b(t)\sin(\phi)\end{aligned}\tag{3.1}$$

In the equation 3.1, (x, y) are the coordinates of the firefront as a function of the parameter “ ϕ ” and time “ t ”. “ a ” and “ b ” are the parameters of the ellipse defined by the wind velocity at the particular time “ t ”. In figure 3.1, the forward rate, the lateral rate, and the backward rate of the forest fire is defined as, $(b + c)$, a , and $(b - c)$ respectively when “ c ” is defined as $\sqrt{(b^2 - a^2)}$, the distance from the focus to the center of the ellipse. A large number of data for elliptical forward, lateral and backward firefront rate has been documented by Canadian Forest Fire Behavior Prediction Systems (CFFBPS [45]) for a very large set of constant parameters affecting a fire. It has also been observed that within certain limits, a/b is a function of wind speed only [44].

Figure 3.1: Elliptical Firefront at time “ t ”

It is assumed, consistent with the Huygens Principle, that all the points on the elliptical firefront are separate ignition points burning for the interval dt producing small elliptical firefronts separately. By convention, the wind direction is expressed as a clockwise angle with the positive Y-axis. Considering a wind direction of “ θ ” (in figure 3.1 it is 20°) with positive Y-axis, the ellipse generated by any point $(x(\phi, t), y(\phi, t))$ follow the equation 3.1 where “ t ” is replaced by “ dt ” and using local coordinates centered at $(x(\phi, t), y(\phi, t))$ and oriented at an angle “ θ ” with the original X-Y axis. The parameter a, b and c are defined by the fuel, topography and weather-wind condition. The time interval “ dt ” is considered sufficiently small so that a, b, c and θ can be considered constant in that short interval of time. The new firefront at $t + dt$ is represented by the outer envelop of the ellipses (figure 3.2) generated at each point on the curve at time t (hence, this technique is also called the Envelop Model). The parameters of the ellipse a, b and c are functions of time and space when wind velocity is a function of time only. The parameter a/b as discussed before is a function of wind velocity only hence is a function of time.

Figure 3.2: The envelop of ellipses

Richards, in [36], derived the curve $x(\phi, t + dt), y(\phi, t + dt)$ given the curve $x(\phi, t), y(\phi, t)$ for finite dt by using a linear transformation that transforms ellipses to circles. The equation of the envelop of circles was then easy to calculate by a limiting process in $d\phi$. The point $x(\phi, t + dt), y(\phi, t + dt)$ was then calculated using the inverse of the linear transform. The time derivatives $x_t(\phi, t), y_t(\phi, t)$ can also be calculated by taking a limit with respect to dt .

In this modeling technique, also called Envelop model, each point on the fire-front is considered to be a new source of fire generation and the fire-front is propagated as a continuously expanding fire polygon or ellipse at specified time-steps. The fire polygon is defined by a series of two-dimensional vertices (points with X, Y coordinates). The number of vertices increases as the fire grows over time (polygon expands). The expansion of the fire polygon is determined by computing the spread rate and direction from each vertex and multiplying by the duration of the time-step dt .

Using the mentioned technique, Richards evaluated the equations governing the Envelop model.

The equation is given by:

$$\begin{aligned} X_t &= \frac{a^2 \cos \theta (x_s \sin \theta + y_s \cos \theta) - b^2 \sin \theta (x_s \cos \theta - y_s \sin \theta)}{(b^2 (x_s \cos \theta - y_s \sin \theta)^2 + a^2 (x_s \sin \theta + y_s \cos \theta)^2)^{1/2}} + c \sin \theta \\ Y_t &= \frac{-a^2 \sin \theta (x_s \sin \theta + y_s \cos \theta) - b^2 \cos \theta (x_s \cos \theta - y_s \sin \theta)}{(b^2 (x_s \cos \theta - y_s \sin \theta)^2 + a^2 (x_s \sin \theta + y_s \cos \theta)^2)^{1/2}} + c \cos \theta \end{aligned} \quad (3.2)$$

Here, “ X_t ” and “ Y_t ” are the rate differentials and the angle θ is the wind direction. “ x_s ” and “ y_s ” are the orientation of the vertex on the fire front in the terms of component differentials. The location of the new fire-front is available by multiplying the rate differentials with the step time. The elliptical forest fire shapes are governed by the parameters “ a ”, “ b ” and “ c ” in equation 3.2. Researchers [11], [44] have formulated a number of empirical relations with the wind speed and the elliptical dimensions of the fire. The formulas have different forms and produces different fire shapes given a wind speed. Finney [12] used the relationship developed by Anderson [46] for the length to breadth ratio (LB) given by Equation 3.3 of the elliptical firefronts assuming fire growing as an ellipse (not double ellipse). This model has been used in FARSITE for the simulation of wildfire.

$$LB = 0.936e^{(0.2566U)} + 0.461e^{-(0.1548U)} - 0.397 \quad (3.3)$$

The parameter “ U ” in Equation 3.3 is called the **mid flame wind speed** that is the speed of the wind measured at the midpoint of the flames, considered to be most representative of the speed of the wind that is affecting the fire behavior. The Anderson’s original equation was modified by Finney in [12] by subtracting the constant 0.397 from LB in Equation 3.3. This was required to

make $LB = 1.0$ for flat terrain and no wind. Considering the rear focus of the ellipse to be the ignition points [44], the head to back ratio (HB) is obtained by:

$$HB = \frac{(LB + \sqrt{(LB^2 - 1)})}{(LB - \sqrt{(LB^2 - 1)})} \quad (3.4)$$

Using the Equations 3.3 and 3.4, the elliptical dimensions a , b and c can be computed in units of the fire spread rate R via:

$$\begin{aligned} a &= \frac{0.5(R + \frac{R}{HB})}{HB} \\ b &= \frac{R + \frac{R}{HB}}{2} \\ c &= b - \frac{R}{HB} \end{aligned} \quad (3.5)$$

Figure 3.3 shows the propagation for uniform or homogeneous fuel distribution, topography and weather conditions when wind is flowing at 0° with positive Y-axis (Using equations 3.2 and 3.5). Each elliptical curve in this figure represents the firefront for each time instances. Figure 3.4 shows the same for a constant wind direction of 20° with the positive Y-axis. Figure 3.5 shows the wildfire propagation for varying wind direction but uniform fuel distribution and homogenous topography. Very often, these fire propagation models are overlaid on Geographic Information Systems (GIS) that provides other topographical information about landscape and maps using multidimensional grids. Hence, it may be desirable to develop the Envelop model in a grid-based framework, which can be easily done by considering each point on the grid as a point on fire-front. The other mathematical formulations remain the same. For example, the fire propagation in figure 3.6a carried out in a continuous manner can also be carried out on a grid as shown in figure 3.6b.

It should be noted that the grid based model will not be exactly the same as the continuous model because of some discretization error. Discretization error increases with the size of the grids .

