Statistical Model Checking of Relief Supply Location and Distribution in Natural Disaster Management

By

Sohaiba Iqbal

NUST201362766MSEECS61413F

Supervisor

Dr. Osman Hasan

Department of ElectricalEngineering

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Approval

It is certified that the contents and form of the thesis entitled "**Statistical Model Checking of Relief Supply Location and Distribution in Natural Disaster Management**" submitted by **Sohaiba Iqbal** have been found satisfactory for the requirement of the degree.

Advisor: **Dr. Osman Hasan**

Signature: ____________________

Date: ____________________

Committee Member 1: **Dr. Anis ur rehman**

Signature: ____________________

Date: ____________________

Committee Member 2: **Dr.Omer Arif**

Signature: ____________________

Date: ____________________

Committee Member 3: **Dr. Imran Mahmood**

Signature: ____________________

Date: ____________________

Abstract

Examining the efficacy of natural disaster management readiness and response activities is challenging due to the randomized behaviors and uncertainties of natural disaster. These uncertainties are captured by stochastic models quite well and thus have been widely used in disaster response activities for evacuation operations, coordinating logistics support and accurate relief shelter planning. The analysis of these stochastic models is carried out using Monte Carlo simulations to judge the effectiveness of natural disaster management solutions. However, this approach uses the static estimators, which generally rely on sampled number of events taken from the random space. The safety-critical nature of such domain requires a more quantifiable analysis. In order to overcome this challenge, we propose to use statistical model checking. The paper presents a framework for the formal statistical analysis of relief supply location and distribution of natural disaster management in PRISM. In PRISM model checker, we model and analyze a real-world natural disaster management plan incorporating key factors i.e. demand of medical supplies at hospitals, predestined routes from warehouses to hospitals, capacity of warehouses and transportation plans ensuring successful delivery of medical supplies to the hospitals.

Dedication

I dedicate this thesis to my parents and family for their love, affection and support.

Certificate of Originality

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any degree or diploma at NUST SEECS or at any other educational institute, except where due acknowledgement has been made in the thesis. Any contribution made to the research by others, with whom I have worked at NUST SEECS or elsewhere, is explicitly acknowledged in the thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except for the assistance from others in the project's design and conception or in style, presentation and linguistics which has been acknowledged.

Author Name: **Sohaiba Iqbal**

Signature: ________________

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Chapter 1

Introduction

Our lives are overwhelmed with adverse events such as natural disasters that occur on specific spatiotemporal scales. The Typical examples of natural disaster include earthquakes, the outbreak of diseases, volcanic eruptions, cyclones, tornadoes, floods and bridge collapses [32]. All these sudden adverse events may lead to disastrous consequences. The Pakistani earthquake (2005), registered 7.6 in the Richter scale, led to the death of 75,000 people injuring another 106,000 [1]. Primarily, such multifaceted disasters are outcomes of interaction of countless components limited to three major entities i.e. the physical environment [31]; the social and demographic characteristics of communities [30] [12]; and the constructed environment. The constructed environment comprises of roads, bridges and buildings [19] [21]. To reduce the effect of such disastrous consequences a comprehensive pre-disaster and post-disaster planning is inevitable. Thus, numerous solutions, such as risks reduction and disaster prevention plans [3], relief supply locations and distribution (RSLD) plans [3], evacuation and emergency response plans [27], rescue and relief plans [27] and reconstruction plans [33] are generally considered.

Most of the traditional disaster management plans [29, 36], consider only the static and deterministic location and distribution of medical supplies. The models of such disaster management plans are not completely adequate for the post-disaster cases due to absence of stochastic parameters, such as the storage capacity of medical supply [2], location and distribution of medical supplies [16] [27], planning and routing of vehicle [24] [20]. Similarly, these models fail to consider the availability of selected vehicles and paths in case of a disaster event

To avoid the above-mentioned limitations, the stochastic modeling is considered quite practical instead of static and deterministic, as it also caters for the random and unpredictable parameters of a natural disaster management plan [4,22]. Stochastic programming (SP) [5] is one of the most popular stochastic modeling approaches and is used mostly in planning, preparedness and post-disaster activities of a natural disaster event [3]. In SP the uncertain data is incorporated into the objective of mathematical stochastic program. This uncertainty is usually differentiated by a probability distribution of parameters. Although the uncertainty is rigorously defined, in practice it can vary in detail from a few scenarios to a specific joint probability distribution. The outcomes are exhibited as `w` of a set `W`. The latter can be, for example, a set comprising of possible demands of next few months [14].

