Decision Support for Emergency Response in Interdependent Infrastructure Systems

by

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Abstract

In recent years, extreme events, such as hurricanes, earthquakes, floods and fires, occur more frequently and at a higher intensity. The growing complexity and interdependence of modern infrastructure systems makes them vulnerable to such events. Emergency response is the process of implementing appropriate actions to reduce human and economic losses following these events. Efficient response requires an understanding of the existing infrastructure systems and their interdependencies. In this thesis, we propose a decision support system for helping emergency responders in making efficient decisions during extreme events. Fires are chosen as an example of the extreme events and firefighting operations as the emergency response to these events. Everyday, fire managers are faced with making increasingly complex manpower decisions; trying to minimize costs and risk levels. The effectiveness of firefighting operations is crucial in minimizing both cost of suppression and economic losses. The contributions of this thesis focus on two levels of fire management plans: operational and strategic. We first develop a methodology to optimize the allocation process of firefighting resources in multiple-fire incidents. The developed methodology employs reinforcement learning, a machine learning algorithm that optimizes the allocation of firefighting units to minimize the total economic losses in the long run. To consider the concept of infrastructure interdependencies in evaluating the economic impact of the incidents, we model a large petrochemical complex using the Infrastructure Interdependency Simulator (i2Sim). In addition, a capacity planning methodology is developed to investigate the impact of manpower investment on the effectiveness of firefighting operations. The developed methodology aims at finding the optimal number of firefighters to be recruited to contain fires and effectively extinguish them. It performs an economic analysis to evaluate the efficiency fire management plans. Finally, we propose a methodology to evaluate the effectiveness of emergency response plans in improving infrastructure resilience. This methodology focuses on two dimensions of resilience: resourcefulness and rapidity. These dimensions are measured by the optimality of allocating firefighting units and by minimizing economic losses. The proposed methodologies are tested using a case study of a large petrochemical complex and promising results are achieved.

Preface

The contributions pointed in this dissertation have led to a number of already published, or currently under preparation for publications in journals and conferences. My research work and all my publications have been done by me under the supervision of Prof. José R. Martí. The co-authors of the publications have provided us with constructive feedback. The outcomes of each chapter in terms of publications are as follows.

Major parts of chapter 2 was first presented in the 9th International Conference on Critical Infrastructure Protection 2015 and was published as a book chapter in [1] :

- K. Alutaibi, A. Alsubaie, J. R. Martí, "Allocation and Scheduling of Firefighting Units in Large Petrochemical Complexes," *International Conference on Critical Infrastructure Protection.* Springer International Publishing, 2015.

Work presented in chapter 5 was presented in The International Emergency Management Society (TIEMS) 2015 Annual Conference in [2]:

- K. Alutaibi, A. Alsubaie, J. R. Martí, "Improving Critical Infrastructure Resilience through Scheduling of Fire-fighting Resources," in *The International Emergency Management Society 2015 Annual Conference (TIEMS 2015)*, 30 Sept.–2 Oct., Rome, Italy.

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FSM Fire Severity Measure . . . 17

HP Human Performance . . . 61

HRT Human Readable Table . . . 23

i2Sim Infrastructure Interdependencies Simulator . . . 16

LC+L Least Cost Plus Loss . . . 32

NFPA National Fire Prevention Association . . . 2

NIFC National Interagency Fire Center . . . 2

PM Physical Mode . . . 21

RL Reinforcement Learning . . . 24

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I will forever be grateful for the opportunity to be a member of the i2Sim group. I would like to extend my thanks to my colleagues in the i2Sim group for all the discussions, inspirations, and interesting ideas during our weekly meetings.

I would like to acknowledge the financial support provided by the Ministry of Interior (Civil Defense), Saudi Arabia.

A special thanks to my parents for their love and prayers. Also, I thank my brothers and sisters who gave all the support. Finally, I am forever grateful to my wife and my children for their unconditional love, patience, understanding and support.

Dedication

To my children; Joody, Naif and Omar.

Chapter 1

Introduction

1.1 Motivation

In recent years, extreme events, such as hurricanes, earthquakes, floods and fires, occur more frequently and at a higher intensity. The growing complexity and interdependence of modern infrastructure systems, such as water, electrical power and transportation, makes them vulnerable to such events. Emergency response is the process of implementing appropriate actions to help reduce human and economic losses following these events. During emergency response, crucial decisions are taken among various organizations and at different levels. Efficient response requires an understanding of the existing infrastructure systems and their interdependencies. In this thesis, we propose a decision support system for helping emergency responders in making efficient decisions during extreme events. Fires are chosen as an example of the extreme events and fire fighting operations as the emergency response to these events.

Fires are very expensive to fight and may result in devastating human, economic and environmental effects. Everyday, fire managers are faced with making increasingly complex manpower decisions; trying to minimize costs and risk levels. Figure 1.1 shows the total number of fires and the cost of suppression for the period 1985-2014 as reported by the United States National Interagency Fire Center (NIFC) [5]. Although the number of fires has not changed so much over the last decade, the cost of fire suppression has increased by 33.8 percent. In 2014, the cost of suppression was estimated at more than $1.5 US billion [5]. Also, the estimated direct economic losses in 2014, due to fires, was $11.6 US billion. These estimated losses do not include indirect losses, such as business interruption [6]. The effectiveness of firefighting operations is crucial in minimizing both cost of suppression and economic losses. Therefore, there is a need to develop a Fire Management Decision Support System (FMDSS) for fire managers to suppress fires in a cost effective way.

One of the critical decisions facing fire mangers is how to assign firefighting units to respond to multiple simultaneous fire incidents. The typical response to a single fire incident is not always the best response to multiple fire incidents, and the latter can be improved upon [7]. This type of special assignment requires deep understanding of the existing infrastructure systems and their interdependencies. Current technologies can help build a decision support system capable of planning better responses during multiple fire incidents that affect critical facilities.

According to the National Fire Prevention Association (NFPA), the number of assigned firefighting units to respond to a fire incident should

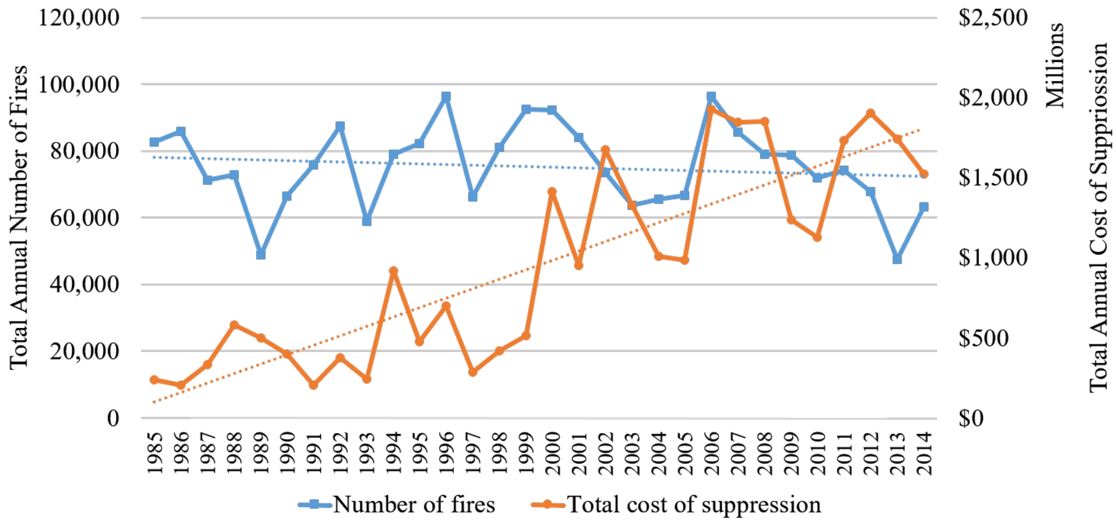

Figure 1.1: Total number of fires and the cost of suppression the United States for the period 1985-2014.

be determined by either risk analysis, pre-fire planning or both [8]. Typically, experts make resource allocation decisions based on their experience and available information about the incident. The size of the fire is usually the major factor in assigning the number of units. Other important factors such as economic impact or criticality of the site are not taken into account by traditional decision-making procedures. Better responses are required in the form of allocating an optimum number of firefighting units to minimize the economic losses.

Identifying potential economic consequences of fires is crucial in the decision-making process. Decision support systems based on economic models can help not only determine the most efficient allocation of limited resources, but also with strategic fire management planning and budget request justification. The evaluation of economic consequences requires a deep understanding of the infrastructure systems' behavior during fires. As infrastructure systems do not exist in isolation from one another, an incident in one system may result in disruption to the functionality of other critical infrastructure systems. As a result, the indirect losses far exceed the direct property losses [9]. The evaluation of economic impact due to fires requires methodologies that address the performance of infrastructure systems (e.g., the transportation system) and also the interdependencies between them (e.g., the effect of electricity on communication). The proposed work utilizes the concept of the infrastructure interdependencies in evaluating the economic impact of the incidents.

This research project supports two levels of fire management plans: operational and strategic. The operational level involves daily decisions about allocating and scheduling firefighting resources to fire locations (e.g., the number of firefighters assigned to a fire). The strategic level of planning includes medium to long term time horizons such as the evaluation of potential benefits and consequences of alternative management plans (e.g., increasing the number of firefighters). The proposed work in this thesis can be used before an accident for training and planning, during an accident for decision support, or after an accident for evaluating suppression strategies. The work is also applicable for wildfires.

Recent incidents have highlighted the limitations of existing response systems such as a lack of situational awareness and effective coordination between emergency response departments (e.g., fire, police) [10]. Increasingly the emphasis has shifted from protection and prevention towards preparedness and response [11]. This shift is realized by the concept of resilience. The effectiveness of the emergency preparedness and response plan has a high impact on infrastructure resilience. In this thesis, we study the resilience of infrastructure systems as affected by fire incidents. We propose a methodology to evaluate the impact of resources allocation decisions during fire incidents in improving infrastructure resilience. This methodology can be used for any type of hazards. It can also be used for other resource allocation problems in any interdependent environment such as telecommunications, transportation, electric power grids and water supply systems.

In the following, a literature review is provided on different topics covered in this thesis.

1.2 Literature Review

1.2.1 Emergency Response

The concept of emergency management has received considerable attention in recent years. In the literature, it is common to define four phases of emergency management: mitigation, preparedness, response and recovery [12], [13], [14]. Figure 1.2 shows the four phases of emergency management.

The mitigation phase involves the policies and measures that are taken to reduce the probability of emergency situations or reduce the negative impact of unavoidable situations. The preparedness phase includes all planning and training activities designed to minimize losses when an emergency occurs. The response phase includes efforts that are taken immediately after a disaster strikes, such as saving lives and fighting fires. The recovery phase involves all the operations to return life to normal and to restore basic services [14].

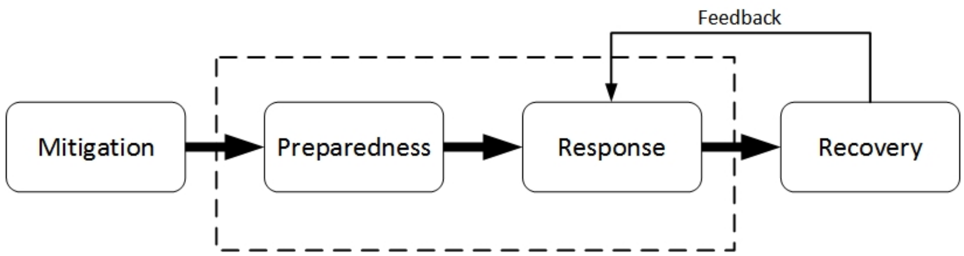

Figure 1.2: Emergency Management Phases.

Even though all phases are overlapping, the focus of this thesis is on the response phase. Whenever an emergency situation occurs, effective and efficient emergency response can be deeply influenced by efficient allocation of the available resources. In this respect, many researchers have focused on developing approaches dealing with allocation and deployment of emergency resources [15], [16]. Fiedrich et. al. [15] proposed a dynamic optimization model for allocating emergency resources to operational areas after an earthquake. The objective of the model is to minimize the total number of fatalities during the Search-and-Rescue period. Similarly, mathematical programming models are proposed for allocating and scheduling rescue units by Wex et. al. [17] and Schryen et. al. [18]. Barbarosoglu et. al. [19] developed a hierarchical multi-criteria methodology for assigning helicopters' tasks during a disaster relief operation. The focus of this work was to minimize the operational cost. Emergency response during multiple hazard events have been also addressed in several recent publications Dillon et. al. [20], Li et. al. [21] and Abkowitz et. al. [22]. Most of the decision making process in these studies is based on risk prioritization.

The context of this thesis is emergency response during fire incidents in which FMDSS are used. Fire management systems can be defined as the set of processes and practices used to minimize the negative impacts of fires. Several review articles have explored the most recent studies in the development and use of FMDSS (e.g., Martell (2015) [23], Duff et. al. (2015) [24], Pacheco (2015) [25] and Mavsar et. al.(2013) [26]). Most of the reviewed systems do not take economic efficiency of fire activities into consideration. Effective fire management systems should be able to evaluate the cost and the damage for fire operations.

1.2.2 Resources Allocation in Firefighting Operations

The key challenge in firefighting operations during large incidents is how to efficiently utilize the available resources to reduce the impact of the fire. In the past decades, researchers have addressed this challenge by designing FMDSS to model fire behavior, dispatch decisions, impact assessment and processes optimization, e.g., LANIK [27], DEDICS [28] and WFDSS [29]. However, most of the existing work focuses on wildfires and lacks the capability of producing artificial intelligent (AI) decisions for allocating available resources [30]–[31]. A number of models have been developed for fire behavior prediction, such as BEHAVE [32], FARSITE [33], HFire [34] and Prometheus [35]. These models only focus on fire behavior simulation, using heat and smoke sources [36]. Generally, optimization of firefighting resources and simulation of firefighting operations are developed separately without integration into a unifying framework [37]. Such integration is proposed in this thesis.

There is also some research available considering models for fire simulations and firfighting resources allocation [38], [39], [40] and [41]. While these models provide considerable insight into the interaction between fire dynamics and resources allocation, they are limited to specific types of fires (wildfires) and cannot be extended to fires in interdependent infrastructure systems. Also, they do not capture the effect of emergency responders decisions on economic losses during the response efforts. The concept of infrastructure systems resilience can assist emergency responders in allocating the optimal number of firefighting units during single or multiple fire incidents in order to minimize both direct and indirect losses and the time required to return to normal operation.

Most of the existing fire decision models focus on initial assignment of the resources without dynamically changing the assigned amounts [42]. In our work, assignment decisions are made dynamically and associated with the final expected losses. This representation considers the long-term consequences of fire incidents.

In recent literature, simulation and optimization models have been integrated for dispatching decisions in firefighting operations. A simulation-based model using stochastic processes and queuing theory was developed in Petrovic, Alderson and Carlson [41] to represent wildfire dynamics and allocate limited resources during suppression. These models have been used to evaluate the allocation of firefighter resources and evaluate the dispatching rules [43]. Integrated fire behavior simulation and optimization to allocate firefighting resources has also been addressed in [39], [38] and [40].

Agent-based discrete event simulation models were developed by Hu and Ntaimo [37] to simulate fire suppression based on dispatch plans using a stochastic optimization model. Lee et. al. [44] developed a model that combines an optimization model with a stochastic simulation model to assign the number of resources by type that must arrive at the fire within a specified time limit and budget. An intelligent resource allocation system to minimize the damage due to wildfire was introduced by Homchaudhuri [45], who used a genetic algorithm optimization to determines the location of the firefighting crews. However, this system and the other wildfire FMDSSs are limited to this particular fire type and cannot be extended to interdependent infrastructure systems.

1.2.3 Fire Strategic Planning

Fire managers are faced with two types of decisions: strategic and operational (tactical). The strategic decisions involves making long term planning on budget allocation and the deployment or relocation of firefighting resources before fires occur. A number of strategic fire management systems have been developed in different countries and throughout the years. Examples of these systems are LEOPARDS [46], KITRAL [47], SINAMI [48] and FPA [49].

The Level of Protection Analysis System (LEOPARDS) [46] is a Canadian model developed in 1995. The model focuses on strategic fire management planning at a regional level. It uses historical data, such as fire weather, fire incidence data, operational rules and infrastructure information, to evaluate the fire pre-suppression and suppression activities under budget constraints.

In 1996, the University of Chile and the Chilean Forest Service introduced a fire management tool called KITRAL ("fire" in indigenous Chilean language) [47]. The objective of KITRAL is to improve the efficiency of forest fire management at the national level. It evaluates different fire management plans at both strategic and operation levels. Based on fire behavior simulation, it provides an optimal deployment of firefighting resources. Also, it evaluates different strategic deployment plans by simulating future fires and choosing the most effective plan. The LEOPARDS and KITRAL models have the same limitation in that they do not consider the potential damage to goods and services caused by fires [26].

SINAMI is another strategic fire management planning tool developed in Spain. This model uses the historical data of the last 10-years to analyze the relation among different budget levels and potential losses. An economic analysis is used to determine the most efficient fire management programs and budget [48]. This analysis considers the management costs (pre-suppression and suppression costs) and the net value change of an array of limited number of goods and services.

In 2006, the U.S. Department of Agriculture (USDA) Forest Service and the US Department of Interior developed the Fire Protection Association (FPA) system to evaluate the effectiveness of alternative fire management programs [49]. It uses cost-effective analysis to find the optimal allocation of pre-suppression resources, including numbers, types and locations of fire stations. A goal programming model is used to decide the effectiveness of alternative fire programs. The FPA model does not involve any theoretical economic foundation in their analysis [26].

Among the above FMDSSs, SINAMI model performs an economic analysis based on the Cost-Plus-Net-Value Change (C+NVC) concept to evaluate the efficiency fire management programs [26]. The C+NVC concept evaluates the fire operation costs and the related damage caused by fires. In this thesis, the C+NVC concept is incorporated within the decision support system.

Although earlier efforts have focused on strategic planning, economic efficiency analysis is also important for operational decisions and activities [50]. Operational decisions (tactical decisions) are crucial for any fire management system and its goal is to provide optimal decisions in order to minimize the resulted damage by fighting fires in efficient ways. Operational planning, such as evaluating alternative fire suppression strategies, has been the focus of several recent research projects and papers. However, few recent studies attempted to include economic tools in the design of efficient fire management strategies such as Ntaimo et. al. [51, 52] and Arrubla et. al. [53]. Mendes [54] stated that there is a clear need to incorporate economic analysis in this area. In this thesis, we use economic analysis to help fire managers to determine appropriate responses during daily operations.