Figure 3.3: Fire Propagation under Constant Conditions and Uniform Fuel Distribution (wind direction 0°)

Figure 3.4: Fire Propagation under Constant Wind Conditions (wind angle 20°)

Figure 3.5: Fire Propagation under Varying Wind Condition and Homogenous Fuel

(a) Continuous Model

(b) Discrete Model

Figure 3.6: Forest Fire Propagation

3.2 Heterogeneous Model

Fire propagation rate and direction is primarily affected by weather and topology of the terrain. There are other factors that have their effects on fire behavior. Those factors include vegetation or fuel distribution and moisture content. However, in this thesis only two factors viz. weather/wind and topology into the fire propagation model have been considered. This provides a fairly good overall realistic simulation of forest fire and serves the purpose of this research which is development of optimization framework that uses such fire propagation models. In a homogenous terrain, the rate and direction of fire propagation is primarily determined by the wind speed and direction only. In heterogeneous terrain, the fire propagation rate is higher when fire moves upslope and the rate decreases when fire moves down-slope. The direction of fire propagation is affected by the slope and aspect at each point of the terrain. In order to obtain a more realistic forest fire propagation model, the slope and wind correction model is required to be incorporated. Sharples (2008) [47] has listed the different wind-slope models available, such as models of McArthur [48], Rothermel [13], Albini [49], Finney [12], McAlpine [50], Nelson [51], and has proposed a more general framework for such a correction. This framework is briefly described below. When dealing with heterogeneous terrain, two significant topographic parameters are: topographic slope and topographic aspect. Topographic slope is defined as the maximum inclination of a terrain surface at a particular point. Considering the terrain modeled as an elevation function $h(x, y)$, where $h(x, y)$ is the elevation at a point (x, y) , the topographic slope at a point is formally defined as the length of the gradient vector field. The gradient vector field can be obtained by the following equation :

$$\nabla h(x,y) = \left(\frac{\partial h}{\partial x}, \frac{\partial h}{\partial y} \right) \quad (3.6)$$

And thus, the length of the gradient vector field is given by the norm:

$$\|\nabla h(x,y)\| = \sqrt{\left(\frac{\partial h}{\partial x}\right)^2 + \left(\frac{\partial h}{\partial y}\right)^2} \quad (3.7)$$

The topographic slope is typically described by the topographic slope angle, “ γ_s ”, $\tan \gamma_s = \|\nabla h(x,y)\|$.

The alignment of topographic slope is known as the topographic aspect γ_s . A vector normal to the surface at a particular point can be decomposed into a horizontal component, in the $x - y$ plane, and a vertical component, perpendicular to the $x - y$ plane. The direction of the horizontal component defines the topographic aspect, which is expressed as the angle between the horizontal component and the north (positive Y-axis). The topographic aspect direction points down-slope. The topographic aspect in terms of the elevation function $h(x,y)$ can be expressed as the direction of the negative gradient vector field. The aspect angle at a point is shown in figure 3.7.

Figure 3.7: Schematic Diagram Showing the Topographic Aspect of the Terrain

The wind-slope correction can be approached using two methods: scalar and vector. In the scalar method, the rate of fire propagation at a particular point in the terrain is the product of the wind induced rate of spread (R_w), and a scalar quantity that is a function of the slope at the given point. In the McArthur's model, the rate of fire propagation at a particular point in the terrain is given by equation :

$$R(w, \gamma_s) = R_w e^{(0.069\gamma_s)} \quad (3.8)$$

Here γ_s is the slope faced by the firefront at a particular point. The general framework of wind-slope correction in forest fire propagation is proposed in Sharples (2008) [47] and can be expressed by:

$$R(w, \gamma_a) = B_{-\gamma_a} S_{\gamma_a} B_{\gamma_a} R_w \quad (3.9)$$

Here “ B_{γ_a} ” is the change of basis matrix which facilitates a transformation from cardinal coordinates to the terrain-following coordinates. The terrain-following t, u coordinates aligns with the upslope and across slope directions. The cardinal coordinates x, y are the global coordinates of the terrain where y -direction is towards the north and x -direction is towards the east. shows such a coordinate system. The matrices “ B_{γ_a} ” and “ S_{γ_s} ” are given by equation 3.10

$$B_{\gamma_a} = \begin{bmatrix} -\cos\gamma_a & \sin\gamma_a \\ -\sin\gamma_a & -\cos\gamma_a \end{bmatrix} \quad (3.10)$$

$$S = \begin{bmatrix} 1 & 0 \\ 0 & \sigma \end{bmatrix} \quad (3.11)$$

Figure 3.8: Schematic Diagram Showing the Cardinal and Terrain following Coordinate systems

The term “ σ ” in Equation 3.11 is the scalar factor similar to the one used in Equation 3.8. Performing the matrix operation as in Equation 3.9, the rate vector of fire propagation at a particular point is available whose magnitude and angle correspond to the rate and direction of forest fire propagation at that point of the heterogeneous terrain. The detailed steps performed in equation 3.9 are as follows: first a coordinate transformation is obtained from cardinal coordinates to the terrain following coordinates (B_{γ_a}). The scalar slope-correction relationship (S_{γ_s}) is applied to the upslope component to the wind induced rate of spread vector. With the multiplication of the vector “ $B_{-\gamma_a}$ ”, the rate of fire propagation vector is obtained in the cardinal coordinates from the terrain following coordinates.

Figure 3.9: An Arbitrarily Generated Terrain

In Figure 3.9, an arbitrarily generated terrain is shown that is used in this research as an example terrain to apply the fire propagation model and verify resource allocation and fireline building strategies generated by the proposed Genetic Algorithm based technique. A grid based method is used in the simulation with a grid size of 3×3 units. Since most of the forest fire propagating software like FARSITE and others use raster files to represent the terrain, wind-weather conditions, and other information such as vegetation/fuel distribution, a grid based representation of terrain is more suitable for generation of resource allocation and fire fighting strategies. Furthermore, the grid based method facilitates easy integration with Geographic Information Systems (GIS) that are widely used in disaster management.

(a) Only Wind-Slope Correction,

(b) Wind-Slope Correction with Uncertainty in Wind Speed and Direction

(c) Wind-Slope Correction with Uncertainty in Wind Speed and Direction

Figure 3.10: Fire Propagation after Considering Wind and Slope Correction and added Uncertainty

Figure 3.10 shows a simulation of forest fire propagation on the mentioned terrain (figure 3.9). Figure 3.10a shows the fire propagation with only wind-slope correction without any uncertainty. The simulated result shows the tendency of the fire rate increase towards the upslope of the terrain. Furthermore, uncertainty has been incorporated in wind direction and speed. Figures 3.10b and 3.10c shows the effect of uncertainty in wind speed and direction. The wind direction in this simulation is considered to follow a normal distribution with a mean of 0° and a standard deviation of 3° and changes at each time step during the simulation. The rate and direction of fire propagation “ R ”

at each point of the terrain is calculated using Equation 3.9 when “ R_w ” changes in both direction and magnitude since because of uncertainties in wind direction and magnitude.

CHAPTER 4

GENETIC ALGORITHM

As mentioned in Chapter (1) on “Introduction”, the objective of this research is the optimization of certain parameters of wildfire fighting to minimize the damage caused due to wildfire. In this research, the Genetic Algorithm (GA) based search and optimization tool is used for making wildfire suppression strategies. This chapter presents a brief introduction and working principles of the *Genetic Algorithm*. There are a number of search and optimization algorithms prevalent in the field of **Artificial Intelligence**. The reason for choosing the GA for this research is also discussed in this chapter.

Genetic Algorithms are a particular class of evolutionary algorithms that are based on the mechanics of natural selection and natural genetics ([9][52][53]). This class of algorithms was originally developed by John Holland and his colleagues and students at the University of Michigan [54]. There are several interpretations of the term **genetic algorithm**. According to Whitley[55], a strict interpretation of term **genetic algorithm** refers to the model developed by J. Holland and his student DeJong [56] in 1975. Till today, most of the developed theories for the genetic algorithm applies primarily to the model developed by John Holland as well as the variations which is called as **the canonical genetic algorithms** [55]. Other theoretical advances [57] also apply primarily to the model by J. Holland.

The key idea that all Artificial Evolutionary approaches utilize is the mechanisms observed in the process of natural evolution. Genetic Algorithms, like Darwin’s Law of “**survival of the**

fittest”, combine survival of the fittest among the candidate solutions with randomized, yet organized, information exchange to form search algorithms with capabilities of natural evolution. In each generation a new set of artificial creatures (strings) are generated using the different parts of the fittest of the older generation and in some occasions new parts are tried for good measure. Though randomized, genetic algorithms exploits the historical information of the previous search points to speculate new search points with improved performance. The concepts of biological evolution, that in each generation the new individuals are more fit to the environment than the older ones, are utilized in the Genetic Algorithm. Based on this, the solutions obtained from strings in every new generation yield better and improved performance index.