The main feature of SP based analysis the capturing of behavior of above-mentioned elements of random and uncertain nature in the models [15]. Afterwards, these models are then used to evaluate the correctness and accuracy of a natural disaster management scheme. Simulation based analysis of all existing SP models is carried out as cause and effect models. Static estimators are used in these Monte Carlo simulation based analysis methods for computing the probability [?]. These estimators generally rely on a limited number of events extracted from the random space [**?**]. In a statistical model, the estimator function is used to estimate the value of an unknown parameter [6].

In conducting a formal quantitative analysis in this safety-cricital domain, we propose to use statistical model checking [13] for modeling and verification of RSLD in natural disaster management. We choose RSLD among other components of natural disaster management because it is one of the most challenging issues in the field of logistics and such operations are renowned for their complexity. Improved planning and preparedness against natural disaster can help save lives and empower communities to start again normal life more quickly by reducing the sufferings of the survivors. [37]. RSLD include a number of stochastic factors such as disaster location [20], path destruction, vehicle destruction, selection of number of vehicles and transportation time of a specific path [20]. These factors have a serious effect on the survivability, management and adaptability of RSLD and thus analyzing RSLD can provide very beneficial insights about the efficacy of a given RSLD scheme. To proceed with our proposed framework, firstly we have developed a formal stochastic model of the given disaster scenario. Our model incorporates various probabilistic and non-deterministic factors of the given RSLD system. Probabilistic factors include path selection, vehicle destruction and path destruction while non-deterministic factors include path traveling time, occurrence time of disaster, selection of available vehicles [20] etc. Secondly, we have proposed a set of generic properties for the verification of the model by incorporating or excluding time based constraints, such as hospital demand fulfillment with respect to RSLD factors. The proposed methodology allows us to determine the efficiency of a given RSLD scheme by observing the impact of various factors, such as probability of vehicle destruction, probability of path destruction and probability of hospital demand fulfillment, on the expected time of various desired characteristics, such as hospital demand fulfillment in case of a natural disaster. The proposed methodology is implemented in PRISM [17], that is a probabilistic model checking tool. The main motivation behind this choice includes its ability to express a wide range of stochastic models, such as continuous-time Markov chains (CTMCs), discrete-time Markov chains (DTMCs) and markov decision processes (MDPs). PRISM support properties such as linear temporal logic (LTL), probabilistic LTL (PLTL) and cost/rewards [17]. In order to describe the effectiveness and utilization of the proposed framework, we use it to analyze a real-world scenario of RSLD plan and implemented in Seattle, Washington [20]. We have used statistical model checking for RSLD analysis, contrary to Monte Carlo simulation. In statistical model checking runs (or paths) extracted directly from the formal model are used as events for verifying quantitative properties [17]. The analysis can be termed as complete if all the paths are analyzed otherwise a probabilistic bound on the analysis error is provided, which is one of the distinguishing features of statistical model checking compared to simulation [13, 23]. The usage of a formal model for the analysis is another feature that makes statistical model checking superior than traditional simulation based analysis.

1.1 Motivation

Natural disasters such as earthquakes, the outbreak of diseases, volcanic eruptions, cyclones, tornadoes, floods and bridge collapses can have a huge impact on geographical regions and it may require years to recover. In 1928 when Hurricane Okeechobee hit United States, Caribbean and Bahamas, it causes death of more than 4000 people and an overall damage of 100 million to the system was estimated. Natural disasters can be unpredictable like the foods and the earthquakes, but it can be predictable like hurricanes and tornadoes. In either case, the underdeveloped countries are more affected by natural disasters and they bring a lot of destruction. The impact of such disastrous consequences may be reduced by following several approaches or management plans. The best approach is to educate people and to prepare them for what can happen. The preparation may include an efficient resource distribution plan to ensure timely availability of resource in affected areas to minimize the effect of damage. Scientists have developed several Natural disaster management models so that more human lives can be saved and the overall damage can be reduced. The development of a generic framework and the formal analysis of these models is an innovation which can contribute a lot in RSLD domain making it efficient and practical for any disaster event.