1.3 Problem Statement and Research Objectives

Emergence response during fire incidents is a challenging problem. When economic efficiency is considered, infrastructure interdependence makes this problem more complex. An ineffective response can greatly impact the resilience of the disrupted infrastructure. There is a need to incorporate economic efficiency into the decision making process, primarily during fire suppression planning, capacity planning and to help improve infrastructure resilience. Within this context, the following objectives are set for this research project:

1. To formulate the fire management plans in the context of infrastructure interdependencies.

2. To develop a resource allocation and dynamic scheduling algorithm for emergency response during multiple fire incidents.

3. To develop an economic efficiency model and incorporate it within the decision-making process.

4. To develop a methodology for evaluating the impact of resource allocation decisions on infrastructure resilience.

5. To formulate the fire management problem as an optimization problem and provide a solution algorithm for this problem.

6. To study the impact of human factors during fire incidents for improving the overall efficiency.

1.4 Thesis Contributions

The main contributions of this thesis are summarized as follows:

1. Development and implementation of a resource allocation and dynamic scheduling algorithm for emergency response during multiple fire incidents.

2. Introduction of a methodology for evaluating the impact of infrastructure interdependencies on firefighting operations.

3. Evaluation of the impact of resources allocation decisions during fire incidents on infrastructure resilience.

4. Development of an economic efficiency model to evaluate direct and indirect losses during emergency responses.

5. Development of a planning model for capacity investment in firefighting resources.

1.5 Thesis Organization

This thesis is organized as follows:

Chapter 1 introduces the main focus of the thesis and discusses the motivation for the research project and its objectives.

Chapter 2 describes the developed system and provides a detailed case study of multiple fire incidents in a large petrochemical complex.

Chapter 3 applies the developed system to allocate resources to minimize economic losses resulting from fires. Linear and none-linear damage functions are considered. Finally, the human performance factor is discussed and evaluated.

Chapter 4 provides a description of the capacity planning problem in a fire department. The concept of C+NVC is presented. This concept is incorporated within the developed system to determine the most efficient fire management plans.

Chapter 5 describes the resilience of infrastructure systems under fire incidents. The developed system is used to evaluate the impact of resources allocation decisions during fire incidents for improving infrastructure resilience.

Chapter 6 summarizes the contributions of this thesis and makes recommendations for future studies.

Chapter 2

System Development

2.1 Introduction

This chapter presents the development of a fire management decision support system for assisting fire managers in making efficient decisions. This system relates suppression operation costs to the reduction in expected damages. It is assumed that the goal of fire managers is to minimize the total cost which consists of the fire operational costs and the net damage. The main functions of the proposed system are: (a) resources allocation optimization: this includes damage and economic impact analysis, optimization of resources allocation and scheduling decisions during fire incidents, (b) manpower capacity planning: this includes making decisions on planning of manpower management over long-term planning and evaluating the cost and consequences of alternative plans, and (c) improving resilience of interdependent infrastructure systems: this includes the evaluation of resilience of infrastructure systems and making effective decisions to strengthen re-

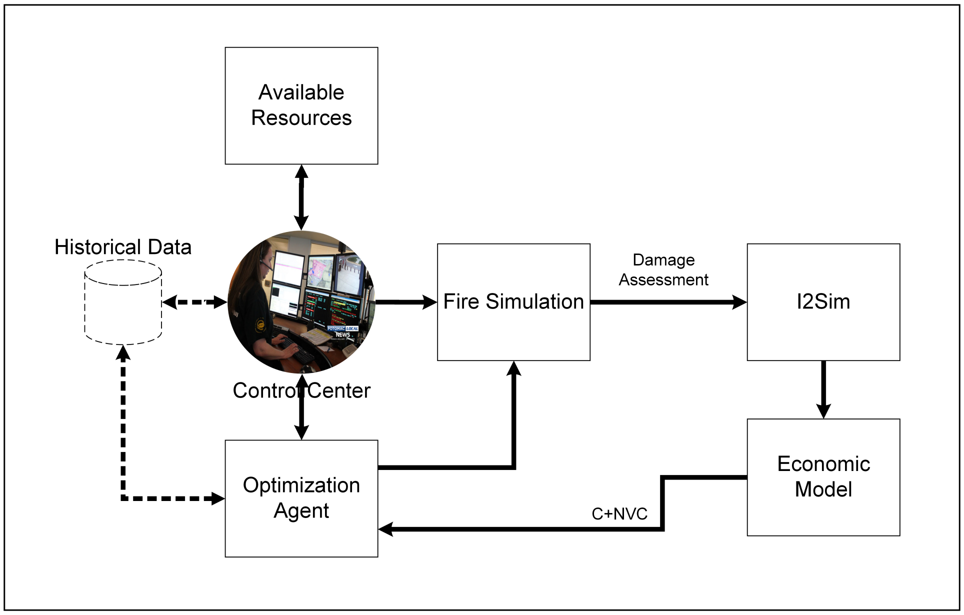

Figure 2.1: Overall architecture of the proposed FMDSS.

silience. These functions are covered separately in Chapters 3 to 5.

Figure 2.1 presents the overall architecture of the proposed fire management decision support system. It has four main components: (i) a fire simulation model for modelling fire behavior and evaluation of fire damage, (ii) Infrastructure Interdependencies Simulator (i2Sim) for evaluating the interaction among critical infrastructure systems, (iii) an economic model for evaluating both operational costs (pre-suppression and suppression costs) and damage (direct and indirect losses), and (iv) an optimization agent for minimizing the sum of management costs and net damage.

The above main components are described in sections 2.2 through 2.5. Finally, Section 2.6 describes a case study that is used throughout this thesis to show the effectiveness of the various functions of the developed system.

2.2 Fire Simulation Model

This section describes the fire simulation model. The objective of this model is to assess the damage level produced by fires. In order to evaluate the damage, we first introduce a fire severity measure to estimate fire duration. This measure relates the required number of firefighters to the estimated fire suppression time. Secondly, a damage function is used to associate the fire duration with a particular level of damage. These are described in more detail in the following subsections.

2.2.1 Fire Severity Measure

The fire simulation model starts with a definition of the Fire Severity Measure (FSM). This measure is used to describe the severity of fire. Examples of potential severity measures include fire duration, peak fire temperature, fuel load, heat release rate, etc. [55], [56]. Although these measures of fire severity are often closely related, there is no standard quantitative measure of fire severity [57]. In this thesis, FSM is defined as the total man-hours needed to control a fire. This number can be estimated with the help of firefighting experts. A large FSM value means that a large number of firefighters is required to suppress the fire. For a given fire, different resources allocation decisions can be made and each decision may result in different fire durations which in turn results in different FSM values.

Fire duration has a strong positive correlation with damage and can form a basis for design decisions. Thus the fire damage, $d(T)$, can be expressed as a function of the fire duration time T. The fire duration time can be calculated by:

$$T = \frac{FSM_i}{\sum_j^n x_{ij}} \tag{2.1}$$

where

FSM_i is the severity measure of fire i

n is the total number of fire stations

x_{ij} is the total number of firefighters assigned to fire i from fire station j during the suppression process.

To capture the dynamics of fire, the damage assessment table, Table 2.1, can be used to map the fire duration time into five damage levels. These levels are: 1) minimal damage, 2) low damage, 3) intermediate damage, 4) high damage, and 5) excessive damage. During simulation, the expected damage level can change over time in the increasing direction. For example, the level of damage in a burning building can change from low damage to intermediate, but not in the opposite direction. Also, each level of damage is associated with the repair or reconstruction period of time, as shown in Table 2.1. For example, if the fire suppressed and resulting level of damage is intermediate, then the recovery time is estimated to be three months.

2.2.2 Damage Function

In general, damage functions increase with the magnitude of the extreme event such as a flood or a fire, and eventually exhibit saturation [58]. Here,

Color Code	Level of damage	Recovery time	Description
Green	Minimal	Minimal	No damage but light maintenance is required for safety.
Blue	Low	1 Month	Heavy maintenance is required and some equipment repair services are needed.
Yellow	Intermediate	3 Months	May cause minor damage and some equipment needs replacement.
Orange	High	6 Months	May cause major damage requiring short-term reconstruction.
Red	Excessive	12 Months	May cause significant damage and large reconstruction effort is required.

Table 2.1: Damage assessment table.

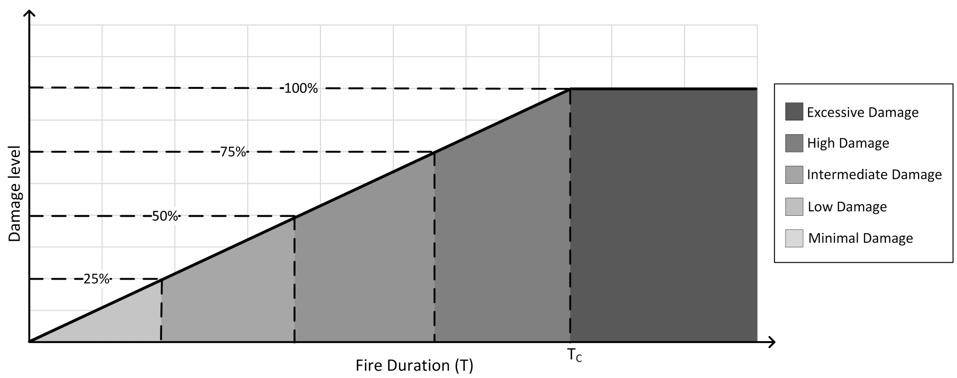

Figure 2.2: Illustration of the damage function.

a two-piece linear damage function is assumed with this form:

$$d(T)_{lin} = \begin{cases} \frac{T}{T_C} & \text{if } T < T_C \\ 1 & \text{if } T \geq T_C \end{cases} \tag{2.2}$$

where

T_C is the time for the fire damage to reach 100%. This function is illustrated in Figure 2.2.

The assumptions in the damage functions are conservative since the level of damage is influenced by several other factors such as wind speed and direction and fuel type and load. The case of considering non-linear damage curves are discussed in section 3.4.1.

2.3 i2Sim Modeling and Simulation Framework

Understanding how interconnected infrastructure systems behave when subjected to external events such as fires remains a major challenge for emergency responders. Also, an effective emergency response requires consideration of the interactions among the multiple layers of an effective emergency response: decision layer, damage layer, finance layer, and production layer. In order to understand this behavior, simulations can be used to model the interactions between these dissimilar systems.

The infrastructure interdependencies simulator (i2Sim) introduced by Marti [3] provides a simulation framework that captures the interactions among these systems. i2Sim has been used in modeling infrastructure systems in different emergency response applications [59], [60], [61], [60]. In this thesis, i2Sim is selected for five main reasons: (i) the ability to choose the global simulation objective (e.g., economic, environmental or security), (ii) the ability to simulate and produce reasonable results even when data is limited, (iii) the ability to simulate multiple infrastructure interdependencies (e.g., water, power and oil), (iv) the ability to simulate the effects of resource allocation decisions in real time, and (v) the ability to integrate other simulators and assess the impacts of decisions made in one infrastructure on the other.

The simulator provides an environment for representing multiple interdependent infrastructure systems. To capture the interactions among these systems, i2Sim defines a common ontology based on a cell-channel approach. The i2Sim ontology is described in the following section.

2.3.1 i2Sim Ontology

The i2Sim ontology is based on a cell-channel approach. It represents the functionality of each cell using input-output relationships. The i2Sim components are defined as follow:

- **Cell (Production Unit):** A cell is used to model system components such as hospitals, electrical substations and water stations.
- **Token (Resource):** A token represents the resources that circulate throughout the system, such as, electricity, water or gas.
- **Channel (Transportation Unit):** A channel carries the tokens from one cell to another. They represent the relationships between the system components. Examples include roads, transmission lines and water pipes.
- **Distributor (Control Unit):** Distributor is a decision point where actions can be taken to allocate the resources.
- **Aggregator (Control Unit):** Aggregator is another decision point. It combines two outputs of the same token into one channel.
- **Physical Mode:** Physical Mode (PM) represents the level of physical damage of the cells or channels.

- **Resource Mode:** Resource Mode (RM) represents the availability of input resources to the cells.

- **Sources:** These are the producers of the external tokens. Sources represent infrastructure systems that are not included in the i2Sim model.

- **Reservoirs:** These are the storage elements in the i2Sim model.

- **Sinks:** These are the components that send internal tokens to outside the i2Sim model.

- **Modifier (Affecter):** A modifier represents the external information that is received as input into cells, channels, distributors and aggregators.

For each cell, there is one output (product) and one or more inputs (resources). The operating state of each cell is influenced by the availability of the tokens (resources), the level of the PM (physical damage of the cell) and modifiers (external information) that are received as input into the cell. Figure2.3 shows the possible operating states of cells and channels. The PM are discretized into five possible color-coded levels. The five color-coded levels are red=0%, orange=25%, yellow=50%, blue=75% and green=100%.

2.3.2 i2Sim Models

The i2Sim components can be used to model multiple dissimilar infrastructure systems. Infrastructure system components are defined as cells and the connections between them, such as transmission lines and oil pipelines, which are defined as channels. Resources and services, such as oil, water and

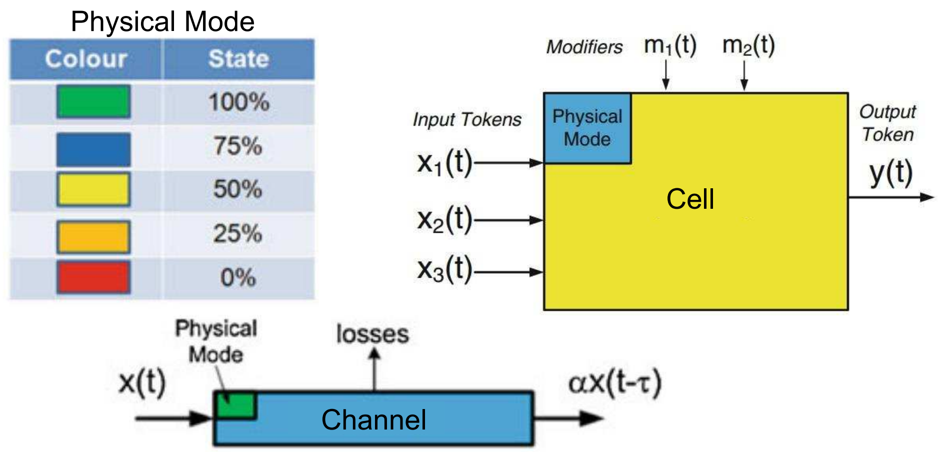

Figure 2.3: Conceptual cell and channel models [3].

power, which are defined as tokens that move between cells (i.e., through channels). The relationship between the inputs and the output is predefined by a function which describes the operation of the cell. This function is also known as a lookup table or Human Readable Table (HRT). The operability of the cells is determined by the minimum available resources. An example of an HRT representing an Emergency Room (ER) in a hospital is shown in Figure 2.4. In this example, the operability of the unit is 50% due to the lack of water. At this level, the ER can treat only 10 patients per hour. In our case study, we use the HRT function to simulate the operability of the petrochemical plants.

The combinations of cells and channels in the i2Sim model set up a mathematical formulation of the relationships between infrastructure systems. A system of discrete time equations is created, which is solved simultaneously for all components at every time step along the timeline to find the operating point of each production cell. [3, 62]

	$y(t)$	$x_1(t)$	$x_2(t)$	$x_3(t)$	$x_4(t)$	$m_1(t)$
Operability	Patients per hour	Electricity (kW)	Water (L/h)	Doctors	Nurses	Physical Integrity
100%	20	100	1,000	4	8	100%
75%	15	50	500	3	6	80%
50%	10	30	300	2	4	50%
25%	7	20	200	2	3	20%
0%	0	0	0	0	0	0%

Figure 2.4: An example a Human Readable Table (HRT) for an Emergency Room (ER) [3].

The interaction between these systems can be captured using the i2Sim simulation layers. Figure 2.5 shows the basic i2Sim simulation layers. The exchange of information between these layers is performed through the modifiers. The availability of this information assists emergency responders to evaluate feasibility or effectiveness of different response plans to reduce the risk to life and property in the event of an emergency.

2.4 Optimization Agent

Finding optimal decisions to control the behavior of interdependent infrastructure systems is crucial during extreme events. In some critical situations, the dynamics of the systems are not completely predictable and it is necessary to quickly find new optimal actions as incidents evolve. Simulation gives decision makers the opportunity to evaluate the options for action. An optimization agent, based on Reinforcement Learning (RL), is developed to optimize the global objective by dynamically assigning firefighting units to

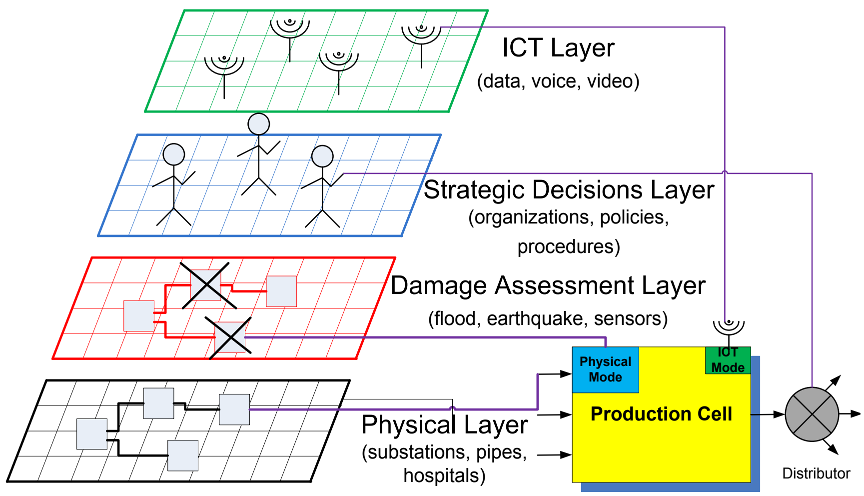

Figure 2.5: i2Sim simulation layers [3].

the most critical fire. This agent is integrated with the i2Sim model and the fire simulation model.

2.4.1 Reinforcement Learning

RL is a machine learning technique which involves learning by taking actions in a trial-and-error manner. It consists of an agent, a finite set of states S, a set of available actions A, and a reward function R. The agent is the learner and the decision maker and everything it interacts with is called the environment.

Unlike supervised learning methods such as neural networks which require training data with input and expected output, RL can learn directly from the interaction between the agent and its environment. By interacting with its environment, the RL agent learns to map its current state to the best action (state-action pair) to maximize long-term rewards [63]. A key advantage of the RL paradigm is in its ability to deal with delayed reward situations [64]. This makes it suitable for emergency response operations, where rewards are often obtained a long time after the action. For example, the impact of a fire suppression plan will not be apparent immediately, but rather at some point in the future. RL has been applied successfully to a wide range of problems in a variety of disciplines, including scheduling in sensor networks [65], resource allocation in business process management [66], optimal allocation resource in water resource management systems [67], learning user behavior in social networks [68], and spacecraft payload processing [69].

RL has five main components [63]:

1. An agent represents the learner and the decision maker that interacts with the environment.

2. A policy is a function which defines the behavior of the agent. It determines the proper action to take at each time-step based on the state the agent is in.