The central theme of research on genetic algorithms is the robustness and the balance between efficiency and efficacy required for survival in different environments. In Artificial Intelligence, the implications of robustness is varied. Using robust artificial systems, costly redesigns can be reduced and in some cases can be eliminated. Using higher level adaptations, the existing systems can function longer and even better. Features for self-repair, self guidance and reproduction are widely available in biological systems when they hardly exist in artificial systems. The robustness, efficiency and flexibility are much essential components in artificial systems which include engineering systems, computer systems or even business systems. It has been observed that robust performance is better delivered by nature and the know-how of adaptation and survival are best learned from nature. Genetic Algorithms are not only accepted for an argument based on the evidence seen in nature but are also theoretically and empirically proven to provide robust search in complex spaces. Genetic Algorithm has its wide-spread application in different fields of science because of its simplistic yet powerful nature in its search for improvement.

To understand the advantages of the Genetic Algorithm, it is required to understand how the GA is different from other popular search techniques. Current literature identifies three major search techniques [9] as:

- Calculus Based Methods
- Enumerative Methods
- Random Methods

A lot of study has been carried out on Calculus-Based methods. They are further sub-divided into **direct** and **indirect** methods. The indirect method seek the local optima by letting the gradient of the objective function to zero. The direct method seeks local optima by hopping on the function and moving in a direction represented by the local gradient . This is also called as the **hill climbing method**. Both the discussed methods are local in scope, i.e. provide local optima. The argument is more clear by looking at the figure 4.1. Figure 4.1a shows a search space with only **one** maximum. On the other hand, figure 4.1b shows a search space with more than one maxima. For the former case, the Calculus-Based method though will provide the global maximum solution (only because its a unimodal case) but has a high chance to fail to obtain the same for the latter case. As seen in figure 4.1b, if the search starts from one of the corner, say $(-2, -2)$, this search technique will converge to the local maximum. Another big disadvantage of such methods is the dependency on the existence of derivatives. Even numerical approximations of derivative has its shortcomings. Real world search spaces are fraught with discontinuities, noise, and vast multimodality, and hence not friendly to Calculus-Based methods.

Figure 4.1: Unimodal and Multimodal Functions

Enumerative search methods find the global optimum by searching through every point on the objective function. Though simple, these kinds of techniques are highly inefficient because many search spaces are too large for an exhaustive search. Even **dynamic programming** [58] breaks the problem down to moderate size and complexity. Random search techniques overcome these drawbacks, however, a complete random search can still be considered as inefficient. The Genetic Algorithm is an example of search technique that uses randomness to guide a highly exploitative search by coding of parameter space. The fundamental difference between GA and other mentioned search methods can be listed as follows:

- Coding of parameter set is used in GA but not the parameter set.

- GA searches from a population of points (multi-point hill climbing) and not from a single point.
- GA does not require derivatives or other auxiliary knowledge but uses objective function to evaluate the fitness of each solution
- The transition rules used in GA is probabilistic, not deterministic.

The ability of the Genetic Algorithm to handle complex, multimodal and noisy search spaces and deliver globally optimum or near global solutions are the reason for choosing this tool for our research. The problem, as mentioned in Chapter 1 and in Chapter 5, requires a use of such a tool. The search space for the problem is complex and it is hard to represent the objective function in terms of parametric functions let alone the derivatives.

The building blocks of the Genetic Algorithm can be listed as follows:

- Initialization of Population
- Selection
- Genetic Operations (Crossover and Mutation)

Generation of initial population is the first step in the implementation of any Genetic Algorithm. A population is a number (user defined) of prospective solutions of the problem and initial populations are generally selected randomly in the search space. Each member of the population, i.e., each prospective solution is encoded as a string, such as binary string, which is sometimes referred to as a **genotype** (Holland, [54]) or **chromosome** (Schaffer [59]). After the generation of initial population of solutions, each solution or chromosome or string is assigned a **fitness value** that

represents the goodness of the solution. The GA requires an **evaluation function** which helps calculate the effectiveness of each solution. The **fitness** (or performance index) of a string is defined as $f_i/\bar{f}$ where f_i is the evaluation of string i (using evaluation function) and the $\bar{f}$ is the average evaluation of all the strings in the population. Assignment of fitness can be based on the string's rank in the population [60] or by something called as the tournament selection [61].

Selection:

After the assignment of fitness to all the members of the population, **selection** of the strings or solutions is performed. Selection models “**survival of the fittest**” of the nature's principle. There are several strategies for selection including **Roulette Wheel** selection, **Tournament** selection and **Ranking** selection. In “Roulette Wheel” or proportionate selection scheme, strings are selected according to the fitness value. Strings with lower fitness values have lower chances of getting selected to the next generation as compared to the strings with higher fitness values. In the “Tournament” selection strategy, the strings are grouped randomly and the adjacent pairs compete with one another according to the fitness values of the strings. The size of the group is generally user defined. In “Ranking” selection, the members of the population are ranked according to their fitness and the offsprings are assigned as a function of rank.

Crossover:

In Crossover genetic operation, random information is exchanged between two randomly selected strings. Crossover can be of several types: **single point**, **2-point**, **N-point** and uniform. After the selection of the fittest strings of the old population, crossover takes place to generate members of the new generation. The frequency of crossover is governed by the user defined crossover rate. Increasing the rate results in higher exchange of information between the fittest

strings of the old generation. In a single point crossover, shown in Figure 4.2a, information is exchanged between two strings (encoded) after a randomly generated crossover point. Two point crossover, as shown in figure 4.2b, eliminates the bias towards the end of string bits of the single point crossover method. Here, the information is exchanged between two crossover points.

Figure 4.2: Crossover Operation

Mutation:

Mutation operation (shown in Figure 4.3) is seen as a secondary reproduction operator. Mutation improves global search and is more helpful than crossover as the population converges. Mutation allows creation of new solution points in different places of the search space by providing randomness to the search technique. A high mutation rate makes the search too random resulting in a loss of information by potential loss of good solutions. Generally during the implementation of Genetic Algorithm, the mutation rate is kept low.

To sum the process up, the GA starts with a random creation of a population of strings representing candidate solutions and thereafter generates successive populations of strings that improve over generations. The processes involved in the generation of new populations mainly consist of operations such as Reproduction, Crossover and Mutation.

The steps involved in GA can be summarized as follows:

- Step 1: Initialize a population-string of individuals. Each individual string represents a candidate solution
- Step 2: Evaluate the fitness or performance index of each individual
- Step 3: Carry out the genetic operations (See Figure 4.3) viz. reproduction (selection of sub-population for next generation), crossover (swapping of corresponding parts of strings at a random point for two individuals selected on the basis of their fitness), and mutation (randomly changing the value of strings at randomly selected position of the string).
- Step 4: Test for termination criterion.

Figure 4.3: Various Genetic Algorithm Operations

Different forms of Genetic Algorithms exist in today's literature. A variation of **Canonical Genetic Algorithm**, called the Micro Genetic Algorithm (μGA), is presented in [62]. In Micro Genetic Algorithm, a small population with some very simple genetic parameters are used and it was shown the method provides near optimal solution much earlier than the Canonical Genetic Algorithm for some specific problems. Like simple Genetic Algorithm, μGA uses binary coded parameters but considers only a population size of 5 [62]. In spite of having a small population, which would otherwise lead to premature convergence in simple GA, μGA can converge to the optimal region by bringing new strings to the population at regular intervals.