1.2 Problem Statement

Simulation based analysis of all existing SP models is carried out as cause and effect models. Static estimators are used in these Monte Carlo simulation based analysis methods for computing the probability [?]. These estimators generally rely on a limited number of events extracted from the random space [?]. In a statistical model, the estimator function is used to estimate the value of an unknown parameter [6].

In conducting a formal quantitative analysis in this safety-cricital domain, we propose to use statistical model checking [13] for modeling and verification of RSLD in natural disaster management. We choose RSLD among other components of natural disaster management because it is one of the most challenging issues in the field of logistics and such operations are renowned for their complexity. Improved planning and preparedness against natural disaster can help save lives and enable communities to restart normal life more quickly by reducing the sufferings of the survivors. We have used statistical model checking for RSLD analysis, contrary to Monte Carlo simulation. In statistical model checking runs (or paths) extracted directly from the formal model are used as events for verifying quantitative properties [17]. The analysis can be termed as complete if all the paths are analyzed otherwise a probabilistic bound on the analysis error is provided, which is one of the distinguishing features of statistical model checking compared to simulation [**?**] [13]. The usage of a formal model for the analysis is another feature that makes statistical model checking superior than traditional simulation based analysis.

1.3 Proposed Solution

We propose a generic formal framework based on statistical model checking of RSLD in natural disaster management. To proceed with our proposed framework, a formal stochastic model of the given disaster scenario was developed. The formal stochastic model incorporates various stochastic elements such as, path destruction, vehicles destruction and many non-deterministic elements, such as time for path traversal, vehicle selection and hospital selection etc. The proposed methodology allow us to determine the efficiency of a given RSLD scheme by observing the impact of various factors, such as probability of vehicle destruction, probability of path destruction and probability of hospital demand fulfillment, on the expected time of various desired characteristics, such as hospital demand fulfillment in case of a natural disaster.

1.4 Thesis Outline

The report is organized as follows: Literature Review is provided in chapter 2. To provide a brief understanding of overall work, PRISM model checker and statistical model checking is described in Chapter 3. Formal RSLD model is elaborated in Chapter 4. Chapter 5 covers RSLD modeling in PRISM model checker. RSLD formal verification is described in Chapter 6. Finally, conclusion of the thesis is in Chapter 7.

Chapter 2

Literature Review

The pre-disaster scenarios include activities such as disaster planning and disaster management while the post-disaster scenarios include activities that take into account the stochastic considerations such as location and distribution of supplies [27], medical supply storage capacity, vehicle planning and routing path time calculation and selection [20]. The deterministic disaster management models, for instance [29, 36] lack stochastic considerations and are best suited for pre-disaster scenarios instead of post disaster scenarios. To cater the modeling of post-disaster scenarios of a natural disaster management scheme, stochastic modeling approach is considered quite triumphant as it allows incorporating its random and unpredictable nature.

A comprehensive survey on RSLD models is presented by Ali et al. [3]. The existing models are mainly characterized by disaster related factors, such as evacuation, disaster types like earthquake, flood and hurricane, relief supplies pre-positioning, relief supply distribution and shelter location. A multi-commodity mixed integer stochastic network flow model regarding location distribution was presented by Yi et al. [38] incorporating two key factors, i.e. evacuation of resources and transportation of medical supplies.