3. A reward function maps each state-action pair to a scalar value and reward, so that the performance can be evaluated in a mathematical equation.

4. A value function calculates the accumulated reward over time of a specific state-action pair. The agent's goal is to maximize the collected rewards it receives over time.

5. A model of the environment represents the system which the agent interact with.

A common algorithm for solving RL problems is Temporal Difference Learning (TD). The TD algorithm is described in the following section.

2.4.2 Temporal Difference Learning (TD)

TD is the reinforcements learning algorithm that is most successful and broadly applied algorithm to RL problems [63]. TD methods apply a value function that estimates the future reward for taking a particular action in a state. These methods can be classified based on the approach they follow in search of the optimal action policy: on-policy and off-policy methods.

In on-policy methods, the agent follows a policy to explore the environment. Simultaneously, the agent tries to find the optimal policy that maintains exploration of possible actions. In other words, the policy that is being optimized is also used to explore the environment. An example of this type of methods is the State-Action-Reward-State-Action (SARSA) algorithm. On the other hand, in off-policy methods, the agent has two different polices: a behavior policy and an estimation policy. The agent learns the estimation policy from the actions performed by the behavior policy. An example of this type of methods is the Q-learning algorithm [63].

Both methods can find the optimal policies. The main difference between these methods is in the speed of convergence. The on-policy methods have shown faster convergence than the off-policy methods in different fields of application [70, 71].

During extreme events, such as fires, response time is critical. With this kind of situation, on-policy methods can help to assist emergency responders to optimize the allocation of limited resources. In this thesis, SARSA is utilized in our decision-making process.

2.4.3 SARSA Algorithm

SARSA is a learning algorithm for sequential decision making that learns the value of applying an action in any state. In its simplest form, SARSA is defined by the following equation [63]:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)], \tag{2.3}$$

where

a_t: is the action taken at time t

s_t: is the state assumed at time t

r_{t+1}: is the reward at time $t+1$

$Q(s_t, a_t)$: is the learned state-action value function at time t

$0 \leq \gamma \leq 1$: is a discount factor, which determines the importance of future rewards

$0 \leq \alpha \leq 1$: is the learning rate, where a factor of 0 will make the agent not learn anything, while a factor of 1 would make the agent considers only the most recent information.

The goal of the agent is to learn a policy π that maximizes the reward over the agent's lifetime. This policy maps the current state s into the most desirable action a to be performed in s:

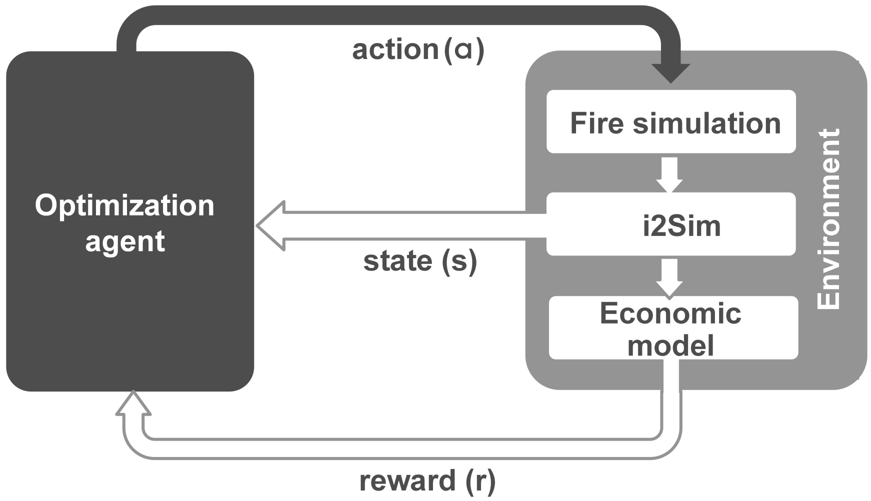

Figure 2.6: Reinforcement Learning (RL) learning model.

$$\pi = \{(s,a) \mid s \in S, a \in A\} \tag{2.4}$$

The desirability of each state-action pair can be represented by a value function, Q:

$$Q : S \times A \rightarrow R \tag{2.5}$$

At each interaction with the environment, the agent observes the environment's state $s_t \in S$. Then, it selects an action $a_t \in A(s_t)$, where $A(s_t)$ is the set of all possible actions at state s_t. After taking an action, the agent moves to a new state s_{t+1} and receives from the environment a reward r_{t+1}. The value function $Q(s,a)$ is then updated based on in Equation 2.3. This procedure continues and the agent adjusts its policy until either the optimal assignment is reached or the stopping criteria is met.

2.4.4 Reinforcement Learning (RL) Model

Figure 2.6 shows the proposed RL model. It consists of an agent, a finite set of states S, a set of available actions A, and a reward function R. The agent is the learner, and the decision maker and everything it interacts with is called the environment. The objective of the agent is to minimize the cost of business interruption.

A state $s \in S$ contains the PM and RM values in the i2Sim model. For example, the state list for two simultaneous fire incidents at two different locations (x *and* y) is formatted as (PM_x, RM_x, PM_y, RM_y), where PM and RM reflect the physical state and the functionality of each cell. As mentioned in section 2.3, PM and RM are discretized into five levels. Therefore, the total number of states considering two fire incidents is (number of PM for location1) $\times$ (number of RM for location1) $\times$ (number of PM for location2) $\times$ (number of RM for location2).

The set A of possible actions which can be taken when in a state $s \in S$ consists of available resources that can be assigned. If it is assumed that the number of available resources is 100 firefighters, this enables the formation of 20 units of five firefighters each. Based on the number of fire incidents, the fire simulation model creates a list of possible actions from $A = \{0, 20, 40, 60, 80, 100\}$. For example, the available actions for each state in two simultaneous fire incidents are {(0,20), (0,40), (0,60), (0,80), (0,100), (20,0), (20,20)...}, corresponding to a total of 21 actions.

The reward r is based on the output of the economic model. It represents the total value of all products produced by all production units (cells) in the i2Sim model. More details on how to calculate this value are provided in the following sections.

The agent begins learning by sensing the current state s_t of the modeled system reflected by the physical and resource modes of the i2Sim model. It then searches for the best action a_t (action with the highest reward on that state) in a look-up. This table stores state-action pairs (s, a) and their current Q-values, $Q(s, a)$. Table 2.2 shows a look-up table sample. The Q-values are initialized randomly. Upon performing the best action, the system transitions to state s_{t+1} and receives a reward r. Next, the agent updates $Q(s, a)$ based on Equation 2.3. After consecutive runs, the agent learns the best path with the help of the learned state-action value Q.

(state, action)	Q(state,action)
(1,1,1,1,0,20)	51
(1,1,1,2,0,40)	620
(1,1,1,3,40,60)	422
(1,1,1,4,0,80)	911
(1,1,1,5,20,0)	1
(1,1,2,1,40,60)	37
(1,1,2,2,50,50)	8156
...	...
...	...
(5,5,5,5,20,80)	422

Table 2.2: Look-up table sample.

2.5 Economic Efficiency Model

Economic efficiency of fire management can be defined as the ability to allocate limited resources in a way that minimizes the sum of management costs and net damage. A formalization of this concept was introduced in the early 1916s by Headley [72] and Lovejoy (1916) [73]. It was assumed that increasing the cost of management (pre-suppression, suppression) would decrease the fire induced damage. Sparhawk (1925) [74] formulated this concept into the Least Cost Plus Loss (LC+L) model. The objective of this model is to find an optimal pre-suppression (protection plan) cost. The model has been investigated and improved over time into the Cost-Plus-Net-Value Change C+NVC model [75], [76] and [4].

In the $(C+NVC)$ model, the cost (C) sums all firefighting expenditures, such as purchasing equipment and wages for firefighting crews, as illustrated in Figure2.7. The net value change (NVC) include both direct and indirect losses induced by fire. The direct losses are the losses incurred due to the immediate effects of fires. The indirect losses are the losses related to a cascade of effects of fires due to functional or physical interdependence. Theoretically, as the fire operation costs increase, the net fire damage is expected to decrease [48]. The result of this analysis is a U-shape function, with a minimum point that represents the optimum fire management program (i.e P* in Figure2.7). For a given level of pre-suppression cost, the most efficient fire program is achieved where the summation of suppression cost and net value change is minimized.

In this thesis, we used the C+NVC model to evaluate both strategic and operational planning decisions faced by decision makers in a fire department. The strategic planning, which we refer to as the strategic capacity planning, involves making decisions about manpower management over a long-term time line. Over the strategic time frame, the fire department must plan

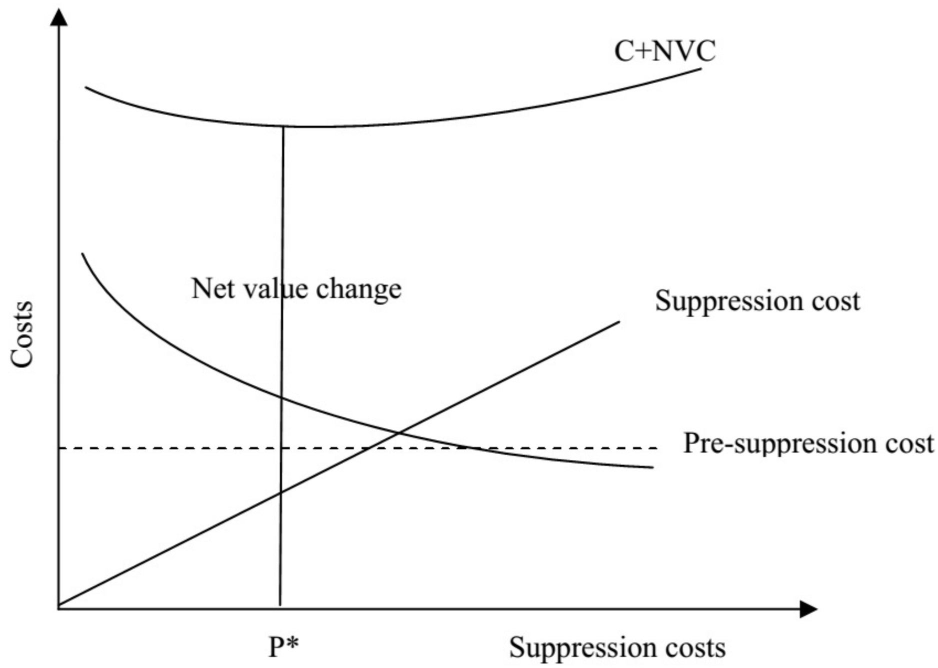

Figure 2.7: Illustration of the C+NVC model [4].

for recruiting to meet desired staffing levels. The objective is to find the most efficient fire management program by minimizing the summation of the fire operation costs (C) and net fire damage (NVC). This minimization problem can be represented mathematically as:

$$\text{MIN: C + NVC} = \sum_{t=1}^{T}(C_t + NVC_t), \tag{2.6}$$

where

C_t: fire operation costs (manpower and equipment) in period t

NVC_t: net loss due to fires in period t

T: planning periods

Operational planning deals with the allocation and scheduling of a limited number of resources. Operational planning differs from strategic planning in that for operational planning the manpower capacity is considered fixed which means that the cost component of C+NVC is not the incremental cost between the different programs. As a result, the objective is to develop efficient allocation and scheduling strategies that minimize net fire damage NVC.

The net fire damage NVC can be expressed as the net loss in the value of the overall production level. Mathematically, it can be calculated by subtracting the value of the production level of all products pre-fire from the value of production level of all products post-fire. Different allocation strategies can be evaluated using the following equation:

$$\mathrm{NVC} = \sum_{i=1}^{n}\sum_{j=1}^{m}(Q_{1ij} - Q_{2ij})V_j \tag{2.7}$$

where

Q_1: production without fires

Q_2: production with fires

n: number of production units

m: number of product categories

V_j: market value of product j

2.6 Case Study

In order to evaluate the effectiveness of the proposed FMDSS, a case study of multiple fire incidents in a large petrochemical complex was conducted. This case study is based on real data and aims at optimizing firefighting resource management while considering operational and strategic decisions.

2.6.1 Petrochemical Industry

All experimental results in this thesis use a petrochemical complex as a case study for this research, for the following reasons. Firstly, the petrochemical industry is considered to be one of the most important basic industries. Petrochemicals are derived from oil and natural gas and incorporated into a great variety of products in the food industry, medical industry, textile industry, plastic industry, and fertilizer industry. The petrochemical industry is a major contributor to the growth of the world economy. In 2011, the global petrochemicals market was valued at $472.06 US billion and is expected to reach $791.05 billion by 2018. The global petrochemicals consumption is expected to reach 627.51 US million tonnes by 2018 [77].

Secondly, the operation of petrochemical plants involves very complex processes of physical and chemical reactions. These processes often require a wide variety of extreme operating conditions at high temperatures and pressures and other complex technical operations. Due to the large amounts of flammable gases and liquids involved, the petrochemical industry is continuously exposed to the risk of fires, explosions and other accidents. One of the safety measures to reduce this risk is to restrict the storage of flammable materials. Therefore, petrochemical plants are most often grouped together into a single complex to transport products immediately into pipelines. As the number of plants located in the complex increases, benefits increase due to increase in efficiency, close access to specialized suppliers and reduction in transportation costs. On the other hand, any additional plant may decrease the overall safety of the complex [78].

Thirdly, the petrochemical industry is increasingly characterised by a high degree of physical interdependence. An interruption in one plant can be extremely disruptive to the operation in one or more other plants. This phenomenon is called the "domino effect". Although the domino effect has been reported in the technical literature since 1947, there is no agreed definition of what constitutes domino effects in the context of accidents in industrial plants [79]. Khan and Abbasi [80] defined domino effect as "a chain of accidents, or situations when a fire, explosion, missile or toxic load generated by an accident in one unit in an industry causes secondary and higher order accidents in other units".

In this thesis, we generalize the definition of the domino effect by including any distractions in production generated by a primary accident in one or more plants. Also, we consider the bidirectional effects of accidents by including the economic impacts on both the consumers' side and the producers' side. For example, if Plant A supplies Plant B with its raw materials, any interruption in the production process of Plant A could result in an interruption in Plant B. Conversely, if any interruption in the production process of Plant B occurs, Plan A might suspend its operation.

2.6.2 Case Study Data

The case study considered in this thesis is an industrial city that has a large petrochemical complex. This complex consists of 12 petrochemical plants. Each plant produces one or more petrochemical products as listed in Table 3.1.

The industrial city has 300 firefighters (100 firefighters per shift) forming 20 units deployed to five fire stations, where each station has four firefighting units. Two simultaneous fire incidents, Fire 1 and Fire 2, were simulated in Plant 10 and Plant 4, respectively. We assume that Fire 1 requires 600 man-hours to be suppressed, while Fire 2 requires only 200 man-hours. It is assumed that this type of accident occurs once every ten years.

The simulations involved 15 hours of concurrent suppression operations for the two fire incidents. New assignments of the firefighting units were determined every hour.

2.6.3 Example of Interdependence in a Petrochemical complex

Each plant in a petrochemical complex requires raw materials for production. Oil refinery and upstream plants supply raw materials to production plants. The relationship between the plants can be expressed according to their position in the production chain as primary producer, primary consumer, secondary consumer, and tertiary or higher-order consumer. The primary producers are the plants that do not receive their raw materials from other plants, mainly they receive raw materials from oil refinery. The other plants receive some of their raw materials from primary producers and

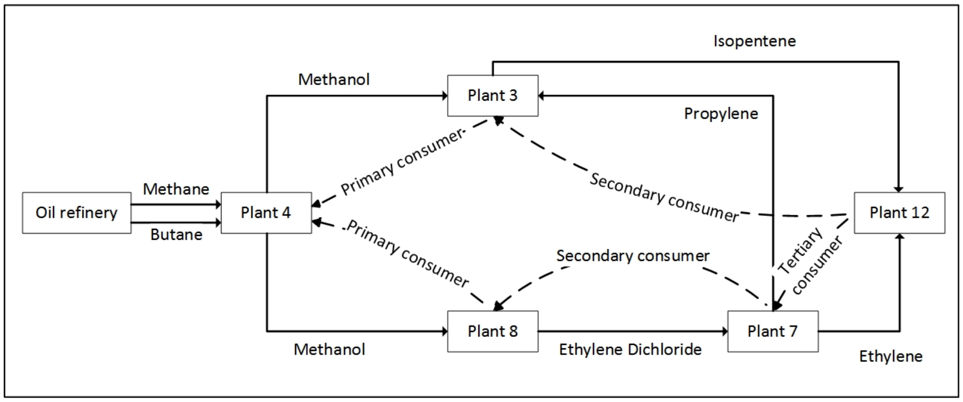

Figure 2.8: An example of interdependencies and relations between petrochemical plants.

may supply other plants with raw materials or export. Due to this interdependence, a single disruption to an upstream plant can impact the entire complex.

Using this criterion, Figure 2.8 presents an example of interdependence and the relations between the petrochemical plants during the production process. Plant 4 is an example of a primary producer because it receives its raw materials, Methane and Butane, from the oil refinery. It supplies Plant 3 and Plant 8 (primary consumers) with Methanol. Plant 7 and Plant 12 are considered as secondary consumers because they receive some of their raw materials from primary consumers, Plant 3 and Plant 8. Plant 12 can be also described as a tertiary consumer because it receives Ethylene from a secondary consumer, Plant 7.

During the operation process, any disruption in the production process in Plant 4 can lead to a shutdown in the production process in primary consumers, Plant 3 and Plant 8. This shutdown has a domino effect that spreads to all secondary and tertiary consumers, Plant 7 and Plant 12. Furthermore, any disruption to a secondary consumer (e.g., disruption in Plant 7) might suspend the production process in the primary producer, Plant 4, and all primary consumers, Plant 3 and Plant 8. As a result of this, other secondary consumers, Plant 12, suspends its operation due to lack of raw materials.

The previous example illustrates the high level of interdependence between petrochemical plants that need to be considered when developing emergency response plans.

2.6.4 General Assumptions

While this thesis has focused its attention on the fire managements decisions in line with the expected losses, the following assumptions were made in the case study:

1. No humans were in danger during the incidents, otherwise saving them would have been the highest priority.

2. The environmental impact, such as toxicity, was not taken into account.

3. All the plants had the same level of flammability.

4. No other organizations (e.g., police and ambulance services) were involved.

5. The wind speed and wind direction were the same in both fire incidents.

6. During multiple-fire incidents, there has to be a minimum number of firefighting units to be allocated to each incident because of the presence of explosive chemicals in the petrochemical industry.

7. All the plants have the same level of fire safety over the planning period.

2.7 Conclusion

In this chapter, we discussed the development of a fire management decision support system. The system estimates the damage associated with fire incidents, calculates the economic loss resulting from the damage and then provides the optimal assignment of the available firefighting units. A key novel addition is the consideration of infrastructure interdependencies in the decision making process. The joint optimization of the number of assigned firefighting units and the estimated damage significantly reduces the economic loss.