Steady State Genetic Algorithm, is another popular variation of simple or Canonical genetic Algorithm. In Steady State GA, a percentage (user defined) of the population based on their fitness is retained back to the next generation. In Steady State GA, according to the selection procedure

chosen, two parent strings are selected and crossover takes place between them. The newly formed offspring then replaces the worst member of the population without replacing the parents and the process continues in this way. The advantage of this method is that the best points on the search space encountered by the GA is maintained in the next generations. When objective function evaluation takes longer computation time and string lengths are large with large number of members in the population, Steady State Genetic Algorithm has shown to give better results.

Other variations in the Genetic Algorithm exists such as **CHC** (Cross generational elitist selection, Heterogeneous recombination and Cataclysmic mutation) algorithm developed by Eshelman (1991) [63] which restarts the search when population starts to converge. Other techniques similar to Genetic Algorithms in some different ways are: Ant Colony Optimization [64], Simulated Annealing [65], Evolutionary Programming [66], and Stochastic optimization [67].

CHAPTER 5

PROBLEM FORMULATION AND APPROACH

Broadly speaking, the objective of this research is to develop a framework for optimal decision making for the containment of forest fires. This thesis considers fireline construction as the fire-fighting strategy, and determines allocation of fireline construction resources and shapes of firelines for optimal containment of wildfire. As mentioned in Chapter 1, in both direct or indirect attack, fireline building plays a very important role and for some large uncontrollable fire, fireline building can be the only option to contain the fire. Because of its importance, fireline building strategy has been used in this research. After the initial attack to mitigate the wildfire, firelines are built around the firefront that contains the wildland fire. Firelines, as mentioned earlier, can be considered as a strip of trail or road that is built with the purpose of separating the fire from the fuel so that the forest fire stops from further propagation. The optimization problem is to perform optimum resource allocation and to find the optimal fireline that can be built with the given resources and which minimizes the total burned area and also ensures that fire does not escape. Fire is said to escape when firefront reaches the semi constructed fireline and hence cannot be contained within the fireline. In this research, a finite number of firefighting teams are considered who build firelines with specified shapes.

Preliminary approach of solving the problem is based on considering a fixed shape for the overall fireline. Since under homogenous conditions (uniform terrain, fuel and constant wind direction and speed, etc) wildfire takes elliptical shapes, an elliptical fireline can be considered to

contain the fire. As shown in Chapter 3, even in homogenous conditions with variable or constant wind direction, fire takes elliptical shapes i.e. the rate of firefront propagation is not uniform along its perimeter. It is highest at the head of the fire (for homogenous conditions, the direction of fire propagation or the head of the fire is dependent on the wind direction) and least at the tail direction. Hence, overall fireline with a pre-determined shape such as ellipse or circle can be useful for homogenous conditions. However, the consideration of not using such a fireline shape is affirmed with the non-uniformity in fuel and terrain and uncertainty associated with forest fire propagation and many other factors. An elliptical fireline or a fixed shape of the overall fireline though is not a wise idea but shows how the proposed strategy making with the aid of optimization tool can be helpful in forest fire containment.

It is known, the rate of fire propagation is not uniform along its perimeter but higher towards the head and lower towards the tail direction. Common sense and even the rules of forest fire fighting suggests to concentrate more in attacking the head of the fire than the tail and other directions. To enable this, more flexibility is to be added into the fireline building so that it can create a number of shapes to handle uncontrollable wildfires. To reach the mentioned goal, this research considers different polynomial curves for the firelines built by different firefighting groups. The optimization problem is to find the initial locations of the firefighting teams in the given terrain from where they would start building the fireline as well as the parameters of the polynomial curves that define the shapes of the firelines. This means each firefighting group, after their initial position on the terrain being evaluated, will build polynomial curve shaped firelines so that more flexibility can be added to the overall fireline shape. It may be noted that such a technique can generate elliptical, circular or any other pre-determined shape.

This thesis considers a finite number of firefighting teams (as in real world scenarios) available to build firelines with specified shapes. The optimization problem is to find the initial locations of the firefighting teams in the given terrain from where they would start building the fireline as well as the parameters of the polynomial curves that define the shapes of the firelines. Furthermore, in a real world scenario, weather/wind condition is difficult to be predicted and the uncertainty or noise associated with the wind speed and direction results into inaccurate fire behavior prediction. Fire behavior prediction is also affected by the uncertainty present in terrain and fuel distribution modeling. Thus the optimal fireline to be built should be robust enough to contain the fire under such uncertainties or random effects. This kind of intelligent resource allocation promises better and more robust results in minimization of forest fire damage in a real world scenario. In view of the above, the cases considered in this thesis are as follows:

- Prob.I: A homogeneous case where terrain and weather conditions remain constant and
- Prob.II: a heterogeneous case where terrain has varying slopes and weather (primarily wind) condition varies with time.

Mathematically, the optimization problem can be formulated as follows. Consider N teams of firefighters. Their initial positions on the $2 - D$ terrain are given by (x_k^0, y_k^0) $k = 1, 2, 3 \dots N$. The team ' k ' builds the fireline given by the functions $y = f_k(x, d_k)$ where f_k is the function representing the shape, and d_k is the vector of parameters for the function f_k . The structures of functions are assumed to be known a priori.

Considering an elliptical shape of fireline, the optimization problem is to find the five parameters of the ellipse, x_c, y_c, a, b and θ that minimize the performance index represented by the following equation:

$$PI = \begin{cases} \text{Area enclosed by the elliptical fireline} = \pi ab & \text{Fire does not escape} \\ \infty & \text{Fire escapes the elliptical fireline} \end{cases} \quad (5.1)$$

The five parameters of the ellipse can be described as, (x_c, y_c) the center of ellipse, a, b are the semi-major and semi-minor axis of the ellipse and θ is the orientation of the ellipse. In this method, a finite number of teams are considered with a cumulative fireline building rate r . The time taken to build the fireline is given by:

$$t = \text{Perimeter of the fireline} / r$$

$$\text{Perimeter} = \pi(3(a+b) - \sqrt{10ab + 3(a^2 + b^2)}) \quad (5.2)$$

The requirement of such a calculation will be explained in the later section of the chapter.

Generalizing this technique to any arbitrary shape of fireline, the optimization problem is to determine the initial positions (x_k^0, y_k^0) , and parameters d_k of functions that minimize the following performance index (PI):

$$PI = \begin{cases} \text{Area enclosed by curves } y = f_k(x, d_k), k = 1, 2 \dots N & \text{Fire does not escape the enclosed area} \\ \infty & \text{Fire escapes the enclosed area} \end{cases} \quad (5.3)$$

The fire is said to escape when firefront reaches the fireline (represented by the above curves) before the teams finish building their respective lines. For this purpose, a constant rate of fireline construction ' r ' (unit length per unit time) is considered. If a team finishes building its own line, it helps the other team who has not built the line. It may be noted that each team starts from its initial position and finishes at the initial position of the next team. The last team finishes at the starting position of the first team to form the enclosed space. Hence, this introduces the constraint on the shape of the firelines which can be represented by:

$$y_{k+1}^0 = f_k(x_{k+1}^0, d_k) \text{ for } k = 1, 2, 3 \dots (N-1) \quad (5.4)$$

$$y_1^0 = f_N(x_1^0, d_N) \text{ for } k = N \quad (5.5)$$

Equation 5.4 essentially says that the initial position of the $(k+1)^{th}$ team lies on the fireline built by the k^{th} team. Equation 5.5 says that the initial position of the 1^{st} team lies on the fireline built by the N^{th} team.