A two-stage stochastic programming (SP) model was proposed by Mete et al. [20]. The first stage activities include the ware house selection and the storage of medical supplies, while the second stage incorporates the medical supplies amount to be delivered to hospitals. The second stage was further analyzed by a mixed-integer programming model (MIP) incorporating parameters such as vehicle assignments and routing. Ozguven et al. [25] proposed an inventory management system. The modeling of system incorporated the uncertainty in demand after the occurrence of a disaster event. Bozorgi-Amiri et al. [7] proposed a model regarding supply chain of relief supplies distribution using Mixed integer non-linear programming. Duran et al. [10] developed a model regarding inventory location using MIP to analyze the response time with respect to pre-positioning of relief supplies. However, all the above-mentioned analysis involves the usage of informal models for judging informally specified properties, which are quite susceptible to modeling and specification errors. Moreover, most of these existing works do not capture the randomized nature of many elements in the model, like vehicle destruction [20, 27, 35] or path destruction [20, 35]. We overcome these limitations by using Markov decision processes (MDP) to capture the behavior of RSLD and expressing the desired characteristics as probabilistic LTL properties in the PRISM model checker.

Besides the above-mentioned informal models, some formal models have also been used. Cloth et al. [8] used the probabilistic model checking to check the endurance of a disaster management scheme. They modeled the system operations as CTMC that is analyzed using model checking algorithms in the stochastic Petri nets to assess the system survivability. Fahadland et. al. [11] analyzed the resilience of the disaster management schemes under different spatiotemporal scales. By using Petri nets they proposed an adaptive process incorporating a set of scenarios. The system behavior is created and adjusted by the model at run-time using the adaptation operator based on the given scenarios. These existing formal methods based analysis certainly advocate the usefulness of using formal methods in this safety-critical domain. However, their context is not to judge the performance of RSLD, which is the main scope of the current paper. To the best of our knowledge, this thesis presents the first formal model and a set of formally specified properties to judge the functionality and performance of RSLD based scheme on the statistical model checking principles.

Chapter 3

Preliminaries

This section provides brief introduction to statistical model checking and PRISM model checker to facilitate the understanding of the rest of the paper.

3.1 Statistical Model Checking

Statistical model checking is an analysis technique which is based on simulation and can be used for analyzing large models. Firstly, The large number of sample paths are generated by statistical model checking. Secondly, at each run the results of the given quantitative properties are evaluated and thirdly, results are evaluated by using hypothesis testing [18] to infer whether a statistical evidence to the satisfaction or violation of the specification [39] is provided by these sample paths. This testing [28] is an important portion of statistical model checking. The statements like `p>p_0` or `p<p_0` are usually verified by hypothesis testing, where `p` is the system model unknown probability and `p_0` is a given threshold value. In statistical model checking, any stochastic system's sample executions are drawn by the distribution specified by the system, afterwards, it is used to find estimates of the probability

measure on executions [18]. There can be a probability of error occurrence, as model's all execution paths are not analyzed. This error can be bounded. The verification accuracy is determined by these bounds and with sufficiently large number of sample paths, we can get very close to accurate results. This approach has many advantages. First, the model only requires the system's sample executions. Thus, it can be applied to larger class of systems such as infinite state systems. Second, the approach can be generalized to a larger class of properties [18]. The main difference between Monte Carlo method and statistical model checking is that in Monte Carlo method, computation of approximate probability with a statistic estimator rely on a limited number of events from the random space while, in statistical model checking, the limited number of events are runs (or paths) of the model. The major advantage is that these paths are extracted directly from the large-size complete and rigorous model. After that the probability is estimated with testing the property over each of the extracted path. The verification is fast to perform as the paths are linear [23].

3.2 PRISM model checker

Properties can be qualitative or quantitative. Qualitative properties cannot be expressed in numerical formats and the analysis of such properties is a difficult task. Quantitative properties are expressed in numerical format and are easier to analyze. Property verification and analysis of a model measures its correctness and accuracy and is termed as model checking. Prism supports two types of model checking i.e. probabilistic and statistical model checking. Some well known model checking tools include PRISM, YMER, MRMC and VESTA. PRISM is an extensively used tool [17] and in case of large models it is considered superior than its competitors. PRISM performs the complete analysis of model and presents the best and worst cases scenarios based on the model behavior. PRISM supports the analysis of following types of model i.e. MDP, DTMC and CTMC. For performing statistical model checking PRISM supports four different methods [17].