A detailed case study of multiple fire incidents in a large petrochemical complex is described. The case study is used throughout this thesis to study the issues of resource allocation, capacity planning, and improving infrastructure resilience. Chapter 3 applies the developed system to allocate resources to minimize economic losses resulting from multiple-fire incidents. Linear and non-linear damage functions are considered. In chapter 4, the developed system is used to evaluate the impact of hiring decisions on effectiveness of firefighting operations. Chapter 5 describes the resilience of infrastructure systems under fire incidents. The developed system is used to evaluate the impact of resource allocation decisions during fire incidents on improving infrastructure resilience.

Name	Product	Ton/year
Plant 1	Methanol	1,007,400
	Butanediol	75,000
Plant 2	Poly Propylene	438,000
Plant 3	MTBE (methyl tertiary-butyl ether)	613,200
	Poly Propylene	1,500,000
	Isopentene	1,460
Plant 4	Methanol	963,600
	MTBE (methyl tertiary-butyl ether)	1,007,400
	Isopentane	5,256
Plant 5	Polyethylene	744,600
	Ethylene Glycol	1,489,200
Plant 6	Ammonia	438,000
	Ethyl hexanol	171,550
	Urea	700,800
Plant 7	Ethylene	2,102,400
	Propylene	1,314,000
	Butene	1,752,000
Plant 8	Ethylene	1,051,200
	Sodium Hydroxide	175,200
	Ethylene Dichloride	3,066,000
Plant 9	Fertilizer	4,818,000
Plant 10	Methanol	3,285,000
Plant 11	Ethylene	1,314,000
	Mono-ethylene Glycol	569,400
	Diethylene Glycol	613,200
Plant 12	Ethylene	700,000
	Propylene	87,600
	Polyethylene	1,095,000

Table 2.3: List of the petrochemical plants and their products covered by this case study.

Chapter 3

Resources Allocation and Scheduling During Multiple-Fire Incidents

3.1 Introduction

During fire incidents, the main duty of firefighters (after saving lives) is to minimize the incidents' losses. According to Hall [9], the total cost of a fire is defined as the losses the fire causes, directly and indirectly, plus the cost of provisions to mitigate these losses. The US NFPA reported that in 2011, the estimated fire-related economic loss was $14.9 US billion. These losses include both property damage (direct losses) and business interruption (indirect losses). Also, the report shows that 65% of the business interruption cost ($9.7 US billion) was caused by fires in industrial properties [9]. Due to the difficulty in pre-calculating the indirect losses, the current firefighting practices target the fires with larger size to reduce property damage. However, the analysis of the fires showed a low correlation between the property damage cost and the business interruption cost [9]. In many cases, the cost of business interruption far exceeds its direct property loss. Hall [9] stated, "Sometimes, though, it can be difficult to determine what the true net loss due to business interruption is." In the method developed in this chapter, the indirect losses, resulting from business interruption, will be estimated and then used as a significant factor in allocating the firefighting resources.

In this study, we use propose a methodology to optimize the allocation process of firefighting resources in multiple-fire incidents. This methodology utilizes the concept of infrastructure interdependencies in evaluating the economic impact of the incidents. It consists of three main parts. The first part uses infrastructure interdependency modeling to represent the interactions among different systems. The second part uses economic modeling to evaluate the economic impact of the fire incidents. The third part determines the assigned number of firefighting units using an optimization agent based on the RL algorithm. The proposed methodology can be used before the fire occurs, for training and planning, during the fire for optimizing the response or after the fire, for evaluating suppression strategies.

The proposed resource allocation methodology is presented in Section 3.2. After that, we examine four different fire suppression methods in Section 3.4. Also, we discuss the impact of considering different non-linear damage functions. Then, we evaluate the human performance factor on the resource allocation decision in Section 3.4.2. Finally, a conclusion is presented in

Section 3.5.

3.2 Resource Allocation and Scheduling Methodology

In terms of the operation planning of fire management systems, allocating and scheduling available resources is one of the most challenging decisions during multiple fire incidents. The direct and indirect economic losses induced by fires should be carefully considered. Thus, it is extremely important to minimize the overall economic losses by optimally allocating and scheduling firefighting units to each fire. In this section, we use the developed system, described in Chapter 2, to propose a methodology for the optimal allocation of firefighting resources during suppression operation. Figure 3.1 shows the main steps of the proposed methodology.

The proposed methodology starts by generating fire incident scenarios using the fire simulation model. These scenarios can be single or multiple fire incidents. After evaluating the required number of firefighters for each fire, the fire duration time is calculated by Equation 2.1. Using a damage function, the fire duration time is mapped into five Physical Modes (PMs) described previously in Section 2.3.1, which form the input to the i2Sim model. Figure 3.2 shows how fire duration is mapped to physical modes using a simplified (linear) damage function.

Next, i2Sim simulates the effects of resources allocation decisions over time. The production of each cell is degraded according to the damage assessed by the fire simulation model described in Section 2.2. Simultaneously, i2Sim simulates the functionality of the interdependent cells and computes

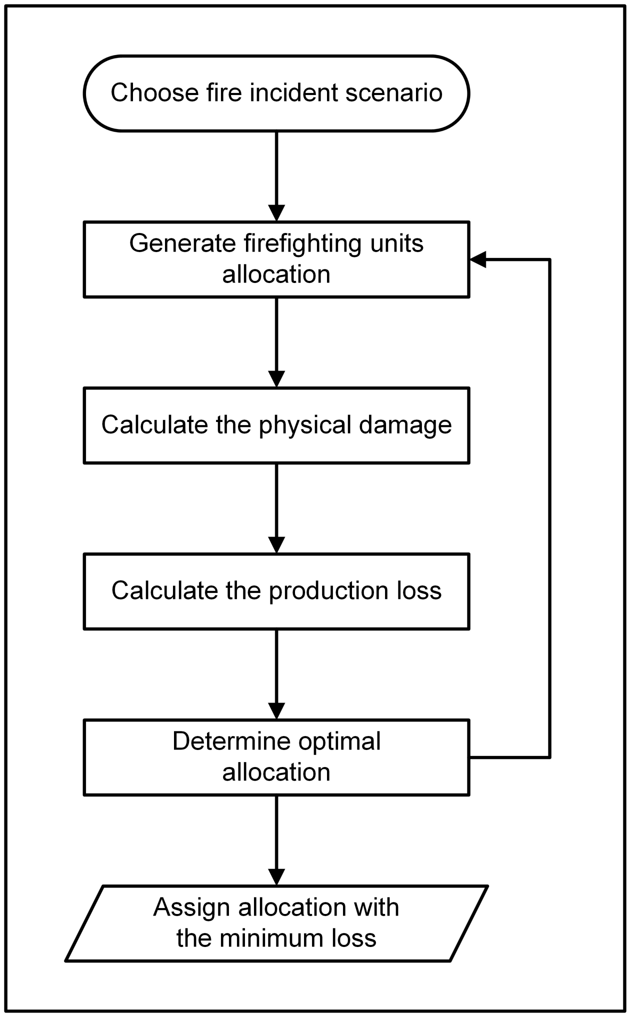

Figure 3.1: Resource allocation methodology.

the outputs of all the production facilities. These outputs become the input to the economic model, which calculates the estimated losses based on market prices. The output of the economic model is the economic loss associated with the current operating state of the cells.

The last step of the methodology is the determination of the optimal al-

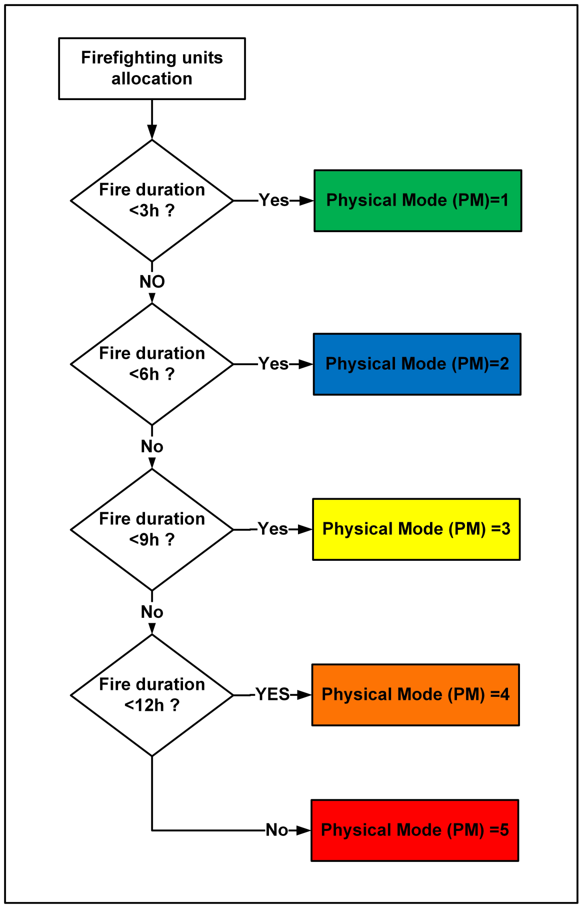

Figure 3.2: Mapping between fire duration and Physical Mode(PM).

location decisions. The optimization agent uses the economic loss as reward or penalty. The objective of the agent is to learn the optimal decision for assigning firefighters that minimizes the economic losses experienced in the long run.

Name	Product	Ton/year	Raw Martials	Ton/year	Source
Plant 4	Menthol	959,000	Methane	210,240,000	Oil refinery
	MTBE	985,000	Butane	876,000	Oil refinery
Plant 6	Ammonia	459,900	Methane	150,000	Oil refinery
	Ethyl Hexanol	171,550	Propylene	300,000	Plant 7
	Urea	693,500			
Plant 7	Ethylene	2,000,000	Ethylene Dichloride	3,248,500	Plant 8
	Propylene	1,000,000	Sodium Hydroxide	204,400	Plant 8
	Butane	2,000,000	Propane	2,007,500	Oil refinery
			Methane	2,007,500	Oil refinery
			Ethane	1,000,000	Oil refinery

Table 3.1: Sample Data Format

3.3 Case Study Modeling

3.3.1 Data Description

The case study described in Section 2.6 considers an industrial city. The city encompasses an area of about 100 square kilometres and has a petrochemical complex consisting of 12 chemical plants. Theses plants produce 28 different petrochemical products. These materials are transported through pipelines between the plants. The petrochemical complex is modeled based on real data. Sample data for three plants is shown in Table 3.1. The first column represents the plant name. The second and the third columns show the products and their annul production (Ton/year), respectively. The fourth and the fifth columns show the raw martials and their total quantity consumed per year (Ton/year), respectively. The last column shows the source of each raw material which can be a product of another plant or received directly from the oil refinery.

3.3.2 i2Sim Model

The first step to build the i2Sim model is to define the production cells. Recall that an i2Sim production cell takes one or more inputs and produces an output based on the defined HRT function as described in Section 2.3.Each plant is presented by one or more production cells based on the number of output products. For example, we use two production cells to model Plant 4 and use three production cells to model Plant 7. Figure 3.3 shows the production cells used to model Plant 7.

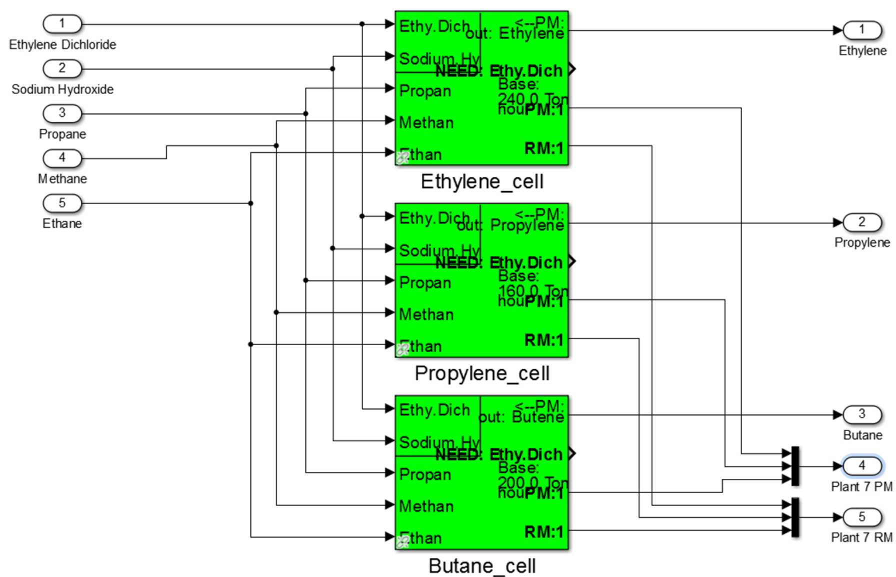

Figure 3.3: Plant 7 production cells.

In total, we need 28 production cells to model the entire complex. Table 3.2 shows the number of production cells used to model each plant.

The second step is to create the HRT tables for the production cells. The HRT tables model the input-output relationship in i2Sim cells as described

Name	Number of products	Number of used production cells
Plant 1	2	2
Plant 2	2	2
Plant 3	1	1
Plant 4	3	3
Plant 5	2	2
Plant 6	3	3
Plant 7	3	3
Plant 8	3	3
Plant 9	1	1
Plant 10	1	1
Plant 11	3	3
Plant 12	3	3

Table 3.2: Number of used production cells.

in Section 2.3. Table 3.3 shows the HRT table for Ethylene production cell in plant 7. The first column represents the operability level of the production cell. This level ranges from 0 to 100 %, where 0 % indicates no functionality and 100 % indicates full functionality. Each level is associated with a particular amount of production as shown in the second column. There are two factors that can influence the plant functionality. One is the availability of the necessary resources (plant inputs) required to operate the plant, which are listed in the 3rd to the 5th column. The second factor is the the physical integrity of the plant, which is given in the last column.

Operability	Plant output (Product)	Plant inputs (Raw materials)					Physical integrity
	Ethylene [Tons/hour]	Ethy. Dich. [Tons/hour]	Sod.Hydroxid [Tons/hour]	Propane [Tons/hour]	Methane [Tons/hour]	Ethane [Tons/hour]	
100%	240	350	20	230	230	100	100%
75%	180	262.5	15	172.5	172.5	75	75%
50%	120	175	10	115	115	50	50%
25%	60	87.5	5	57.5	57.5	25	25%
0%	0	0	0	0	0	0	0%

Table 3.3: HRT table for Ethylene production cell in Plant 7.

The third step is to identify the i2Sim sources model the external tokens. As described in Section 2.3, sources represent infrastructure systems that are not included in the i2Sim model. In this case study, we use sources to model the tokens produced by the oil refinery. Seven sources are used to model the production of the following tokens: Methane, Ethane, Propane, Propene, Butane, Butene and Benzene. Figure 3.4 shows the sources that used to model the oil refinery.

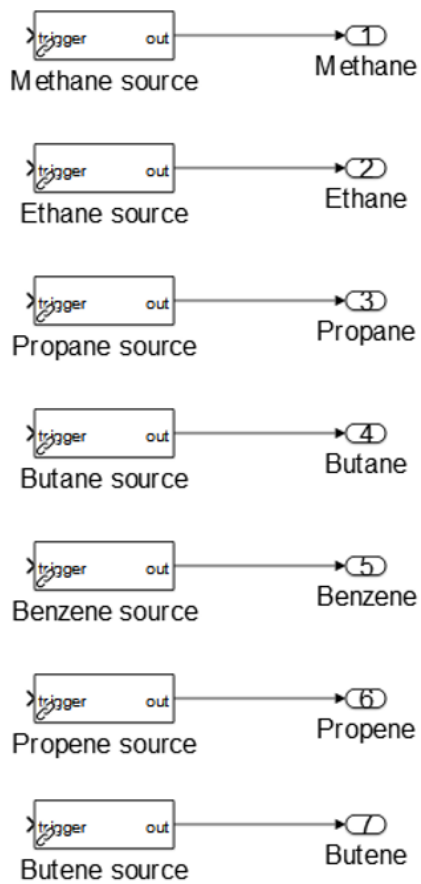

Figure 3.4: Oil refinery sources.

The next step is to determine the distributors, the aggregators and the sinks. The distributors are the allocation units in the i2Sim model. Each distributer has one input and multiple outputs of the same token type. In this case study, we use 14 distributers to distribute 14 petrochemical products among the plants. Also, we have 13 different petrochemical martials to be aggregated in one channel for each one. We use 13 aggregators to combine two similar products into one channel. The last stage of the production process in this case study is the export which is modeled as a sink. Sinks are the components that send internal tokens to outside the i2Sim model.

The last step of modelling the case study is to connect all the i2Sim components via channels. Figure 3.5 shows the i2Sim model for the petrochemical complex.

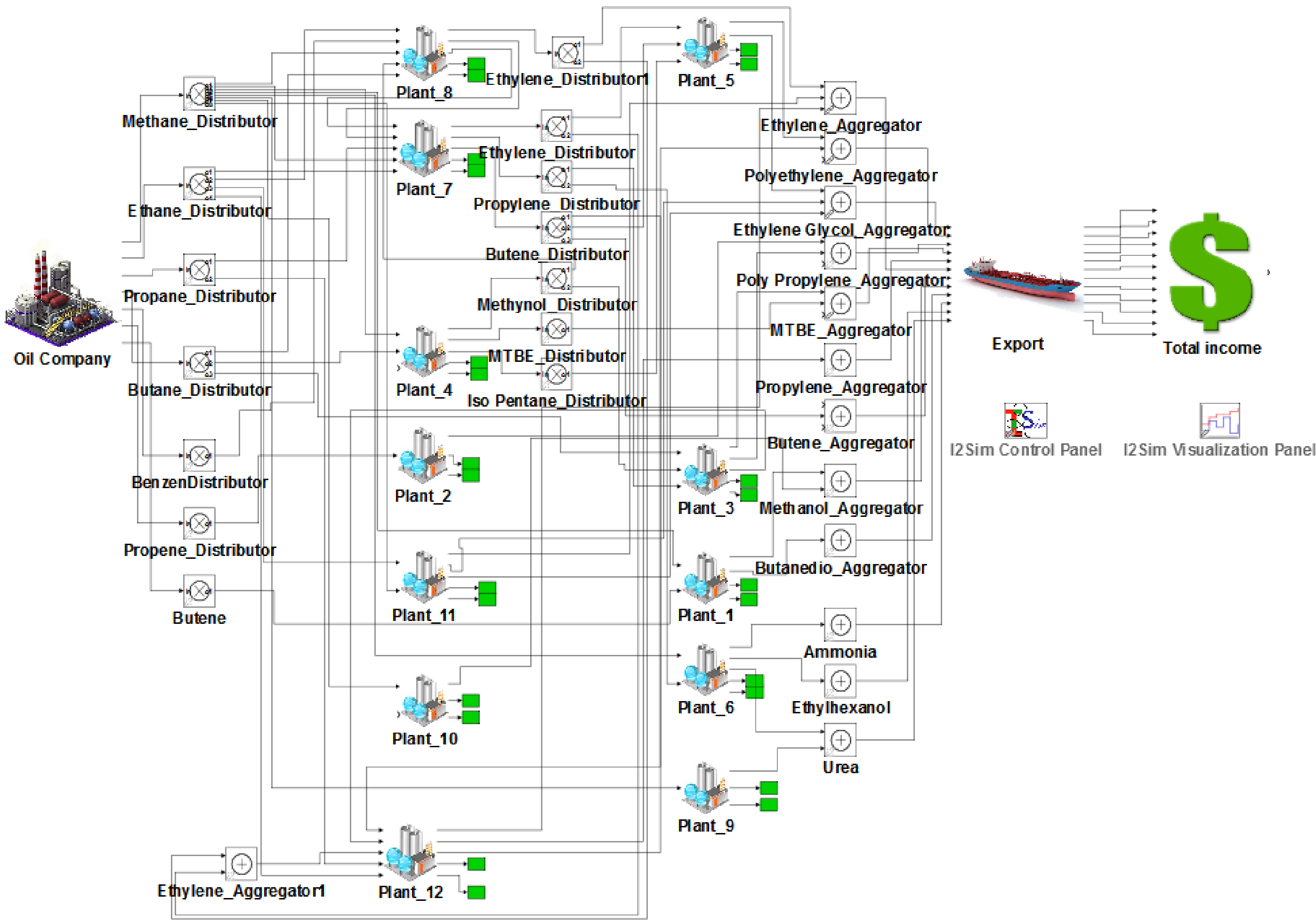

Figure 3.5: The i2Sim model for the petrochemical complex.