This research proposes a Genetic Algorithm based (GA) approach to solve the problem specified in chapter 4. Because of its ability to provide global solution for complex problems with large search spaces, and its robustness, the GA is chosen for this research. The Genetic Algorithm (GA) is a search and optimization technique to find the exact or approximate global solutions to an optimization and search problem. The GA operates by finding a solution that minimizes a performance index. A performance index is the measure of goodness or effectiveness of a solution. In the mentioned problem, the performance index is the total burned area due to wildland fire and is obtained using equation 5.1 or equation 5.3 according to the problem formulation. Since the performance

index for the GA (the total area burned due to fire after fireline building is complete) cannot be explicitly represented as a function of the parameters, Simulation Optimization technique 5.1 is used to evaluate the performance of each solution of the GA. In the proposed simulation-optimization technique, the forest fire progress is simulated with the help of fire propagation models when the fireline is built concurrently. A population of solutions that have different parameters representing different strategies of the firefighting agents are generated by the Genetic Algorithm and their performance is evaluated when the wildfire is propagated concurrently. The fitness value of each solution is sent back to the GA where new populations are generated with the performance index information of the previous generation. After a number of generations, the optimal solution is provided by the GA which minimizes the performance index.

Considering elliptical fireline building technique and to obtain the optimal elliptical fireline, the GA should provide the five elliptical parameters: the center of the elliptical fireline (x_c, y_c) , the semi-minor (a) and semi-major axis (b) and the orientation (θ). The GA generates a population of solution (equation 5.6) and with each solution, the firefighting team builds an elliptical fireline. Considering a cumulative fireline building rate r , the time taken to complete the fireline is evaluated with equation 5.2. This information is passed to the fire propagation model where fire propagation is simulated for time $t_{total} = t_{origin} + t$, where t_{origin} is the time from when fire suppression starts. The performance index of each of the GA generated solutions is evaluated using 5.1. This performance index (PI), i.e., the total area burned, is passed to the GA where further generations are evaluated using there PI values.

$$sample\ solution = [x_c, y_c, a, b, \theta] \quad (5.6)$$

Figure 5.1: Simulation Optimization technique

For the complex scenarios and the generalized case of fireline building, to obtain the optimal fireline for the containment of the forest fire the GA based approach should provide:

- the initial locations of the firefighting teams from which fireline building will start; and
- the parameters of the polynomial curves that define the firelines of to be built. Considering polynomial of second order, the equations for the firelines are given by equation :

$$y = a_k x^2 + b x_k + c \quad (5.7)$$

where $k = 1, 2, 3 \dots N$. represent the N firelines to be built by the N firefighting teams. To obtain an overall closed shape using N different quadratic shaped firelines built by N different crews, each crew should move from its assigned starting point in the terrain to the starting point of the next crew. This constraint is represented by equations 5.4 and 5.5. The equation governing

such fireline is given below (equation 5.8) in which the firefighting agents building the fireline ‘ k ’ move from point (x_k^0, y_k^0) to (x_{k+1}^0, y_{k+1}^0) :

$$y = y_k^0 + a_k(x^2 - (x_k^0)^2) + b_k(x - x_k^0) \quad (5.8)$$

where $x_k^0 \leq x \leq x_{k+1}^0$ considering $x_k^0 < x_{k+1}^0$ without loss of generality. It may be noted that the locations (x_k^0, y_k^0) and (x_{k+1}^0, y_{k+1}^0) are determined by the GA. Furthermore, if GA provides the parameter b_k , the other parameter a_k of equation 5.8 can be computed simply by using the constraints given in equations 5.4 and 5.5, and is given by:

$$a_k = \frac{(y_{k+1}^0 - y_k^0) - b_k(x_{k+1}^0 - x_k^0)}{(x_{k+1}^0)^2 - (x_k^0)^2} \quad (5.9)$$

The initial locations of the firefighting teams in the terrain, (x_k^0, y_k^0) , along with the parameter “ b_k ” of each of the firelines given by equation 5.8 are the required parameters to be optimized by the GA, where $k = 1$ to N . When the locations and the parameters “ b_k ” are available, the parameter “ a_k ” ($k = 1$ to N) can be computed as shown in equation 5.9.

Now, as the firelines are built from one point to another, some combinations of the points as initial and final points for firelines will result in intersection of two firelines which would represent a practically wrong solution. Hence, concepts from the Traveling Salesman Problem (TSP) [68] are introduced here to obtain the proper order of the points so that all the points are touched with no intersection of two or more firelines. In this case, a TSP algorithm can be used to obtain the proper sequence of the points so that an intersection of lines is avoided.

Figure 5.2: Incorrect Traveling Order

Figure 5.3: Correct Traveling Order

Both Figure 5.2 and Figure 5.3 show an example with four firefighting crews. The location of the firefighting crews (1,2,3 and 4) generated by Genetic Algorithm. Figure 5.2 shows the incorrect traveling order with a sequence 1 – 2 – 3 – 4 – 1. The intersection between the generated

firelines signifies an impractical solution. Figure 5.3 shows the correct order, $1 - 3 - 2 - 4 - 1$, after applying the traveling salesman algorithm that negates the possibility of intersection of generated firelines.

CHAPTER 6

PARALLEL GENETIC ALGORITHM

Many real world decision making and resource allocation problems are complex and involve several decision variables. Search and optimization methods used for these problems should be computationally efficient and be able to provide solutions in timely fashion for its real time application. Genetic Algorithms are inherently computationally very extensive. To improve the time efficiency of GAs, a lot of computations can be carried out in parallel. As mentioned by Goldberg in [9], the Genetic Algorithm possesses inherent parallel computational capability. Parallelism is prevalent in natural evolution which is not much exploited by sequential Genetic Algorithm. In this chapter, Parallel Genetic Algorithm architectures are discussed and a method based upon these architectures is presented that can be applied to wildfire fighting problem considered in this research.

Researchers in [69] and [70] have presented a survey on Parallel Genetic Algorithm (PGA). PGAs are not a mere parallel version of sequential Genetic Algorithm, but they seek to reach the ideal goal of having a parallel algorithm whose performance would be better than the sum of the separate performance of its component sub algorithms. Normally, the basic idea behind parallel programs is to divide the task into a number of smaller tasks and to solve them using multiple processors. Such parallel programming is possible with GA since operations on the strings are relatively independent from one another. PGA can be geographically structured as in [71] and [72] that aids localization of competitive selection between string subsets. The performance

enhancement due to the use of PGA is advocated by a number of literature. In references [73] and [74], the evidences of higher efficiency have been described, and in [75],[76] and [77] higher diversity maintenance and multi solution capabilities of PGA are described . Often, use of PGA has shown to provide better performance even when the algorithms are run on a single computer [73], [78].

As mentioned in [69], there are broadly three types of Parallel Genetic Algorithms:

- Global Single Population Master Slave GA
- Single Population Fine Grained GA
- Multiple Population Coarse Grained GA

In Master-Slave GA, there is a single population, like sequential GA, but the evaluation of fitness is distributed among several processors. This method is called Global parallel GA because operations such as crossover and mutation consider entire population. Figure 6.1 shows the structure of the Master Slave algorithm.

Figure 6.1: Master Slave Architecture

In Fine Grained Parallel GAs, one spatially structured population is considered and is suited for massive parallel computers. Selection and genetic operations are restricted to small neighborhood but some interaction between the individuals are permitted by some neighborhood overlap. Figure 6.2 shows the schematics of such an algorithm. Multiple Population Coarse grained GA consists of multiple populations of sub-populations where information exchange takes place occasionally. This exchange of information is called as **migration** that is controlled by several parameters. Figure 6.3 shows the schematics of the method. Swapping or migration is a key feature of Parallel Genetic Algorithm where new individual with high genetic quality are introduced into the sub-populations.

Figure 6.2: Fine Grained Parallel GA

Figure 6.3: Multi Population Coarse grained GA

In this chapter, an architecture of Parallel Genetic Algorithm is discussed and its application to the wildfire fighting problem is presented in Chapter 7. The theory behind such an architecture is important and to understand the same, the key element responsible for obtaining global optimal solutions using the GA is needed to be introduced.