1. CI (Confidence Interval)
2. ACI (Asymptotic Confidence Interval)
3. APMC (Approximate Probabilistic Model Checking)
4. SPRT (Sequential Probability Ratio Test)

CI

Following are the parameters of this method:

- Confidence (alpha)
- Number of samples (N)
- Width (w)

On the basis of number of samples and given confidence level, this method provides confidence interval for the approximate value generated for a property `P= ?`. Let X is the actual result of the property `P= ?` and Y is the approximation generated. Confidence level is usually denoted as 100 (1-alpha)%. This suggests that the actual result lies in the confidence interval [Y-w,Y+w]100 (1-alpha)%. We have used CI method in our analysis.

ACI

This method has same functionality as CI except that it uses Normal Distribution for approximation when finding the confidence interval.

APMC

This method, provides a probabilistic guarantee on the accuracy of the approximate value generated for a `P=?` property.

SPRT

This method is more appropriate for bounded properties, such as `P<=p[..]` and `P>=p[..]`. Based on acceptance sampling techniques, this method uses sequential probability ratio test, which generates samples series, determining while in progress when an answer with sufficiently high confidence can be given.

Chapter 4

Proposed RSLD Model

The prime target of the proposed work is to develop a comprehensive formal model of RSLD scheme in natural disaster management that can be specialized to represent any real-world RSLD scenario. For this purpose, we have identified three major components of a typical RSLD:

1. Source: where goods or medical supplies are stored and vehicles are used for the transportation of supplies

2. Destination: which provides the demands for the goods or medical supplies

3. Transportation paths: which connect the source and destination, as depicted in Fig. 4.2.

The working of RSLD model is described in Fig. 4.1.The proposed RSLD model accepts these parameters as inputs, i.e., the available set of sources and vehicles, the selected destination and its demand, and a set of all possible paths. The algorithm then returns a probability for the demand fulfillment of the destination. Next, we explain the above-mentioned three inputs in detail:

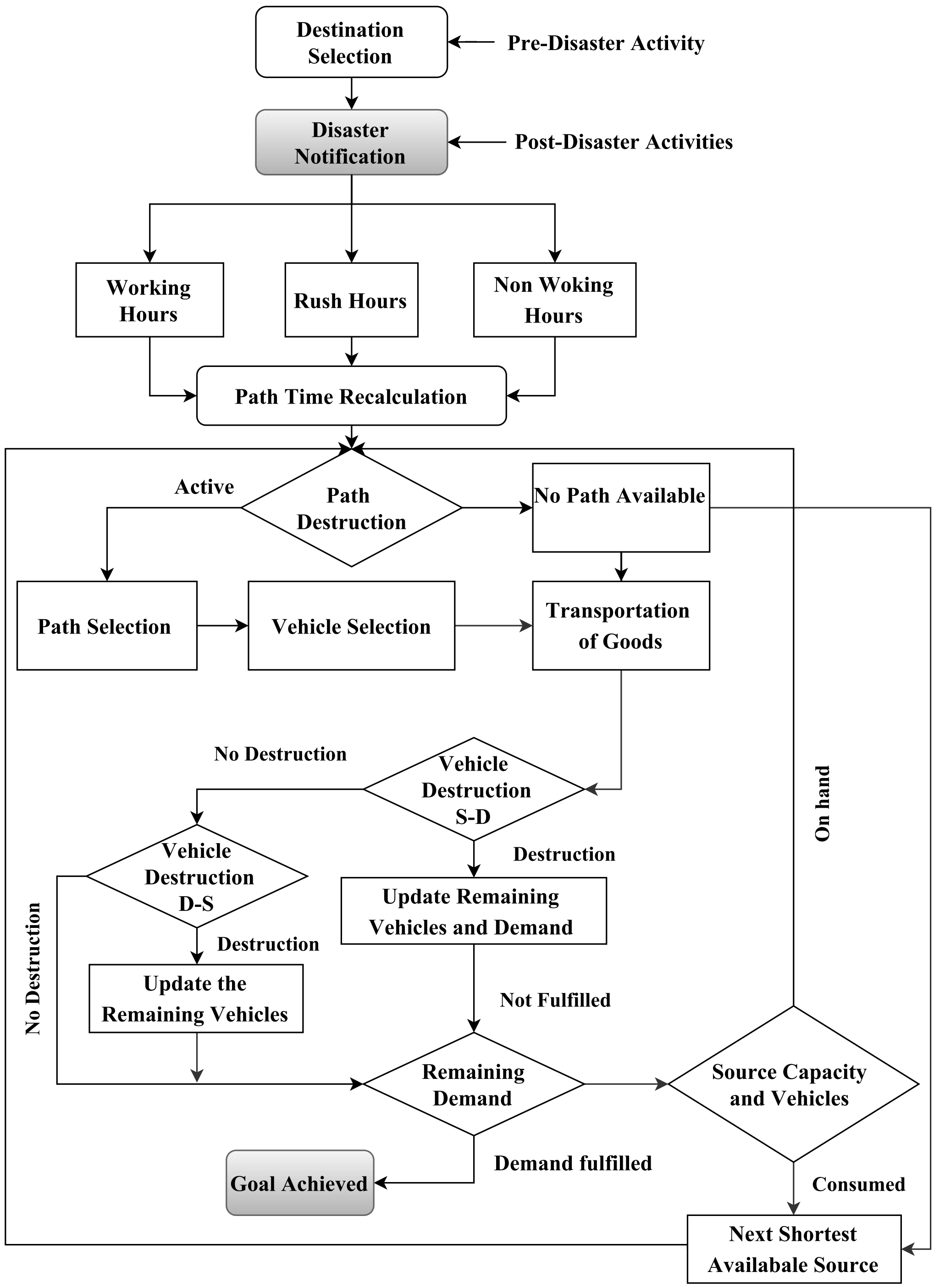


Figure 4.1: Flow Chart

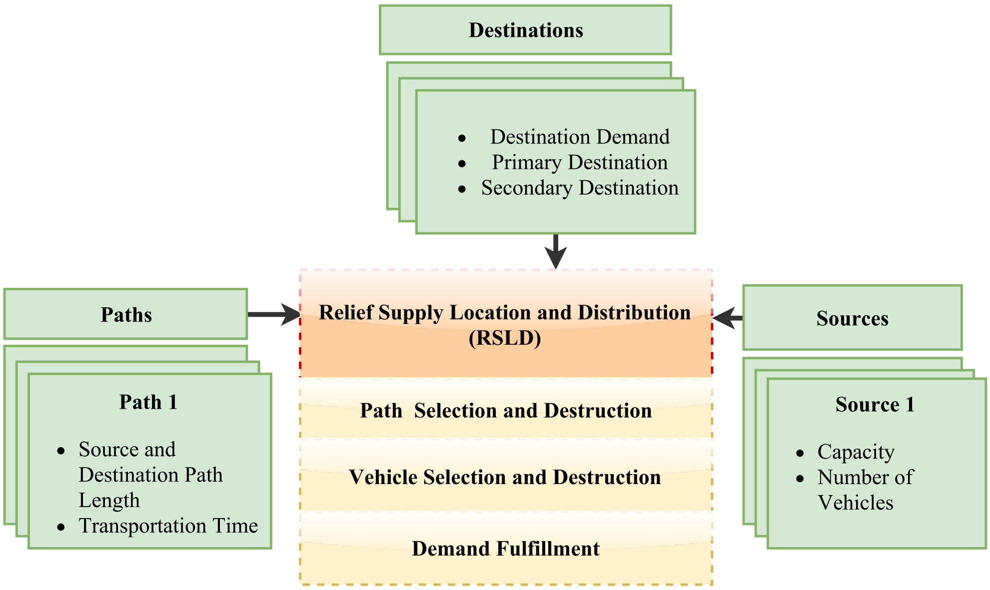


Figure 4.2: Proposed RSLD Model

4.1 Source

The source location and storage capacity for emergency supplies is the most important part of the disaster readiness process [20]. The type of sources depend on the type of disaster, i.e., earthquake, floods, volcanic eruption, windstorms etc. For example, a warehouse can be a source of commodities for earthquake based disaster. Sources are capable of satisfying the needs of one or more destinations depending upon their location and their distance from the destination. In our proposed RSLD model, we assume that sources are always available and operational to meet the required needs. This assumption is made to evaluate the quality of the underlying disaster management plan as, in the case of unavailability of sources, the required demand can never be fulfilled irrespective of the quality of the disaster management plan.