3.4 Results and Discussion

In this section, we consider applying four different allocation methods to the case study. Next, we examine the case of non-linear damage functions. Two non-linear damage functions are considered to evaluate fast and slow damage development. Finally, we extend the model to include the impact of human performance factors on firefighting operations. The most critical human performance factor in firefigting effectiveness is the degradation of performance under stressful mental and physical conditions.

We tested four different allocation methods (operational plans) as listed in Table 3.4. Methods 1 and 2 represent "business as usual" actions during a multiple-fire incident, which means allocating firefighting units based on fire size and giving more units to larger fires. In method 3, fires are treated equally regardless of their size or their criticality. Method 4 corresponds to a situation where the allocation and scheduling process of fire resources is based on economic evaluation of losses.

Method	Methodology	Description	Objective
Method 1	70%-30%	70% to the large fire, 30% to the other fire.	Suppress large fire first
Method 2	60%-40%	60% to the large fire, 40% to the other fire.	Suppress large fire first
Method 3	50%-50%	50% to each fire.	Treat all fire accidents equally
Method 4	Optimized	Assign units based on optimization technique.	Suppress fires to minimize losses

Table 3.4: Allocation methods.

Simulations were carried out for the four fire allocation methods mentioned above. Each method produces a different assignment sequence of firefighting units to each fire. The simulation results are shown in Table 3.5. The first column shows the simulating time in hour. The last column reports the results obtained by the proposed the FMDSS. It shows the dynamic allocation of the firefighting units between the two fires, Fire 1 and Fire 2. U represents the number of allocated firefighting units to each fire. T represents the required man-hour to suppress each fire.

As shown in Table 3.5, the proposed FMDSS, Method 4, was able to recognize the critical fire and suppress both fires with minimum time compared to the other allocation methods. Also, the results show that Method 1 is the worst decision, since it requires the longest suppression time.

In order to evaluate the economic impact of using the four allocation methods, we evaluate the annual production income of the petrochemical complex. Using i2Sim, we simulates the functionality of the petrochemical complex and compute the outputs of all the production cells. The annual production income of the complex is calculated using the market value of these outputs, which is $28,703 US million. Upon comparing this income level with the income after the two fires are suppressed, it is clear that the decision based on economic evaluation (Method 4) achieves the minimum economic loss.

Time (h)	Method 1				Method 2				Method 3				Method 4			
	Fire 1		Fire 2		Fire 1		Fire 2		Fire 1		Fire 2		Fire 1		Fire 2	
	U	T	U	T	U	T	U	T	U	T	U	T	U	T	U	T
1	14	600	6	200	12	600	8	200	10	600	10	200	4	600	16	200
2	14	530	6	170	12	540	8	160	10	550	10	150	4	580	16	120
3	14	460	6	140	12	480	8	120	10	500	10	100	12	560	8	40
4	14	390	6	110	12	420	8	80	10	450	10	50	20	500	0	X
5	14	320	6	80	12	360	8	40	20	400	0	X	20	400		
6	14	250	6	50	20	300	0	X	20	300			20	300		
7	14	180	6	20	20	200			20	200			20	200		
8	20	110	0	X	20	100			20	100			20	100		
9	20	10			0	X			0	X			0	X		
10	0	X														
11																
12																
13																
14																
15																

X: Fire suppressed.

Table 3.5: Results for the resource allocation methods (U: no. units; T: fire timer).

Figure 3.6 shows that the total economic loss in Method 4 was just \$558 US million compared with \$3,525 US million for Method 1, \$1,236 US million for both Method 2 and Method 3. It is worth noting that the total economic loss when no action is taken is a massive \$ 21,006 US million.

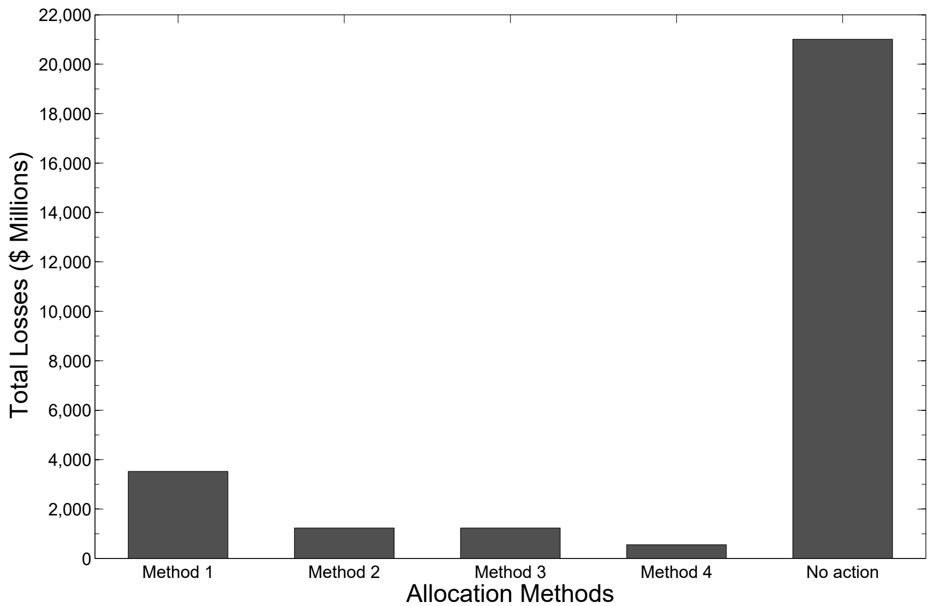

Figure 3.6: Total losses of different allocation methods.

3.4.1 Damage Functions

As we mentioned in Section 2.2.2, the level of damage is influenced by several factors such as wind speed and direction, and fuel type and load. The more convex the damage function, the faster the damage level increases. The more concave this function, the slower the damage level grows. In this section we evaluate the proposed methodology considering slow and fast damage growth.

Two non-linear damage functions are used to describe slow and fast damage growth. We assume the form of the damage function for slow damage growth as a square root form $d(T)_{sqrt}$, where:

$$d(T)_{sqrt} = \begin{cases} (\frac{T}{T_C})^{1/2} & \text{if } T < T_C \\ 1 & \text{if } T \geq T_C \end{cases} \tag{3.1}$$

For fast damage growth, we assume the form of the damage function as a quadratic form $d(T)_{quad}$, where:

$$d(T)_{quad} = \begin{cases} (\frac{T}{T_C})^{2} & \text{if } T < T_C \\ 1 & \text{if } T \geq T_C \end{cases} \tag{3.2}$$

Both functions define level of damage as a function of the time duration of the fire. Figure 3.7 illustrates the difference between the damage functions in terms of damage level related to fire duration time. The first case (a) represents the linear damage function described in Section 2.2.2. Case (b) and (c) represent the slow damage growth (square root function) and fast damage growth (quadratic function), respectively.

Figure 3.8 shows the results of applying these damage functions to the petrochemical complex case study. These results show that the proposed methodology, Method 4 (as described in Section 3.3), is capable of achieving the minimum economic losses regardless of the damage function being used. The results also show that Method 1 is the worst decision with the largest amount of economic losses.

As expected, the faster damage growth results in more economic loss.

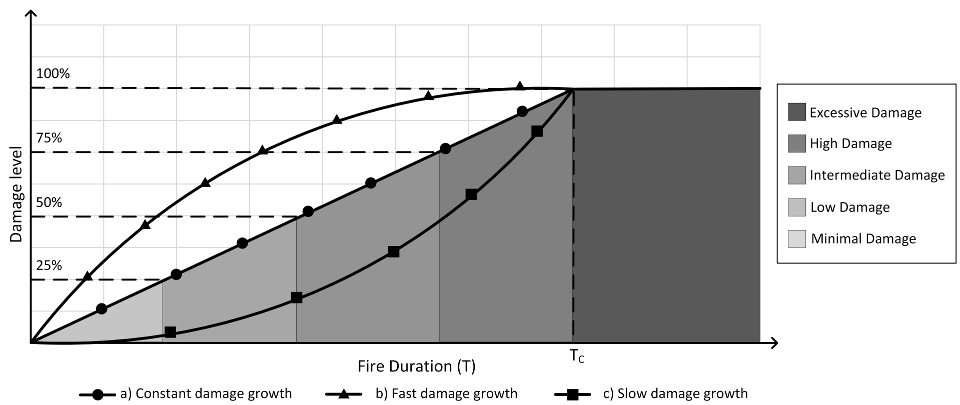

Figure 3.7: Illustration of the difference between different damage functions showing level of damage as a function of time duration of fire for (a) Equation 2.2, linear function reflecting a constant rate of fire damage growth; (b) Equation 3.1, non-linear damage function reflecting fast damage growth; and (c) Equation 3.2, non-linear damage function reflecting slow damage growth.

In the case of the slow growth damage function, the economic losses are the minimal compared to the other damage functions. Slow damage growth allows firefighters the time to control the fire before significant damage occurs. Method 2, Method 3 and Method 4 yielded optimal minimal losses of \$420 million compared with \$1,099 million for the business-as-usual, Method 1.

In the case of the fast growth damage function, the economic losses increase for all the allocation methods, however, Method 4 maintains the best performance compared to the others. Using Method 4, the resulting economic losses are \$1,565 million compared with \$3,853 million for the other methods.

We conclude that the damage growth rate has a significant effect on the time to control the fire and in the resulting economic losses. Also, regardless of the damage growth rate, the proposed methodology is able to allocate

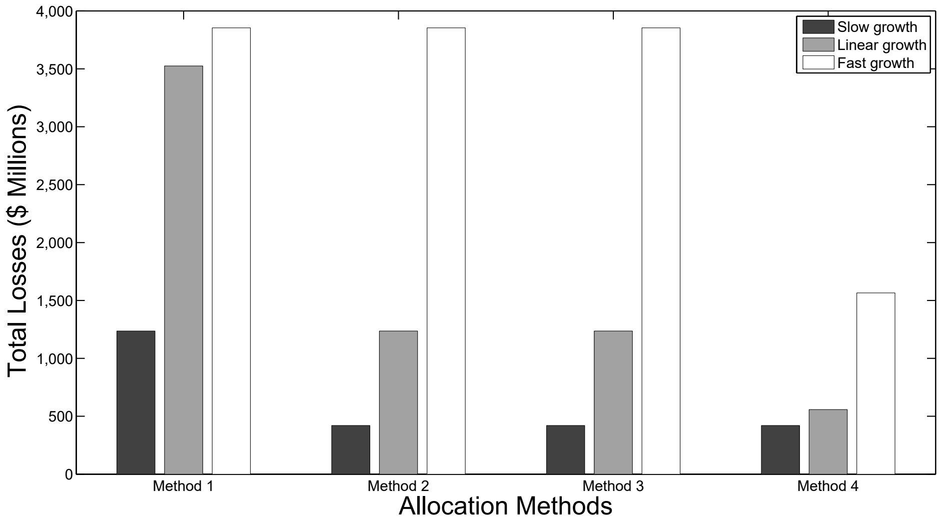

Figure 3.8: Total losses of different allocation methods for three damage functions.

resources efficiently to minimize the economic losses.

3.4.2 Human Performance Factor

In this section, we study the effect of Human Performance (HP) on resource allocation decisions during fire incidents. The most important human performance factor in firefighting effectiveness is the degradation of performance under stressful mental and physical conditions, such as heat, smoke and hydration.

As we discussed in Section 2.2, each fire is described by its severity measure, FSM. This measure estimates the required man-hours to suppress a fire. For example, if a fire is described by FMS=100, then it means that allocating 50 firefighters can suppress the fire in two hours and 100 firefighters can suppress it in one hour. During a long suppression process, the performance of the firefighters is degraded and the suppression process might take more time.

To study this factor, we extend the model described in Section 3.3 by considering the impact of the HP factor on the effectiveness of firefighting operations. We apply the allocation methods in Table 3.4 to suppress two simultaneous fire incidents, Fire 1 and Fire 2, occurring in Plant 10 and Plant 4, respectively. Fire 1 requires 600 man-hours to be suppressed, while Fire 2 requires only 200 man-hours. In order to consider the effect of the HP, we assume that during fire incidents, the firefighters' performance drops by 20% every three hours. Also, every eight hours a new shift replaces the current one.

Using the developed FMDSS in Chapter 2, the following cases are considered in comparing the impact of the HP on the resources allocation decisions.

- **Case 1:** represents the result obtained in Section 3.4.1 for the four allocation methods in Table 3.4 without consideration of the HP factor.
- **Case 2:** represents the results obtained for these allocation methods with consideration of the HP factor.

Figure 3.9 shows the results of applying these allocation methods to the petrochemical complex case study. In general, the results show that the HP factor has a considerable impact in the total loss. Also, the results show that the proposed methodology, Method 4, is more efficient than the other three methods.

There are 24 different combinations of four allocation methods for each of the three damage functions with and without the HP factor. Figure 3.10,

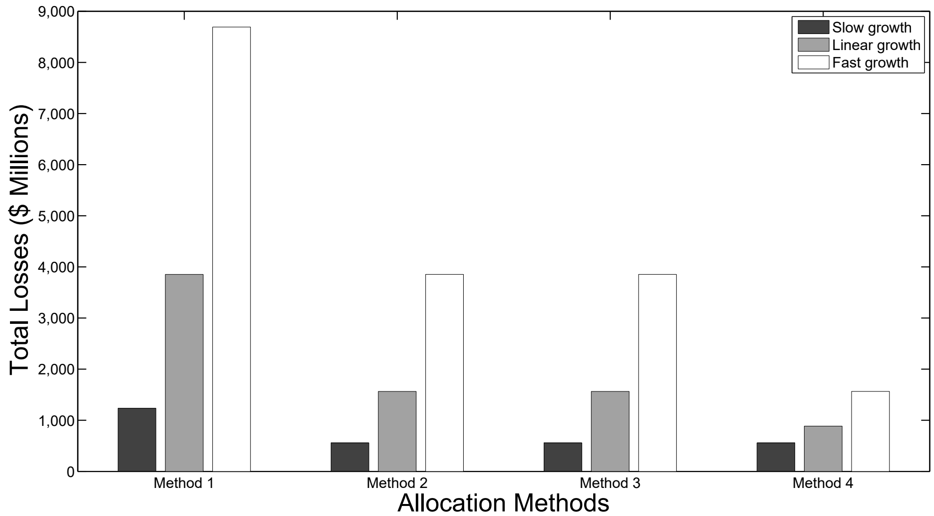

Figure 3.9: Total losses of different allocation methods for three damage functions considering the human performance factor.

3.11, 3.12, and 3.13 correspond to Method 1, Method 2, Method 3 and Method 4 (as described in Section 3.3), respectively. The results of this comparison indicate that the human performance factor has a significant impact on the development of fire damage and also on the economic losses.

The results in Figure 3.10 show that the total loss in Method 1 after considering the HP factor increased by 126% to reach $1,236 US million during the fast growth fire. For the other allocation methods, the impact of this factor is in the same direction as on Method 1 but to a much lesser degree.

3.5 Conclusion

In this chapter, we use economic analysis to help fire managers determine appropriate responses during daily operations. We proposed a methodology

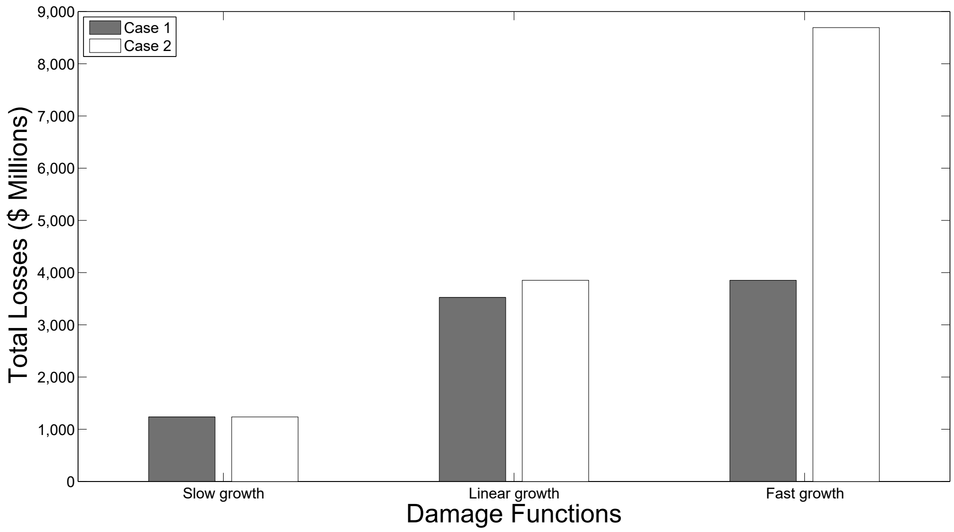

Figure 3.10: Comparison of total losses of Method 1 between Case 1, neglecting the human performance factor, and Case 2, considering the human performance factor.

to optimize the allocation process of firefighting. The concept of infrastructure interdependencies is incorporated into the decision making process. The proposed methodology estimates the damage associated with a given fire scenario, calculates the economic losses resulting from the damage, and then provides the optimal assignment of available firefighters.

Different damage functions are considered to investigate different types of damage behaviour. Also, we evaluate the human performance factor that influences the firefighting operations. By considering these factors, the results show that optimizing jointly the number of assigned firefighters with the estimated damage reduces the economic losses greatly.