The basic working principle of the GA is better understood with the **schema theory**. Goldberg in the book “**Genetic Algorithms, in Search, Optimization & Machine Learning**” [9] provided a detailed description of the **schema theory**. A **schema** is defined as a **similarity template** representing a subset of strings with similarity at certain string positions. Considering binary representation of strings of the GA, schema is a string of symbols formed with $\{0, 1, *\}$. The alphabet “*” is called **don’t care** meaning it can take any value: “0” or “1”. Schema can be thought of as a pattern matching device of the strings. A schema is said to match a particular string only if at every position of the schema, a 1 matches a 1 in the string and a 0 matches a 0 in the string or a * matches either of the two (1 or 0). An example will be a schema “0*11*” matches the strings

“{00110,01111,00111,01110}”. There are two definitions associated with schema, **order of the schema** “ $O(H)$ ” and **defining length of the schema** “ $L(H)$ ”. The number of non-* members of the schema is called the order of the schema when the distance between the farthest non-* members is called the defining length of the schema. In the schema mentioned in the example, the order of the schema thus is 3 and defining length is also 3. The evolution of the number of strings matching a particular schema in successive generations is given by [9]:

$$m(H, t+1) \geq m(H, t) \frac{f(H)}{\bar{f}} \left[1 - p_c \frac{L(H)}{l-1} - O(H)p_m \right] \quad (6.1)$$

In Equation 6.1, $m(H, t)$ is the number of strings representing a particular schema H at the generation t . Similarly $m(H, t+1)$ is the number of strings representing the same schema H in the next generation $t+1$. $f(H)$ is the average fitness of the strings representing the schema H at generation t and $\bar{f}$ is the average fitness of the entire population. p_c and p_m are the probability of crossover and mutation respectively. $L(H)$ and $O(H)$ are the defining length and order of the schema H and l is the length of the strings. It is evident from equation 6.1 that schema, corresponding to a fitness value $f(H)/\bar{f} > 1$, with lower defining length $L(H)$ and lower order $O(H)$ has a higher chance of surviving crossover and mutation than the schema corresponding to same fitness value but higher defining length and order.

If p_m is the probability of mutation of all the distributed nodes of the distributed GA, then it is shown in [79], a **schema** “ S ” of order $O(S)$ will survive the mutation with a probability of $(1 - p_m O(S))$, just as in sequential GAs. Furthermore as shown in [79], the probability of being successfully recombined and the growth rate for good schemata are almost the same as the

sequential counterpart. A further comparison is made between sequential and parallel GAs on the basis of optimum schema processing rate[80]. It is done as follows: it is considered that if ϕ is the ratio between parallel and sequential speeds and if it is defined in terms of processors used, then $\phi = n^\beta$ where β is the degree of parallelization and n is the population size. The time of convergence to the solution is expressed as $t_c = n^{l-\beta}$. β is 0 for sequential GA and $\beta = 1$ for a perfectly parallel GA. The following equation defines the figure of merit that is the number of schemata processed in the whole evolution:

$$M(n, l, \beta) = \frac{\Delta S}{\Delta t} = \frac{S(n, l) - 2^l}{(k \cdot n \cdot \log n) n^{l-\beta}} = \frac{2^l(n-1)}{(k \cdot n \cdot \log n) n^{l-\beta}} \quad (6.2)$$

In equation 6.2, n is the population size, $n \log n$ is considered as the number of generations required to converge to the solution (the worst case scenario) and k is the actual number of generations. For a medium size population $S(n, l)$ can be approximated as $S(n, l) \approx n \cdot 2^l$. Thus the relative merit of sequential GA and distributed GA can be computed via :

$$\frac{M(n, l, 0)}{M(n, l, 1)} \approx \frac{1}{n} \quad (6.3)$$

This suggests, parallel GA is “ n ” times better than sequential GA.

The architecture of the Parallel Genetic Algorithm considered in this research is very simple. The main focus of the research is the application of the Genetic Algorithm into the forest firefighting decision making. Parallel GA is used only to speed up the whole process and in some cases obtain optimal results in a faster way. The architecture considered can be explained as follows.

- Considering D different processors, D different genetic algorithm programs are run in parallel.
- Each GA program optimizes the parameters (x_k^0, y_k^0, b_k) $k = 1, 2 \dots N$
- Genetic operations like mutation and crossover takes place between the populations of each parallel programs.
- Migration is considered where the best solution is after a certain interval of time is passed to the adjacent programs. Though the programs run parallelly and independently, migration helps in information exchange between them. It is considered all the programs can interact with one another.

The architecture of the used strategy is shown in Figure 6.4. The above approach is utilized and applied and the simulation results are shown in the Chapter 7.

Figure 6.4: Schematics of Parallel Genetic Algorithm

CHAPTER 7

SIMULATION RESULTS AND DISCUSSIONS

7.1 Sequential Genetic Algorithm

In Chapter 5, the problem has been formulated and the approach of solving the formulated problem is discussed. This chapter shows the simulation results of the mentioned strategies. As mentioned in Chapter 5, the first approach is to find the elliptical fireline to contain the forest fire where fire propagation is considered to be in homogenous terrain and constant weather and wind conditions. This is just a preliminary approach showing how GA can be used in building fire fighting strategies. In this strategy, the forest fire is contained with the help of an elliptical fireline. As mentioned earlier, following the Richard's mathematical model[36] the fire-fronts are assumed to be elliptical in nature under homogenous conditions. Figure 7.1 shows the fire propagation under homogenous conditions for 4 time steps, with a constant wind direction of 20° . This angle is the angle between the Y-axis and the semi-major axis of the ellipse.

Figure 7.1: Fire Propagation with 20° Wind Direction at Different Time Steps

The problem now is to find the optimal elliptical fireline that will minimize the burned area and make sure that the fire doesn't escape, i.e., fireline building is complete before the firefront reaches the fireline. As stated earlier, the parameters to be optimized by the GA are: the semi minor and semi major axis, orientation and center of the elliptical fireline i.e., a , b , θ , x_c and y_c . It is assumed that the fireline building starts at $t = 4$ time units. The time required by the firefighting agents to build the fireline can be calculated from their known fireline production rate. Using simulation-optimization technique, the firefront coordinates after time $t = 4$ units are provided to the Genetic Algorithm. From the solutions generated by the GA, the time required to build the fireline is evaluated and this time of fireline building is returned back to the firefront propagation program. The fire propagation is again simulated for the extra time required for fireline building and the performance index is evaluated according to the ability of the fireline to contain the fire

and the total burned area. For this simulation, 300 generations and a population size of 301 are used. The mutation probability is generally considered low and has been considered to be 0.0077 and the crossover probability of 0.77 has been considered (generally considered more than 0.5). In this problem, Steady State GA is used with a steady state population size of 31. As mentioned in Chapter 4, in Steady State Genetic Algorithm, a percentage (user defined) of the population, selected based on its fitness value, is retained into the next generation. This subset of the population goes through regular selection for mating purposes but is not altered going into the next generation. This GA variant saves time while evaluating objective functions that require a large amount of computation time, and string lengths that require a large number of members in the population.

In figure 7.2 the optimal fireline obtained using the GA is marked with red. It is the best possible solution because any elliptical fireline bigger than the proposed fireline will result in more burned area, when any smaller fireline will result in escape of the fire. In this simulation, 4 firefighting crews are considered. Figure 7.3 shows a plot of the best performance index of population in a generation as the number of generations increase in the GA. It is seen that the performance index decreases and finally converges to the optimal solution.