In addition to medical supplies, sources of relief supplies also have transportation vehicles to fulfill the destination demands. While deciding the transportation means, we consider two main factors: the requirements (Urgency, distance to the destination and other conditions, such as transportation routes, weather, etc.) and feasible forms of transport (available means, such as trucks, boats, planes etc., cost in terms of time, transmission capacities, etc.) [9,34]. The proposed RSLD model incorporates vehicle destruction as this event can happen with a relatively high probability during a disaster. To the best of our knowledge, this feature is not incorporated in any other RSLD scheme.

4.2 Destination

The destination is defined as the point that generates the demand to receive medical supplies or goods from the sources. The main goal of the logistics chain in relief operations is delivering the aid to the affected people [26]. The destination should be properly identified as its role is equally important in all the stages of natural disaster management - pre-disaster prevention and planning, disaster situation management and post-disaster phases of resolution and return to normality [26,33]. The successful and timely delivery of the medical supplies to their required destinations is the only way to lessen the impact of natural disasters in a scenario where the severity and frequency of natural disasters is rising alarmingly [26]. Destinations can be different with respect to the disaster type, e.g., hospitals or temporary medical centers are commonly used destination points in case of earthquakes and floods.

4.3 Paths

The transportation is a vital component in the logistic chain that ensures possible delivery of supplies from source to destination [34]. The late delivery of supplies can adversely affect the performance of RSLD. Therefore, the main challenge is to ensure secure transportation and timely delivery of supplies by choosing appropriate transportation modes (roads, waterways, air) [9,32]. In general, road and air transport is mostly used by humanitarian operations. However, other modes e.g., water can effectively support distribution activities in both logistical support to the process and the strategy of delivery. Paths or routes selected for transportation of medical supplies are also vulnerable to damage as a consequence of a natural disaster. The proposed RSLD model considers path destruction and allows the incorporation of means to select the shortest path among all the available paths.

Algorithm 4.1 : Source_Destination Module

Input:

S_Dd;Set of primary destinations for each source `s` $[D1...Dd]$, $D1$ represents destination 1 where destination range is from 1 to d

S_ExDd; Set of secondary destinations for each source `s` $[ExD1..ExDd]$, where $ExD1$ represents alternative destination 1

T_D : $[1:3]$; Disaster time (1, 2 and 3 represents working, rush and nonworking hours, respectively) and $P(D) = 1/3$

j : $[1:J]$; Number of paths

$Time\_j\_s\_Dd$: $[1:J]$; Time of each path j from source `s` to destination `h`

$Ww\_working$: $[1:K]$; Time coefficients for working hours

$Ww\_nonworking$: $[1:K]$; Time coefficients for non-working hours

Ww_rush : $[1:K]$; Time coefficients for rush hours

where

s : $[1:S]$; Number of sources

d : $[1:D]$; Number of destinations

V_s : $[0..V]$; No of Vehicles in source `s`.

C_s : $[0..C]$; Source total capacity.

C_v : $[0..v]$; Vehicle transportation capacity .

D_d : $[0..R]$; Destination Demand or Requirement.

$Ppathdes$, $[0.1...0.9]$; probability of path destruction

$Pvehdes$, $[0.1...0.9]$; probability of vehicle destruction

veh_s_Dd; No of vehicles assigned.

avg_speed; Average speed of vehicles.

$dist\_s\_Dd$; distance of destination `d` from source `s`

Xs, Ys; source `s` X and Y coordinates.

Xd, Yd; destination `d` X and Y coordinates.