In the next chapter, we extend the study of the human factor to evaluate the potential benefits and consequences of alternative manpower planning

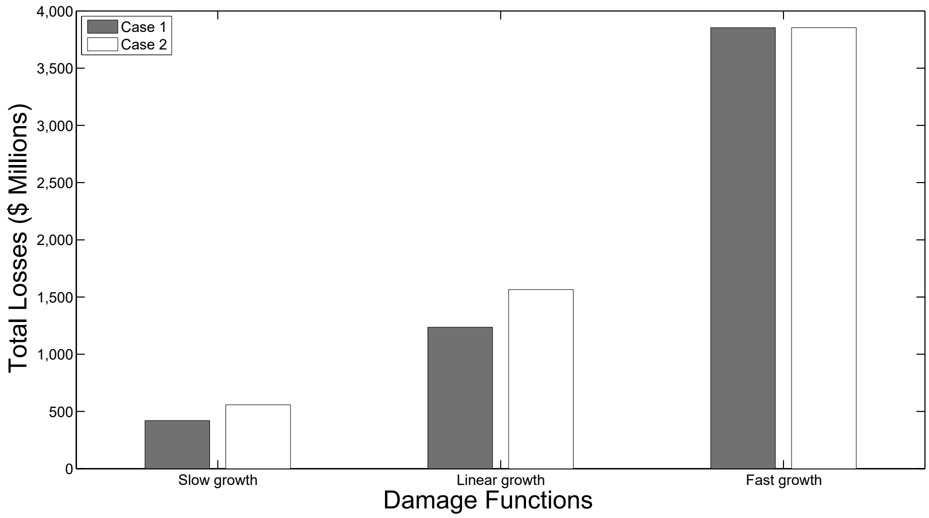

Figure 3.11: Comparison of total losses of Method 2 between Case 1, neglecting the human performance factor, and Case 2, considering the human performance factor.

decisions.

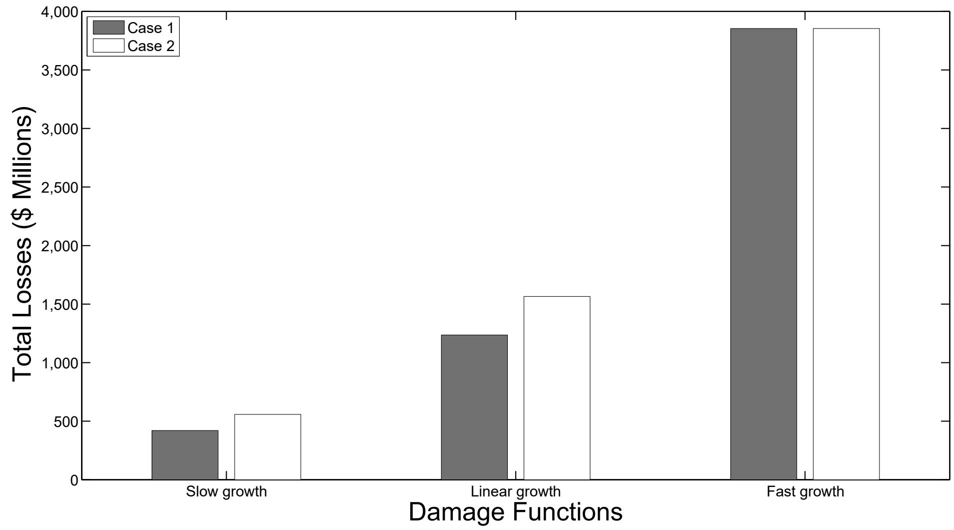

Figure 3.12: Comparison of total losses of Method 3 between Case 1, neglecting the human performance factor, and Case 2, considering the human performance factor.

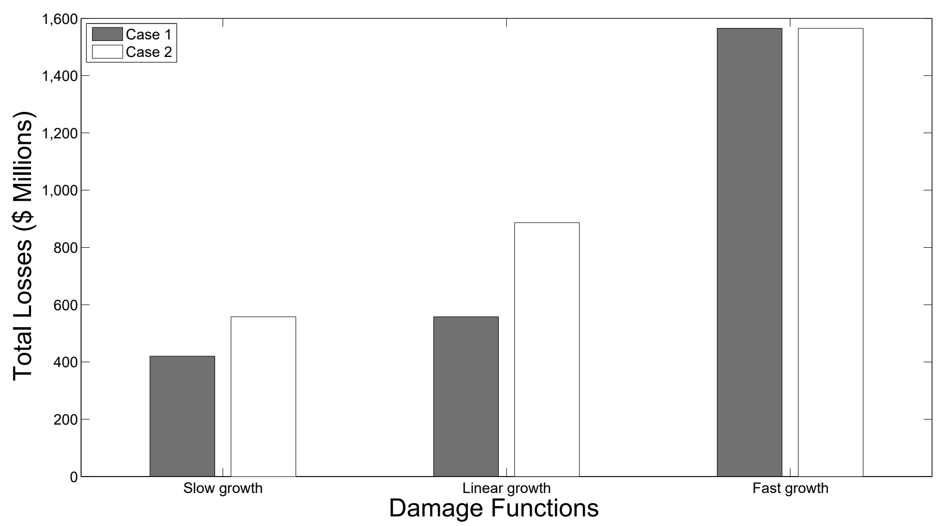

Figure 3.13: Comparison of total losses of Method 4 between Case 1, neglecting the human performance factor, and Case 2, considering the human performance factor.

Chapter 4

Capacity Planning in the Fire Department

4.1 Introduction

Fires are becoming more costly in terms of fire operational costs and economic losses (direct and indirect losses). The increased interdependence of existing infrastructure systems makes economic losses induced by fires very severe and difficult to predict. With a limited budget and resources, fire managers are faced with challenging decisions concerning how best to allocate resources, in terms of minimizing costs and keeping risks at an acceptable level.

In the previous chapter, we discussed the allocation and scheduling decisions of firefighting units during fire incidents. We showed how several factors, including human factors, are able to influence the decision-making process. The human factor is not only significant at the operational level planning, but also at the strategic planning level. The strategic planning includes the most long- range decisions like capacity investment (e.g., increasing the number of firefighters).

In this chapter, we propose an additional function to the developed system in Chapter 2 to investigate the impact of capacity planning decisions on the effectiveness of firefighting operations. The challenge to the decision maker is to determine the most cost-effective plan in terms of reducing overall cost. The developed system is used to identify the optimal number of firefighters to be recruited to contain the fires and minimize damage. In Section 4.2, the proposed methodology to evaluate long-term planning decisions is presented. In Section 4.3 the proposed methodology is applied to the case study of the petrochemical complex. Finally, concluding remarks are given in Section 4.4.

4.2 Proposed Methodology

In this section, we use the developed system described in Chapter 2 to develop a manpower capacity planning methodology. The proposed methodology evaluates the impact of hiring decisions on effectiveness of firefighting operations. It incorporates the C+NVC concept described in Section 2.5 to perform economic analysis to determine the most efficient strategic plan. The objective is to minimize the cost of fire by minimizing the sum of the operation cost (C) and the net value change (NVC). The key question is: what is the optimal number of firefighters to be hired by minimizing the C+NVC objective function?

Figure 4.1 illustrates the proposed manpower capacity planning method-

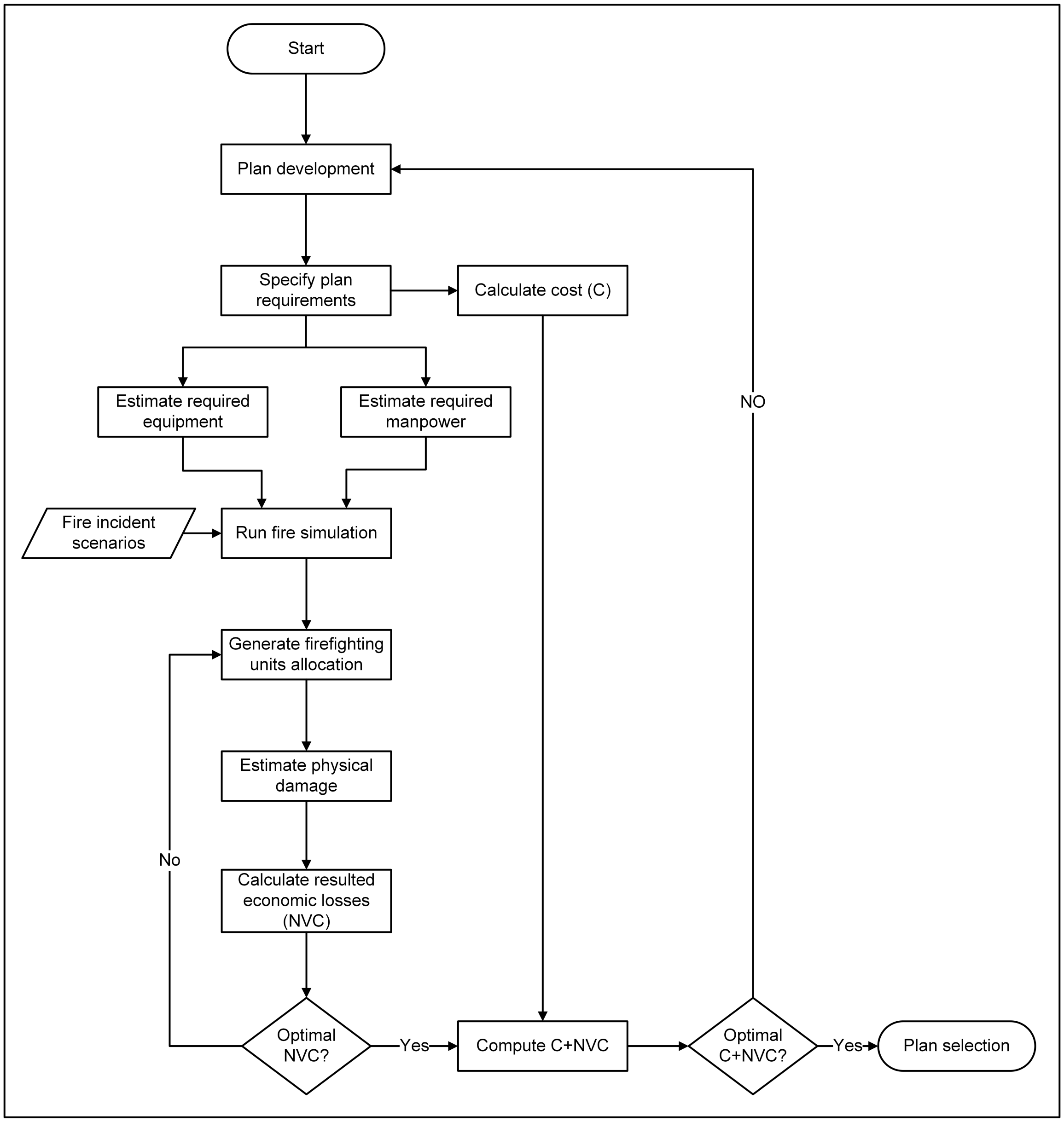

Figure 4.1: Proposed methodology to evaluate long-term planning decisions.

ology. The first step in the proposed methodology is the plan development which includes time frame and budget. The next step is to specify the requirements of the developed plan, such as an estimate of manpower to be recruited and trained, and the required equipment to be purchased such as water pumps and fire trucks. The cost of these requirements represents the fire operation costs (C) in the C+NVC concept.

In order to investigate the effectiveness of the developed plan, we use the fire simulation model described in Section 2.2 to simulate multiple-fire scenarios. These scenarios can be generated by simulation or taken from historical data. For each scenario, different resource allocation decisions are evaluated to find the minimum economic losses. i2Sim and the optimization agent described in Section 2.3 and 2.4 respectively are used to estimate the resulting physical damage and to calculate the expected economic losses which represents the net value change (NVC) part of the C+NVC concept.

At this point, C+NVC can be calculated using the following equation:

$$C + NVC = \sum_{t=1}^{T} (L_{ft}C_{ft} + L_{qt}C_{qt} + NVC_t) \tag{4.1}$$

where

C_{ft}: cost of hiring one firefighter in period t

L_{ft}: number of hired firefighters in period t

C_{qt}: cost of purchasing one unit of equipment in period t

L_{qt}: number of purchased one unit of equipment in period t

NVC_t: net loss due to fires in period t

T: control time (years)

This process is repeated for all alternative plans. Once all of the costs are calculated, a point of economic efficiency can be found where the sum of the operation cost (C) and the net value change (NVC) is minimized. In order to evaluate the effectiveness of each of plan, Equation 2.6 can be rewritten as follows:

$$\text{MIN: C + NVC} = \sum_{t=1}^{T}(L_{ft}C_{ft} + L_{qt}C_{qt} + NVC_t), \tag{4.2}$$

The control time T for the decision analysis is usually based on the decision maker's interest in evaluating alternative strategic plans. In general, economic losses associated with large fire incident increase if longer control periods are considered.

4.3 Results and Discussion

In order to evaluate the effectiveness of the proposed methodology, nine strategic planning scenarios are considered in this study as shown in Table 4.1. Each plan has a number of firefighters to be hired and fire trucks to purchased over the planned period. It is assumed that the control period is 10 years.

Plan 1 is taken as the base case scenario where the number of firefighters is 300 (100 firefighters per shift) and the number of trucks is 20. Plan 2 to Plan 9 represent alternative plans with an increase of 40% in the number of firefighters over the base case for each plan. The annual cost of hiring one firefighter is estimated to be \$93,663 [81]. This cost includes

Planning scenario	Number of firefighters (L_f)	Cost of hire (C_f)	Number of trucks (L_q)	Cost of trucks (C_q)	Total cost (C)
Plan 1	300	$280,989,000	20	$14,000,000	$294,989,000
Plan 2	420	$393,384,600	28	$19,600,000	$412,984,600
Plan 3	540	$505,780,200	36	$25,200,000	$530,980,200
Plan 4	660	$618,175,800	44	$30,800,000	$648,975,800
Plan 5	780	$730,571,400	52	$36,400,000	$766,971,400
Plan 6	900	$842,967,000	60	$42,000,000	$884,967,000
Plan 7	1020	$955,362,600	68	$47,600,000	$1,002,962,600
Plan 8	1140	$1,067,758,200	76	$53,200,000	$1,120,958,200
Plan 9	1260	$1,180,153,800	84	$58,800,000	$1,238,953,800

Table 4.1: Strategic planning scenarios costs (in US dollars).

the personnel salary and benefits such as health and dental benefits, life insurance, vacation and holiday time, average sick leave usage, uniforms and safety equipment. The cost of purchasing a new industrial fully equipped fire truck is approximately $700,000. The last column in Table 4.1 depicts the total cost (C) of each plan.

To evaluate the expected economic loss NVC over the specified horizon, two simultaneous fire incidents, Fire 1 and Fire 2, were considered in Plant 4 and Plant 10, respectively. We assume that Fire 1 requires 200 man-hours to be suppressed, while Fire 2 requires 600 man-hours. To suppress these fires, we use Method 4 described in Table 3.4.

Each plan is evaluated by testing its performance for different fire damage growth functions, namely linear, square root and quadratic. The linear damage function represents fire incidents that have a constant rate of damage over time. Details of the linear damage function were presented in Section 2.2.2. The square root damage function represents all fire incidents that have

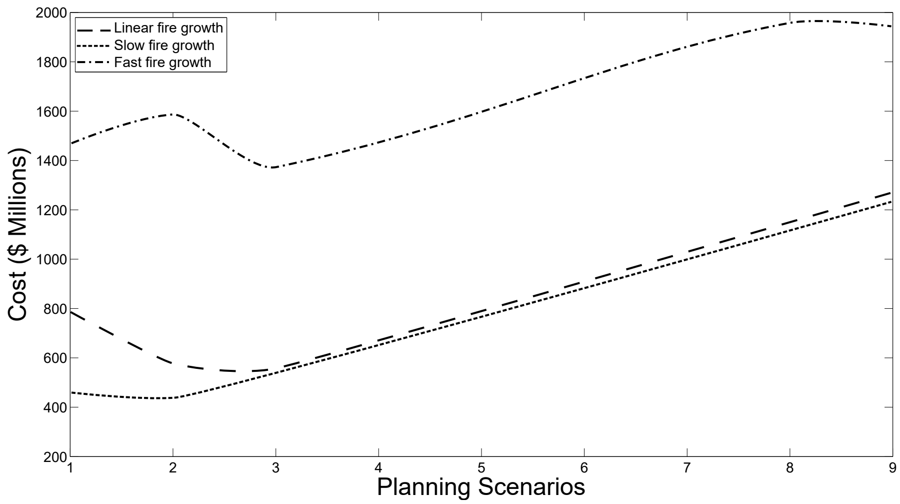

Figure 4.2: C+NVC curves of three damage growth functions, linear, slow and fast.

a slow rate of damage growth, as defined in Equation 3.1. The opposite is observed with the quadratic damage function which represents fire incidents that have a fast rate of damage growth, as already defined in Equation 3.2.

Figure 4.2 shows the obtained curves from the C+NVC model for the three damage growth functions described in Section 3.4.1. The results indicate that the most efficient allocation of funding for hiring is achieved by plan 2 and plan 3 where the minimum of the C+NVC curves is reached. Compared to the base case (300 firefighters), the recommended increase in manpower is from 300 to 540 firefighters for both fast and linear growth fires. This increase resulted in a saving of approximately $230 US million in losses in cost of firefighters.

Tables 4.2, 4.3 and 4.4 show a comparison of the strategic planning scenarios costs for different fire damage growth speeds. The last column in

Planning Scenario	C_f	C_q	NVC	$C+NVC$
	....	($ Millions)	....	
Plan 1	$280	$14	$493.2	$787.2
Plan 2	$393	$19	$164.7	$576.7
Plan 3	$505	$25	$27.3	$557.3
Plan 4	$618	$30	$27.3	$675.3
Plan 5	$730	$36	$27.3	$793.3
Plan 6	$842	$42	$27.3	$911.3
Plan 7	$955	$47	$27.3	$1,029.3
Plan 8	$1,067	$53	$27.3	$1,147.3
Plan 9	$1,180	$58	$27.3	$1,265.3

Table 4.2: Comparison of strategic planning scenario costs for linear damage growth.

each of these tables show C+NVC, the total fire operation costs and the expected economic losses for different strategic plans.

Table 4.2 shows that Plan 3 is the most cost effective plan for linear fire damage growth. Increasing the number of firefighters from 300 to 540 reduces the total losses by 30% (from 787.2 to $ 557.3 US million). We can notice that NVC reached its minimum value at Plan 3. The increase in C+NVC value for Plan 4 through Plan 9 comes from the cost of more firefighters.