Figure 7.2: Optimal Fireline Generation

Figure 7.3: Performance Index vs the Number of Generations

To obtain better results, a grid based approach for terrain representation is considered where the whole terrain is divided into grids of size 3×3 units. Whenever the firefront touches a particular grid, that grid is considered to be on fire and acts as the source of fire propagation in the next time step according to the Huygens's principle of wave propagation. Using N quadratic function shaped firelines with different parameters, a lot of flexibility on the overall fireline shape is added for the forest fire suppression. Since fire propagation rate is not uniform in all directions, such flexibility in overall fireline shape is expected to give better results than any fixed shape of the overall fireline (like the shown elliptical shape). In this problem, N firefighting teams are assumed to be working at a constant rate and when any team finishes its assigned task of fireline building, it helps the next team to complete its assigned task and hence their combined rate of fireline production increases. In this case, Genetic Algorithm has $3N$ parameters to optimize which consists of the initial locations (x_k^0, y_k^0) of the N fire fighting teams and the parameters " b_k " in Equation 5.8 for the N firelines ($k = 1 \text{ to } N$). A sample solution of the GA will look like equation 7.1,

$$\text{sample solution} = [x_1, \dots, x_N, y_1, \dots, y_N, b_1, \dots, b_N] \quad (7.1)$$

In equation 7.1, $(x_1, y_1) \dots (x_N, y_N)$ are the initial locations of the N firefighting resources from where fireline building would start and $b_1 \dots b_N$ are the parameters determining the shape of the firelines.

A moderate grid size of " 3×3 " square units is chosen in this research for the simulation purpose which provides a fairly good resolution of the solution as well as a manageable search space. In each iteration, a traveling salesman problem algorithm (Genetic Algorithm is used) is utilized to

obtain the proper order of the teams' locations as explained in Chapter 5. Simulation of fire propagation model is used to compute the performance index of each candidate solution using Equation 5.3. Once performance indices of all solutions are obtained, the GA operations are used to generate populations in subsequent generations and eventually obtain the optimal solution. During the execution of various operations, the GA often generates solutions that do not satisfy some constraints of the problem or are unacceptable from practical point of view. Keeping those solutions in the pool of populations leads to unnecessary computations and sometimes wrong solutions.

This thesis addresses the above issue by associating a very high performance index value to those solutions. For example, in the problem considered in this thesis, the GA generated solutions are considered un-acceptable if the initial firefighting agent locations and the firelines that are yet to be built are on grids which are already on fire. As described in chapter 5, this thesis addresses two problem cases.

- First is **Prob.I** in which fire propagation is considered in a homogenous terrain (flat terrain without any slope) with constant weather and wind conditions.
- The second is **Prob.II** in which fire is allowed to propagate in an arbitrarily generated terrain (figure 3.9) with slopes and with added uncertainty in wind direction.

Prob. II is designed to give a more realistic simulation of wildfires in uncertain and dynamic scenarios. Since the search space for the GA is large for both the problems, 300 generations and a population size of 301 is used. The mutation probability as mentioned before is considered low for most of the problems and is taken as 0.0077 and the crossover probability of 0.77 is considered. Steady State GA is used with a steady state population size of 31. Using Steady State GA saves

computation time since the objective function evaluation is computationally intensive. The fire is assumed to start at time $t = 0$ and the fire suppression effort starts at $t = 4$ units of time. The fireline building rate of each firefighting groups are considered same and is equal to 12 grids per time step. The results obtained from extensive simulation studies are provided below for both the problems.

Prob.I: In this problem, a homogenous terrain and constant wind and weather condition is considered. The wind direction is assumed to be constant at 20° with the positive Y-axis. The results for the different cases are provided.

Case 1 (Four firefighting teams): The red curve in figure 7.4a shows the initial firefront from when the fireline building starts. The small blue circles show the initial locations of the 4 firefighting crews. Figures 7.4b to 7.4e shows how fireline building and fire propagation goes on concurrently. Figure 7.5 shows the completed fireline (blue curve) and the final firefront (red curve). It is seen that more priority is given to the head of the firefront since rate of fire spread is highest in this direction. Figure 7.6 shows how the performance index of the best solution converges to the optimal value as the generation in the GA increases.

The Genetic Algorithm uses randomness in its searching operation and solution points get more optimal as generation progresses and converges to the optimal solution. For a problem with large search space, enough number of generations should be considered for the GA to reach its optimal solution. We have run 10 simulations considering 4 resources (firefighting teams) and their performance is showed in figure 7.7. It can be seen from this figure that for all the simulation runs, the GA converges to the optimal solution solution demonstrating the consistency of the proposed method.

(a) Initial Firefront and Firefighting Crew Location

(b) One Time Step

(c) Second Time Step

(d) Third Time Step

(e) Fourth Time Step

Figure 7.4: Initial and Final State of Firefront Progression and Fireline Construction for 4 firefighting resources

Figure 7.5: Completed Fireline and the Final Firefront

Figure 7.6: Performance Index of the Best Solution in the Generation Plotted Against the Number of Generations for 4 Firefighting Teams

Figure 7.7: Multiple Simulations

Case 2 (Five firefighting teams): Results obtained with 5 firefighting teams are shown in Figure 7.8 and Figure 7.9. Figure 7.8a shows the initial firefighting crew locations from which fireline building should start while figure 7.8b shows the completed fireline and firefront. Fireline building and fire propagation takes place concurrently as shown in earlier figures. Figure 7.9, like figure 7.6, shows how the GA converges to optimum solution with the number of generations where the number of fire fighting resources considered is 5.

(a) Initial Firefront and Firefighting Crew Location

(b) Completed Fireline

Figure 7.8: Initial and Final State of Firefront Progression and Fireline Construction for 5 firefighting resources

Figure 7.9: Performance Index of the Best Solution in the Generation Plotted Against the Number of Generations for 5 firefighting Teams

Case 3 (Six firefighting teams): Using 6 firefighting teams, their optimum initial locations and the final completed fireline and firefront is shown in Figures 7.10a and 7.10b respectively. Figure 7.11 shows how the GA converges to the optimal solution with generations. It can be seen in Figure 7.10a, the optimal position of the resources are more near the head of the firefront where the rate of fire propagation is maximum. More number of resources (teams) signifies increased rate of overall fireline production and hence it can be seen in Figure 7.10a that the firefighting teams are more close to the firefront than in the other cases (4 or 5 resources).

(a) Initial Firefighting Team Location

(b) Completed Fireline and Firefront

Figure 7.10: Initial and Final State of Firefront Progression and Fireline Construction for 6 fire-fighting resources

Figure 7.11: Performance Index vs Number of Generation for 6 Firefighting Teams

Case 4 (Seven firefighting teams): Similarly, the optimal initial firefighting crew location and the optimal fireline for minimizing the burned area is available in Figure 7.12. The only difference in this case and the others is that a higher population size and a higher number of generations are used because the parameters to be optimized by the GA has increased ($3N = 21$).

(a) Initial Crew location and Firefront

(b) Completed Fireline and Firefront

Figure 7.12: Initial and Final State of Firefront Progression and Fireline Construction for 7 fire-fighting resources

Figure 7.13: Performance Index vs Number of Generations for 7 Firefighting Teams

The above four cases suggest the scalability of the proposed method. For resource allocation of even higher number of resources (teams of firefighting agents), the number of parameters to be optimized by the GA increases by 3 and hence a higher population size and number of generations yields better solutions.

Another important yet expected feature observed in simulating the proposed strategy for all the different cases (Different number of resources) is that the minimum burned area decreases as the number of resources used increases. Figure 7.14 shows the minimum burned area obtained for different numbers of resources used.

Figure 7.14: Minimum Burned Area

Prob.II: In this problem, heterogeneous terrain and changing weather-wind conditions are considered. Along with wind-slope correction to the fire propagation model, uncertainty is added to the wind-slope and the final rate and direction of the forest fire propagation. The source of uncertainty can be noisy wind speed and direction predictions, or uncertainty in terrain modeling or imperfect knowledge about the fuel distribution. Though no heterogeneous fuel distribution is considered, the uncertainty added to the final rate of spread and direction of fire propagation takes care of heterogeneous and uncertain fuel distribution. The wind direction is sampled from a normal distribution with a mean of 20° and a standard deviation of 10° , i.e., wind direction changes in each time step based upon sampling from the above normal distribution. The wind speed is also considered to be normally distributed with a mean of 15 miles/hr and a standard deviation of 3

miles/hr. Wind speed, final rate and direction of forest fire propagation changes from one point to another in the considered terrain at a particular time instant and also changes with time.

Each GA generated solution is used in the fire propagation model to generate the firelines and the firefronts concurrently and hence to evaluate the performance of each solution. It may be noted that a solution may work for one instance of simulation run but may not work for another because of the added uncertainty. To alleviate this problem and to ensure that a solution should work satisfactorily for any scenario that may result in an uncertain and dynamic condition, the research uses Monte Carlo simulations. For each solution, the fire propagation model is run for 50 different scenarios. The Performance Index value for the solution is considered to be the worst of the performance index obtained from individual scenarios. This ensures that the GA generated solution is robust enough to entirely contain all the different shapes of the firefronts that may result due to varying wind-slope, weather, or terrain conditions. Figure 7.15 shows the initial state (Figure 7.15a) and the final state (Figure 7.15b) of firefront progression and fireline construction for the optimal solution obtained considering 4 firefighting groups. Figure 7.16 shows the evolution of best performance index in the generation as the number of generation progresses. Clearly, the area burned for Prob. II is more than Prob. I. This is because of the fact that GA in Prob.II gives a conservative solution to the problem so that the generated optimum fireline can handle uncertainties in fire behavior. The obtained optimum solution is thus robust enough to handle such uncertainties associated with forest fire propagation.

(a) Initial Firefront and Firefighting Crew Location

(b) Completed Fireline

Figure 7.15: Initial and Final State of Firefront Progression and Fireline Construction for Uncertain Scenario (Prob II 4 Resources)

Figure 7.16: Performance Index of the Best Solution in the Generation Plotted Against the Number of Generations (Prob II 4 Resources)

(a) Initial Firefront and Firefighting Crew Location Considering 5 Resources

(b) Completed Fireline

Figure 7.17: Initial and Final State of Firefront Progression and Fireline Construction for Uncertain Scenario (Prob II 5 resources)

Figure 7.18: Performance Index of the Best Solution in the Generation Plotted Against the Number of Generations (Prob II 5 Resources)

Considering the same uncertain scenario, simulation is performed considering $N = 5$ resources. Figure 7.17a and 7.17b shows the initial location of the firefighting crews and final fireline shape respectively. The plot showing how GA reaches the optimal solution with generations for this case is shown in figure 7.18.

7.2 Parallel Genetic Algorithm:

Simulations were carried out to evaluate the parallelization method proposed in Chapter 6 and to compare its performance with respect to the sequential GA. For comparing, Prob.I was considered with 4 firefighting teams. In this method, the total population size is divided into three sub-populations and hence each sub-population is of size $300/3 = 100$. It is thus considered that

3 sub-populations are running in parallel and migration occurs after 5 generations, where the best solutions obtained by each of the GA are shared between each other.

In figure 7.19a and figure 7.19b the initial state and final state of forest firefighting is shown. In figure 7.19a, the blue dots show the initial location of fire fighting crews from where to start building firelines and figure 7.19b shows the completed fireline and final firefronts with no fire escape. The convergence of the solution to the optimal value for each of the sub-populations are shown in figure 7.20. For the parallel GA, 3 processors are considered to be running in parallel and the number of generations considered is 100 (much less than sequential GA) with a population size of 100. Other parameters are considered to be same as sequential GA. It is seen that comparable results with sequential GA are obtained using parallel GA. The important and useful feature of using parallel GA is that, using only a population size of 100 (one third than that of sequential GA), the parallel GA produced comparable results. The usefulness of parallel GA is augmented with the fact that using n processors, the computation time can be reduced to almost $(\frac{1}{n})^{th}$.

(a) Initial Locations of the Firefighting Resources

(b) Final Firefront and Fireline

Figure 7.19: Initial State and Final State of Forest Firefighting

Figure 7.20: Performance Index vs Number of Generations

CHAPTER 8

CONCLUSIONS AND FUTURE WORKS

In this thesis, a Genetic Algorithm based simulation-optimization framework for generating intelligent wildfire fighting strategies has been developed for an efficient containment of complex wildland fires in both homogenous and heterogeneous conditions as well as in uncertain environment. The optimization framework uses the fire propagation model to evaluate the strategies and direct its search direction to obtain the best strategy for fireline construction that minimizes the total burnt area. One of the major contributions of this research is to apply the GA based simulation-optimization technique to a wildfire fighting scenario where wind-terrain conditions and hence the fire behavior is uncertain, and demonstrate that such techniques can be used to arrive at better resource utilization decisions. Ability to handle uncertainties become very important in fight complex wildfires since weather conditions are difficult to predict as well as knowledge about terrain and vegetation is often imperfect. To incorporate heterogeneity in the terrain, the fire propagation model used has been modified to incorporate wind-slope correction. Furthermore, uncertainties in wind direction and speed have been incorporated to obtain robust firefighting strategies. The proposed Monte Carlo based GA approach is shown to effectively handle the uncertainty in the fire behavior. To reduce the computation time, application of Parallel Genetic Algorithm is shown. It is observed that Parallel Genetic Algorithm facilitates faster solution evaluation without compromising the optimal solution. This preliminary study demonstrates that the availability of accurate fire propagation models, new technologies to gather and process information, and accurate weather

prediction models can be used with simulation-optimization techniques as proposed, for more efficient and robust decision making in complex wildfires.

The GA generates a population of several solutions that gets evaluated in each generation via simulation of the fire propagation model. All these calculations make the proposed GA based simulation-optimization technique computationally extensive. In spite of this, real time applicability of this technique is not of much concern because of time scale in which wildfires are fought and also due to the fact that the proposed technique can be easily adapted to facilitate parallel computations. As mentioned earlier, fighting a large forest fire involves a large number of resources. Large number of resources drastically increases the search space and the number of parameters to be optimized by GA. Extensive simulations carried out using different number of firefighting teams demonstrate that the proposed method is easily applicable to varying number of resources. However, to carry out optimization in a large search space using a GA, the number of generations and population size has to be increased. These result into even more number of computations. To alleviate this problem, parallelization were introduced. The application of parallel GA, that facilitates parallel computation and hence reduction of computation time, was presented which demonstrated that the performance, in terms of optimality of solution, of parallel GA was similar as compared to that of the sequential GA.

Genetic Algorithm is essentially a search and optimization technique famous for its robustness and the ability to obtain global optimum. Other search and optimization techniques do exist in literature. Techniques such as other Evolutionary Algorithms, Particle Swarm Optimization (PSO), Ant Colony Optimization and Simulated Annealing are well known for their convergence to global optimum and robustness though each have their own drawbacks. Application of these methods are

possible in the problem formulated before. As mentioned before, each of these techniques will have their own pros and cons when applied to the problem dealt in this thesis.

Future work includes reinforcement learning for obtaining optimal resource allocation policy. The availability of high-fidelity simulation environment provides a good motivation of applying reinforcement learning techniques. The reinforcement learning techniques can be used to obtain optimal decision-making policies once the wildfire fighting problem is formulated in the framework of dynamic programming. Drawback of this method is scalability which can be overcome by using approximation techniques for value functions and by implementing the reinforcement learning in a distributed manner. Another aspect of the proposed method is that it carries out the resource allocation using a completely data driven method. Wildland firefighting, on the other hand, has hitherto been carried out using expert knowledge and heuristic rules. In fact, a method that systematically combines heuristic knowledge of a firefighter with data driven techniques will have much enhanced capabilities. For example, in the proposed method, the search space of the GA can be drastically reduced as solutions achieved much faster if heuristic knowledge of a firefighter is incorporated. One way of incorporation of these heuristics can be application of Fuzzy-Genetic Algorithm. Future works would include development of techniques that can systematically incorporate human expertise into the decision-making algorithm.

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