For slow fire damage growth, using Plan 2 can reduce the total losses by 5% (from $458.7 to $439.3 US million) as shown in Table 4.3. The most cost effective investment is to increase the number of firefighters from 300 to 420 as shown in Table 4.3. Although Plan 4 is able to suppress both fires without any economic losses (NVC =0), its hiring cost is greater than the

Planning Scenarios	C_f	C_q	NVC	$C+NVC$
	....	($ Millions)	....	
Plan 1	$280	$14	$164.7	$458.7
Plan 2	$393	$19	$27.3	$439.3
Plan 3	$505	$25	$27.3	$557.3
Plan 4	$618	$30	$0	$648
Plan 5	$730	$36	$0	$766
Plan 6	$842	$42	$0	$884
Plan 7	$955	$47	$0	$1,002
Plan 8	$1,067	$53	$0	$1,120
Plan 9	$1,180	$58	$0	$1,238

Table 4.3: Comparison of strategic planning scenario costs for slow damage growth.

Planning Scenarios	C_f	C_q	NVC	$C+NVC$
	....	($ Millions)	....	
Plan 1	$280	$14	$1,171.8	$1,465.8
Plan 2	$393	$19	$1,171.8	$1,583.8
Plan 3	$505	$25	$843.3	$1,373.3
Plan 4	$618	$30	$843.3	$1,491.3
Plan 5	$730	$36	$843.3	$1,609.3
Plan 6	$842	$42	$843.3	$1,727.3
Plan 7	$955	$47	$843.3	$1,845.3
Plan 8	$1,067	$53	$843.3	$1,963.3
Plan 9	$1,180	$58	$705.9	$1,943.9

Table 4.4: Comparison of strategic planning scenario costs for fast damage growth.

total losses in Plan 3. Because we are dealing with slow fires, Plan 4 through Plan 9 are able to suppress both fires with no economic losses.

In case of fast fire damage growth as shown in Table 4.4, Plan 3 can reduce the total losses by 9% (from \$1,465.8 to \$1,373.3 US million) by increasing the number of firefighters to 540. The high values in NVC column is due to the fast damage growth resulting from this type of fires.

4.4 Conclusion

The methodology presented in this chapter has focused on integrating the cost of fire damage within strategic planning. The strategic plans deal with the optimal budget allocation and the deployment or relocation of firefighting resources. The concept of the C+NVC was used to perform the economic analysis to determine the most efficient strategic plan. i2Sim is used to model the infrastructure systems in order to understand and evaluate the net value change of goods and services due to the fires. The fire damages were evaluated using three different damage functions. The results have shown that the proposed methodology can be used for more effective strategic planning and better daily scheduling and allocation decisions.

In this chapter, we focused on human resources planning decisions from the fire departments' point of view. Overall, the increasing interdependence of infrastructure systems makes economic losses induced by extreme events very severe and difficult to predict. We believe that methods like ours that address this problem will be a key component of future decisions support systems. In the next chapter, we change our perspective and observe the impact that resource allocation decisions during emergency response have on improving infrastructure resilience.

Chapter 5

Improving Resilience of Interdependent Infrastructure Systems

5.1 Introduction

Modern infrastructure systems, such as water, electrical power and transportation, become more and more interconnected and interdependent [82]. Due to such interdependence, these systems are inherently vulnerable to disruptions in other systems. Despite the fact that a lot of resources have been invested in prevention, not all incidents can be averted. Increasingly, the emphasis in emergency response has shifted from protection and prevention towards preparedness and response [11]. This shift is realized by the concept of resilience. The effectiveness of the emergency preparedness and response plans has a high impact on infrastructure resilience.

A resilient infrastructure is an infrastructure that can withstand sudden disturbances with minimum disruption and recovers within acceptable losses and time [83]. One way to improve resilience is to consider the effectiveness of the emergency preparedness and response plan. The effectiveness of emergency response plans includes prioritization of responses and optimal allocation of available limited resources.

In this chapter, we propose a methodology to evaluate the impact of resource allocation decisions during fire incidents in improving infrastructure resilience. This methodology focuses on two dimensions: system resourcefulness and system rapidity. The system resourcefulness is evaluated by the ability to prioritize fire incidents and the optimality of mobilizing firefighting units. The system rapidity is evaluated by containing economic losses in production and by minimizing the recovery time. This methodology can be used for any type of natural or man-made hazards. It can also be used for other resource allocation problems in any interdependent environment such as telecommunications, transportation, electric power grids, and water supply systems. Section 5.2 of this chapter describes the problem formulation. Section 5.3 provides background information infrastructure Resilience. Section 5.4 presents the proposed methodology. Results and discussion are provided in Section 5.5 and the conclusion is given in Section 5.6.

5.2 Problem Formulation

This research is mainly concerned with developing a methodology to evaluate the impact of allocating firefighting units during fire incidents on infrastructure resilience. Once a fire alarm signal is received, the response mobilization is started by dispatching firefighting units from the fire stations. Emergency responders must determine the optimal number of firefighters that should be allocated to mitigate the potential disruptions resulting from extreme events. The existing strong interdependence between infrastructure systems remains a challenge in modeling the consequences of fire incidents. Because such incidents and their cascading effects are becoming stronger, there is an important need to evaluate this impact of the resources allocation process on infrastructure resilience.

In the analysis of infrastructure systems and emergency response behaviors, two major problem exist, namely:

1. An infrastructure system, I, is a set of production units related to each other, $I = \{P_1, P_2, P_3, ..., P_n\}$, where P_n is the n_{th} production unit, and n is the total number of production units. Given a set of fire incidents $\{f(P_1), f(P_2), ..., f(P_n)\}$, what is the impact on infrastructure system I ?

2. Given a set of firefighting units $\{u_1, u_2, u_3, ..., u_q\}$, where u_q is the q_{th} firefighting unit, q is the total number of available firefighting units, and a desired level of resilience, $R(I)$, what is the best allocation scheme of the available firefighting units during suppression time $[0, T_S]$ such that $T_s = \{(u_1, f(P_1)),\ (u_2, f(P_2)),\ (u_3, f(P_2)), ...\}$, $\forall\ T_s \in [0, T_S]$ to maintain a desired resilience level, $R(I)$?

These problems are discussed in the next section.

5.3 Infrastructure Resilience

Resilience was originally introduced as a property of systems by Holling in 1973 [84]. Since that time, the concept of resilience has been studied in a large number of disciplines such as ecology, psychology, sociology, economics, and engineering. Increasingly, resilience is recognized to be an important dimension of the sustainability of infrastructure systems. Bruneau et. al. [85] emphasize that resilient systems reduce the probability of failure, the consequences of failure such as economic losses and the time for recovery.

According to Bruneau, et. al. [85], there are four dimensions that can improve resilience. These dimensions are as the following:

- **Robustness:** The inherent strength or resistance in any system to withstand a given level of stress or demand without degradation or loss of functionality.
- **Redundancy:** The ability of a system to satisfy the functional requirements using alternate options, choices and substitutions in the event of disruption, degradation or loss of functionality
- **Rapidity:** The speed with which losses are overcome and safety, serviceability and stability are resumed.
- **Resourcefulness:** The ability to identify problems, establish priorities and mobilize resources and services in emergencies to restore the system performance.

Although many of these dimensions have been evaluated as technically-based functions of the physical system, quantifying resourcefulness, as a property, remains challenging because it relies on human skills and their abilities to respond and recover from disaster events [86]. The focus in this chapter is on two of these dimensions, resourcefulness and rapidity, that track the reaction during extreme events. The system resourcefulness is evaluated by the ability to prioritize fire incidents and the optimality in mobilizing firefighting units. The system rapidity is evaluated by containing economic losses in production and by minimizing the recovery time.

Infrastructure resilience can be defined as the ability to reduce the magnitude and the duration of disruptive events [87]. Resilience, as a property of complex systems, can be measured in one of two ways: the amount of disturbance a system can withstand without changing its original state [84] and the time taken for a system to recover after a disturbance [88]. In this sense and after analyzing the literature, the definition provided by Cimellaro et. al. in [86] has been adopted. Cimellaro et. al. define resilience (R) as [86]:

> "*. . . a function indicating the capability to sustain a level of functionality or performance . . . over a period defined as the control time (T_{LC}) that is usually decided by owners, or society. . .*"

Figure 5.1 shows a hypothetical system functionality curve after the effects of an event, E. This figure provides a general overview of the time dependent system functionality and illustrates the important times during system response. As expected, system functionality under the effects of the event degrades from the normal operating level. This functionality with respect to the time of event occurrence can be divided into three stages: pre-event ($t < t_{E0}$), recovery time ($t_{E0} < t < t_{E0} + T_{RE}$) and post-event ($t > t_{E0} + T_{RE}$). In the pre-event stage, the system operates under normal conditions. During the recovery period, the system operates under the influence of the hazard. In the post-event stage, the system returns to normal operation.

Analytically, the resilience measure can be expressed by the following equation [86]:

$$R = \frac{1}{T_{LC}} \int_{t_{0E}}^{t_{0E}+T_{LC}} Q(t)dt \tag{5.1}$$

where

$Q(t)$ is the functionality of the system

t_{0E} is the time of occurrence of event E

T_{LC} is the control time of the system

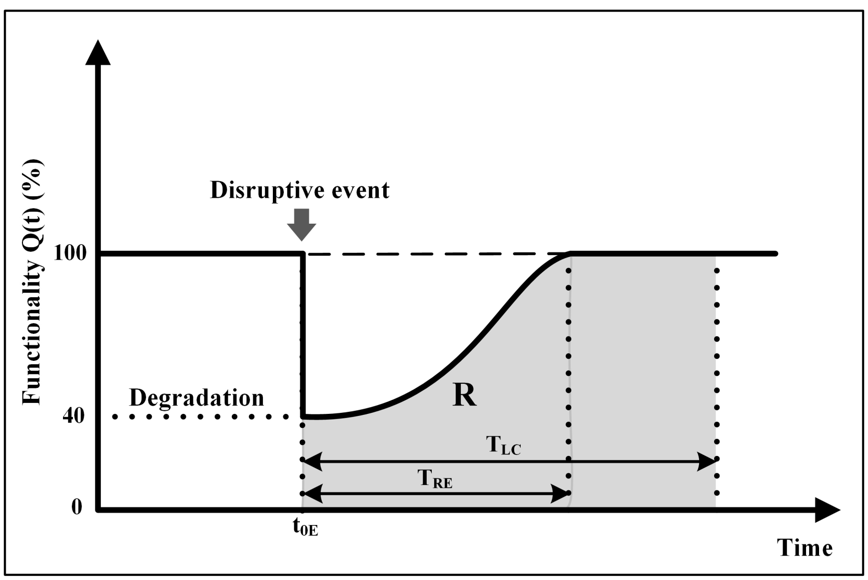

Figure 5.1: Graphical representation of resilience.

For infrastructure systems, the functionality can be expressed as economic losses in production. These losses include losses in production due to a disturbance (direct losses) plus business interruptions due to degradation in production (indirect losses). The analytical functionality $Q(t)$ of the infrastructure system can be expressed as follows:

$$Q(t) = 100 - [L_D(t) + L_{ID}(t)] \tag{5.2}$$

where

L_D is the direct losses function

L_{ID} is the indirect losses function

Both direct losses and indirect losses functions are expressed as a percentage of the total production.

5.4 Proposed Methodology

In this chapter, we use the developed system described in Chapter 2 to evaluate the impact of resource allocation decisions during fire incidents in improving infrastructure resilience. Figure 5.2 depicts the proposed methodology for assessing resilience of infrastructure systems.

The methodology starts with identifying the severity of the fire incident. As discussed in Section 2.2, each fire is described by its severity. This measure defines the required number of man-hours to suppress a fire. Based on this information, emergency responders generate the allocation decisions of the available firefighting units. These decisions are evaluated by the damage

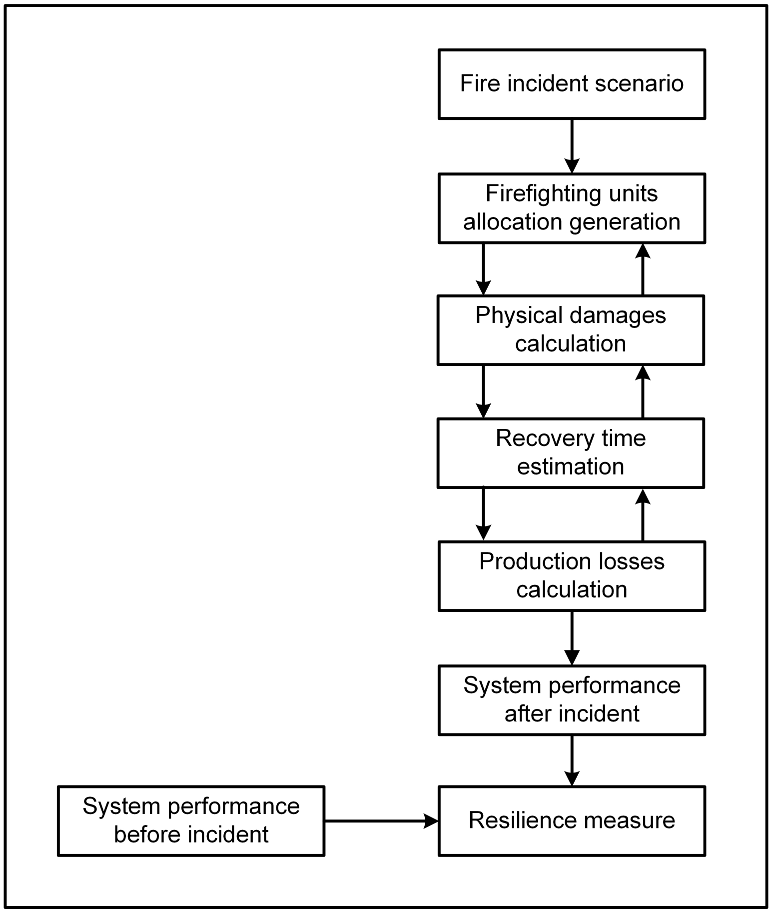

Figure 5.2: Flowchart describing the proposed methodology for assessing resilience of infrastructure systems.

function described in Section 2.2. After each decision, the physical state of the infrastructure system components is evaluated using i2Sim described in Section 2.3. The impact of this damage is translated into recovery time T_{RE}. At this point, the infrastructure performance can be evaluated before and after the hazard. The functionality of this system Q is defined as the unrealized production (compared to nominal) due to inoperability which can be calculated using Equation 5.2. Both direct and indirect losses can be

Allocation Method	Plant 10		Plant 4	
	Level of damage	Recovery time	Level of damage	Recovery time
Method 1	High	6 months	Intermediate	3 months
Method 2	High	6 months	Low	1 month
Method 3	High	6 months	Low	1 month
Method 4	High	6 months	Minimul	Minimul

Table 5.1: Level of damage and recovery time for applied allocation methods.

measured through i2Sim's cells' output. The final step is to evaluate the resilience of the infrastructure system R using Equation 5.1.

5.5 Results and Discussion

The methodology described above has been applied to the case study introduced in Section 2.6. Two simultaneous fire incidents, Fire 1 and Fire 2, were simulated in Plant 4 and Plant 10, respectively. We assume that Fire 1 requires 200 man-hours to be suppressed, while Fire 2 requires 600 man-hours. Four allocation methods listed in Table 3.4 were used to evaluate the impact of resource allocation decisions on the petrochemical complex resilience. For each method, the developed system evaluates the potential damage based on fire duration. The severity of this damage is reflected into a reduction in the production level and recovery time T_{RE}. Recovery time T_{RE} given here is the time needed for repair and reconstruction as described in Table 2.1. A 1-years control period is chosen for evaluating the functionality of the petrochemical complex, $T_{LC} = 365$ days.

Figure 5.1 shows the resulting level of damage for each allocation method and the associated recovery time. Figures 5.3, 5.4, 5.5 and 5.6 show the functionality of the petrochemical complex using different allocation methods. It can be seen that robustness is extremely high for Method 4 (Figure 5.6), which represents the optimized allocation decision. Method 4 was able to prioritize fire incidents and allocate more firefighters to the critical fire. Method 1, which represents the "business as usual" decision, recorded the lowest robustness at 55% as shown in Figure 5.3. It appeared that the rapidity of the complex was the same for all the allocation methods (180 days). The expected equivalent production losses for each allocation method are shown in the third column of Table 5.2, along with the recovery period considering an observation period T_{LC} of 365 days.

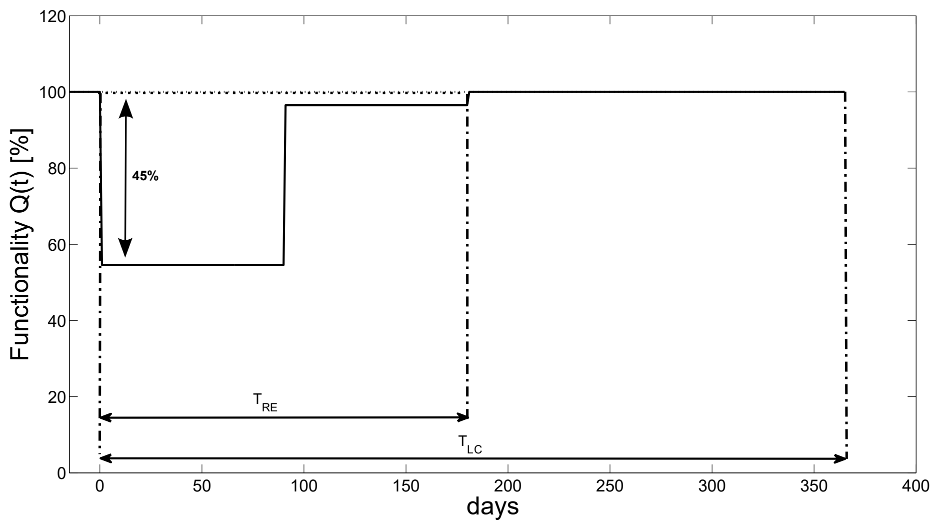

Figure 5.3: Functionality the of the case study after multiple-fire incidents using Method 1.

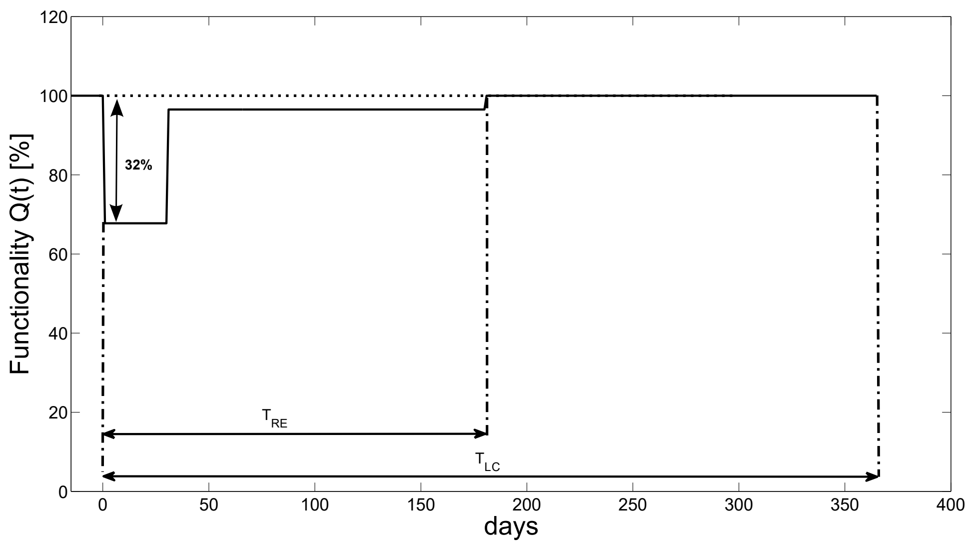

Figure 5.4: Functionality the of the case study after multiple-fire incidents using Method 2.

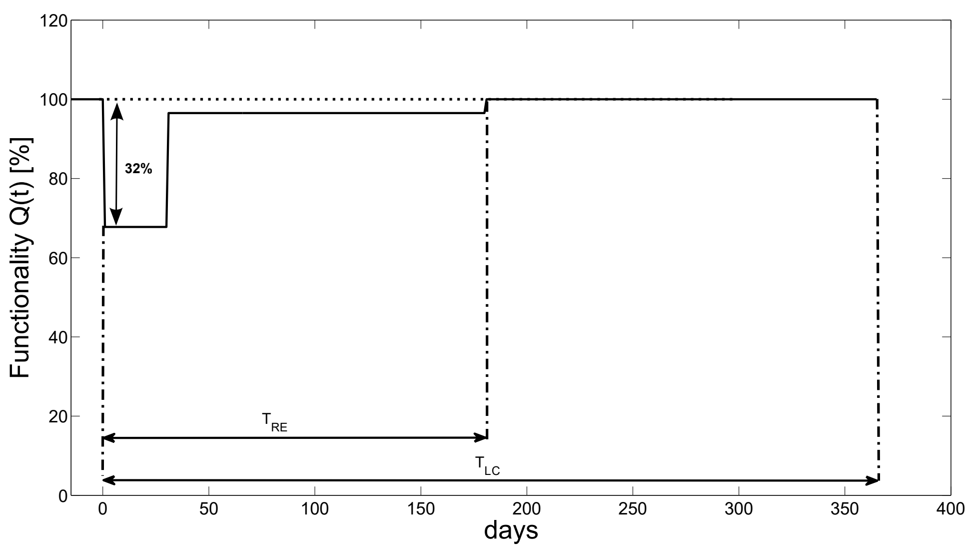

Figure 5.5: Functionality the of the case study after multiple-fire incidents using Method 3.

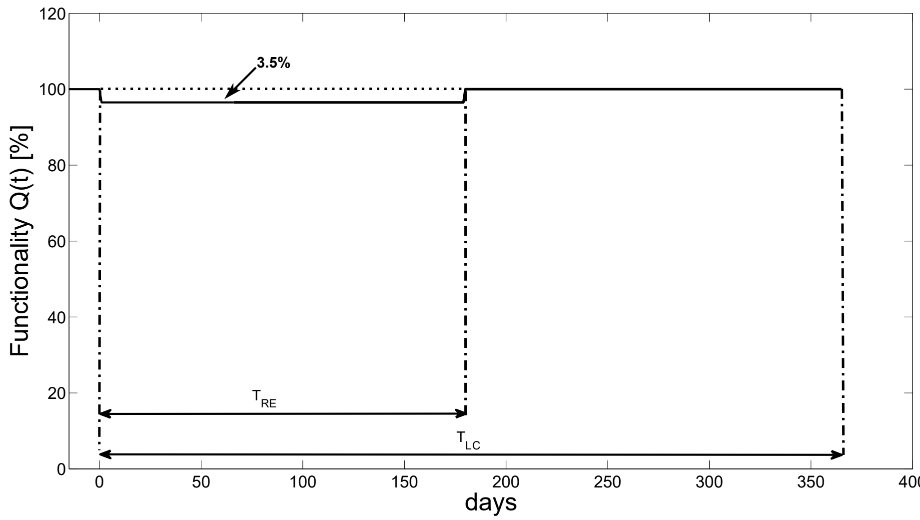

Figure 5.6: Functionality the of the case study after multiple-fire incidents using Method 4.

Allocation Methods	Recovery Time T_{RE} (days)	Production Losses ($ US Millions)	Resilience R(%)
Method 1	180	$3,460	87.78%
Method 2	180	$1,171	95.86%
Method 3	180	$1,171	95.86%
Method 4	180	$493	98.26%

Table 5.2: Recovery time, losses and resilience of the case study for different allocation methods (T_{LC} = 365 days).

The complex resilience value is calculated according to Equation 5.1 for control time T_{LC}. Figures 5.7, 5.8, 5.9 and 5.10 show the calculated resilience for Method 1, Method 2, Method 3 and Method 4, respectively.

The resilience values are summarized in Table 5.2. For this case study, it is shown that the optimized allocation has the largest resilience value of

95.86%, when compared with the other three methods, and it is the least losses in production ($ 493 US million). However, if the common action (Method 1) is taken, the complex resilience is reduced to 87.78%, and the production losses increased drastically to $3,460 US million. For Method 2 and Method 3, the resilience values were the same at 95.86% and production losses at $1,171 US million.

This means that the optimizing resource allocation process during fire incidents improves the infrastructure resilience. We conclude that effectiveness of the emergency response plan has a high impact on improving infrastructure resilience.

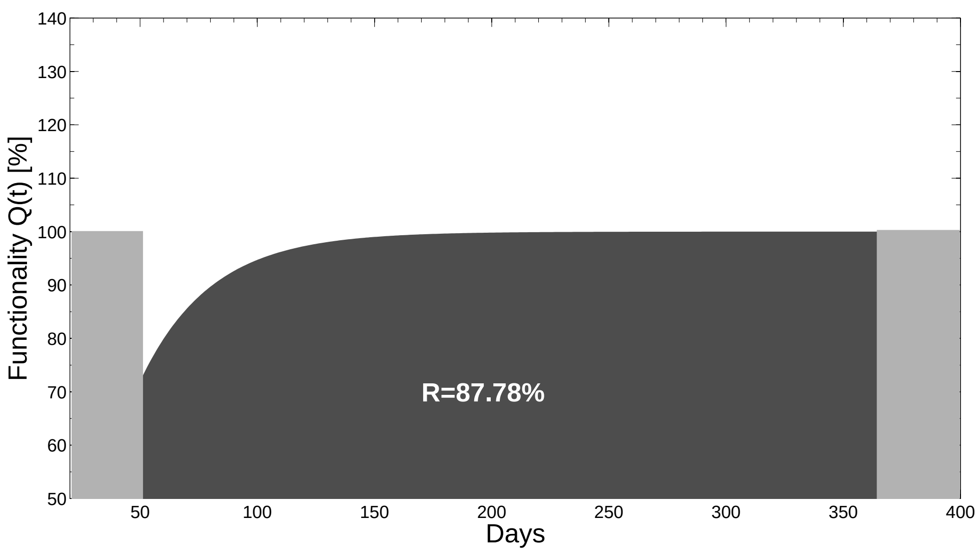

Figure 5.7: Resilience curve showing level of functionality of the case study over time for Method 1.

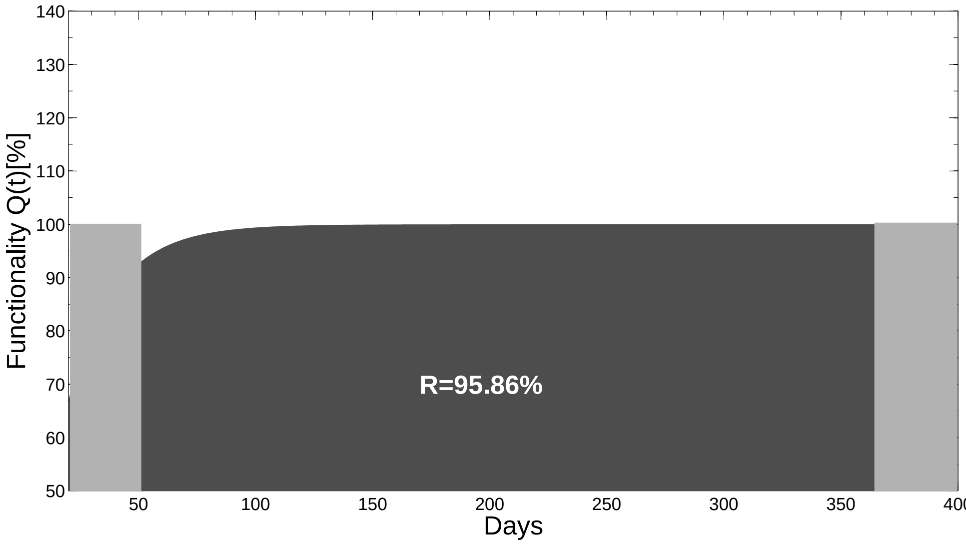

Figure 5.8: Resilience curve showing level of functionality of the case study over time for Method 2.

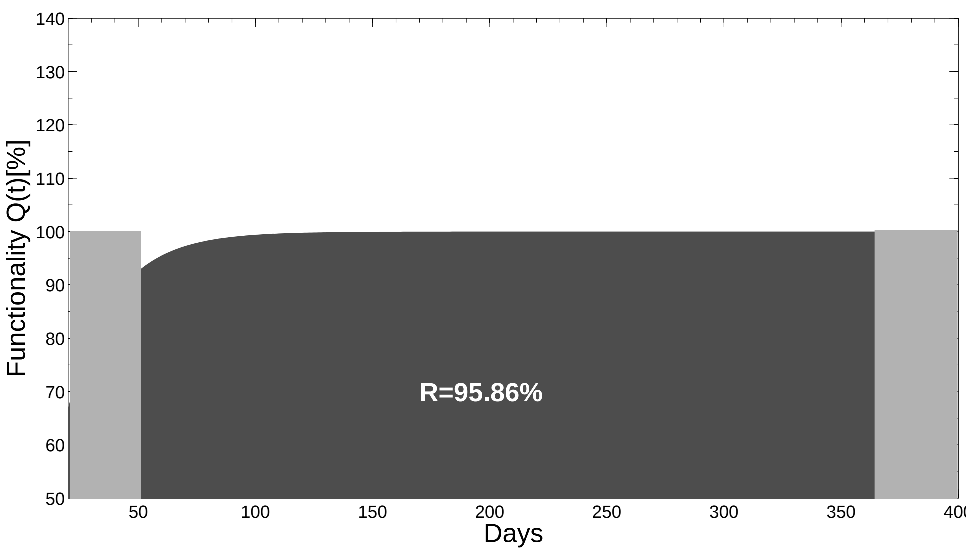

Figure 5.9: Resilience curve showing level of functionality of the case study over time for Method 3.

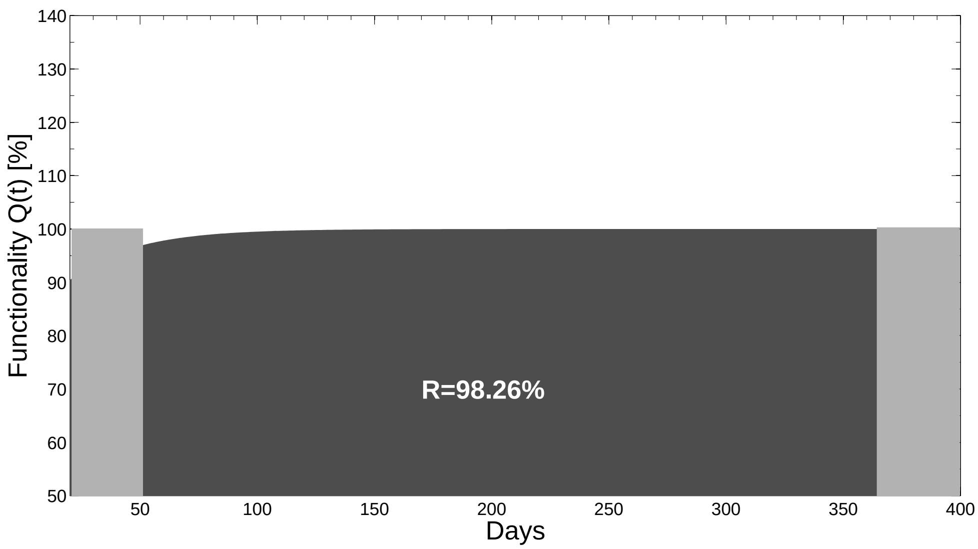

Figure 5.10: Resilience curve showing level of functionality of the case study over time for Method 4.

5.6 Conclusion

In this chapter, we proposed a methodology to evaluate the impact of resource allocation decisions during fire incidents in improving infrastructure resilience. Resourcefulness and rapidity revolve around the ability to maximize the utilization of available resources and to minimize the economic losses by minimizing the recovery time.

A case study of a petrochemical complex was used to explore the impact of allocating limited number of firefighters during multiple fire incidents. We conclude that the decisions of allocating firefighting units are crucial for ensuring an acceptable level of production after suppression. Furthermore, the best retrofit method to improve the resilience measure of any infrastructure system should consider infrastructure interdependence for such decisions.

The proposed methodology allows exploration of how different resource allocation decisions affect infrastructure resilience. It can be used for any type of natural or man-made hazards, which might lead to the disruption of any infrastructure system. It can also be used for other resource allocation problems in any interdependent environment such as telecommunications, transportation, electric power grids, and water supply systems.

Chapter 6

Conclusion

This thesis focuses on the development of a decision support system for assisting emergency responders in making efficient decisions during extreme events. The novelty consists of addressing infrastructure interdependencies in firefighting operation. It formulates the fire management problem as an optimization problems and provides solution algorithms for this problem. It also evaluates the impact of fire operation decisions on infrastructure resilience.

The developed system can be used by fire department to minimize the economic losses during fire incidents. It incorporates economic analysis within the decision-making process and provides cost estimates for different allocations methods. This can help decision-makers to better understand the impact of their decision during emergency response.

In addition, presenting the results of this research as economic impact, expressed in monetary values, can help to bridge the research gaps between industry and academia. With results in this form, decision makers in industries would be better able to understand the value of academic research.

In this chapter, we summarize our efforts to improve the emergency response decisions during fire incidents and present future research directions.

6.1 Resource Allocation and Scheduling During Multiple-Fire Incidents

We proposed and developed a methodology to evaluate resource allocation decisions during multiple-fire incidents. The methodology uses infrastructure interdependency modeling to evaluate the interactions among different systems. In this thesis, the economic impact of the fire incidents (direct and indirect losses) was evaluated to find an optimized allocation with minimum economic losses. Several factors such as fire damage growth rate and human factors were studied to determine their effects on the decision-making process. The developed methodology was elaborated and implemented in a case study of multiple-fire incidents in a petrochemical complex. Our results show that the proposed methodology gives promising results to effectively improve the resource allocation decisions in interdependent environments. It performs better than other allocation methods in terms of economic losses.

6.2 Capacity Planning of Human Resources

We also presented a capacity planning methodology for fire managers to investigate the impact of hiring decisions on effectiveness of firefighting operations. In this thesis, we incorporated the concept on C+NVC to perform an economic analysis to determine the most efficient strategic plans. i2Sim is used to model infrastructure systems in order to understand and evaluate the net value change of goods and services due to fire. The fire damage growth was evaluated using three different damage functions. The results have shown that the proposed methodology can be used for more effective strategic planning and better daily scheduling and allocation decisions.

6.3 Improving Resilience of Interdependent Infrastructure Systems

Finally, we proposed a method to evaluate the impact of resource allocation decisions during fire incidents in improving infrastructure resilience. Our method focused on two dimensions of resilience: resourcefulness and rapidity. Resourcefulness was evaluated by the ability to prioritize fire incidents and the optimality in scheduling firefighting units. Rapidity was evaluated by minimizing economic losses and recovery time. The results showed that incorporating these dimensions into fire fighting decisions has a high impact on improving infrastructure resilience.

6.4 Future Research Directions

In this section we present some of the on-going research and possible extensions related to this thesis.

6.4.1 Improvement to the Fire Damage Assessment

Accurate assessment of fire damage is essential for developing effective emergency response plans. The damage function developed in Section 2.2.2 uses a deterministic value estimated from fire duration. Predicting fire damage is a complex task and surrounded with considerable uncertainties. Some of these uncertainties are due to uncontrollable factors such as weather, fire occurrence, and fire severity. The fire damage function can be extended to consider these uncertainties. It can be modelled using a discrete set of fire scenarios each of which can occur with some known or estimated probability.

6.4.2 Considering Multiple Owners During Multiple-Fire Incidents

In this thesis, a single owner of infrastructure systems was considered during the process of developing the emergency response plans. Multiple owners of interdependent infrastructure systems make emergency repones decisions during multiple fire incidents more challenging, especially if the different fire places are owned by different parties, and insured by different insurer. Further research is needed to study the situation of having multiple owners during multiple-fire incidents.

6.4.3 Understanding the Impact of the Human Factor During Emergency Response

This thesis found that human performance has a direct impact on the effectiveness of firefighting operations. Therefore, understanding firefighters behaviour during the fire suppression process, and the impact on their physical and mental performance, is another important area for future research. In general, there is a lack of data in human performance during emergency situations [89]. Future research should explore human performance during emergency conditions in harsh environments.

6.4.4 Applications to Other Types of Emergency Response

Lastly, the developed system can be used as a decision support system for other disastrous events, such as floods, wildfire, machine failures, industrial accidents and terrorist attacks. In addition, it can be used for interdependent infrastructure risk and vulnerability analysis. Some examples of such applications are summarized below.

- **Wildfire Suppression:** Wildfire is one of the most severe natural hazards in the world. The developed system in Chapter 2 can be further modified to optimize resources allocation for wildfire containment. Geographic Information Systems (GIS) can be integrated to the developed system to provide location information which can be used in evaluating the economic efficiency of alternative wildfire management plans.

- **Evaluating Restoration Plans of Critical Services:** During restoration after a natural disaster, engineers are faced with a large number of theoretical possibilities of how critical services, such as electrical power, can be restored. The proposed methodology in Chapter 5 can be modified to develop restoration strategies and restoration plans. Different event scenarios can be modeled and their impact on the services provided by critical infrastructure systems can be assessed. With this knowledge, alternative restoration plans can be evaluated according to their ability to achieve rapid restoration of critical services.

- **Identifying and Ranking Critical Components:** Identifying critical components for infrastructure systems provides important input for valuing infrastructure investments and managing risks. The developed system can be used to develop a model for risk analysis to identify and rank critical components. By using i2Sim to model interdependent infrastructure systems, the consequences when components within the systems fail to perform properly can be simulated. These consequences can be evaluated by several factors, such as economic losses, affected sites or degradation in performance. Then, the components can be ranked based on its criticality.

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