Algorithm 4.1 Warehouse1-hospitalID1(continued)

Path Time Calculation:

if $Disaster = 1$ **then**

$1/3 : (T\_D = 1) + 1/3 : (T\_D = 2) + 1/3 : (T\_D = 3);$

$T\_D = (1|2|3)- > dist\_s\_Dd = (pow((Xd - Xs), 2) + pow((Yd - Ys), 2), 1/2)));$

where $dist\_s\_Dd$ is computed from distance formula;

$T\_D = (1|2|3) \rightarrow (Time\_1\_w\_IDh = dist\_s\_Dd/avg\_speed);$

$T\_D = (1|2|3) \rightarrow (Time\_j\_s\_Dd = Time\_1\_s\_Dd + random\_value);$

$T\_D = 1 \rightarrow Time\_j\_s\_Dd = Time\_j\_s\_Dd * Ww\_working;$

$T\_D = 2 \rightarrow Time\_j\_s\_Dd = Time\_j\_s\_Dd * Ww\_nonworking;$

$T\_D = 3 \rightarrow Time\_j\_s\_Dd = Time\_j\_s\_Dd * Ww\_rush;$

Path Destruction and Path Selection:

$Ppathdes : (Time\_j\_s\_Dd = Time\_j\_s\_Dd * 0) + (1 - Ppathdes) : (Time\_j\_s\_Dd = Time\_j\_s\_Dd * 1);$

where $Ppathdes$ is probability of path destruction;

$Rs\_d = min(Time\_1\_s\_Dd......Time\_j\_s\_Dd);$

where Rs_d is Route form source `s` to destination `d`;

if Rs_d != 0 **then**

path selected;

end if

Algorithm 4.1 Warehouse1-hospitalID1(continued)

Vehicle Selection:

14: **if** $total(num\_primary\_destinations) >= 1$ **then**

15: $veh\_s\_Dd = V_s/num;$

where num is number of primary destinations of source `s`

16: **else**

17: $Veh\_s\_Dd = (1/Cv) * D_d;$

18: **end if**

Vehicle Destruction:

From Source `s` towards the Destination `d`;

19: $(S\_d = s)\&V_s! = 0\&save\_v\_Dd! = 0 \rightarrow$

$Pvehdes/save\_v\_Dd : (found\_v\_Dd = save\_v\_IDd - 1) + .. + Pvehdes/save\_v\_Dd : (found\_v\_Dd = 0) + 1 - Pvehdes : (found\_v\_Dd = save\_v\_Dd)$

$S\_d = s$ represents source `s` for destinations `d`,

where $save\_v\_Dd$ is number of vehicles transported with goods on the selected path,

$found\_v\_Dd$ is number of non-destructed or safe vehicles;

20: **if** $(found\_v\_Dd = 0|found\_v\_Dd = 1|..found\_v\_Dd = save\_v\_Dd)$ **then**

21: $RD\_d = D_d + (save\_v\_Dd - found\_v\_Dd) * C_v;$

22: $V_s = V_s + found\_v\_Dd;$

where RD_d is the remaining demand of destination `d`;

23: **end if**

From Destination `d` towards the Source `s`;

24: same as line number 19

25: **if** $(found\_v\_Dd = 0|found\_v\_Dd = 1|..found\_v\_Dd = save\_v\_Dd)$ **then**

26: $V_s = V_s + found\_v\_Dd;$

27: **end if**

28: **if** $(RD\_d > 0)\&(C_s! = 0\&V_s! = 0)$ **then**

29: go to line number 9;

Algorithm 4.1 Warehouse1-hospitalID1(continued)

30: **else**

31: **if** $(RD\_d > 0)\&(C_s = 0|V_s = 0)\&(S\_ExDd = S\_Dd)$ **then**;

32: $Wh\_h = w$;

secondary source selected and goto line number 9;

33: **else**

34: **if** $(RD\_h > 0)\&(C_w = 0|V_w = 0)$ **then**

secondary source capacity is consumed or vehicles are utilized;

35: Destination demand is not fulfilled

36: **end if**

37: Destination demand is fulfilled

38: **end if**

39: **end if**

40: **end if**

Chapter 5

Modeling RSLD in PRISM

We selected MDP to develop the formal model for RSLD because it supports both probabilistic and non-deterministic selection. RSLD model has both probabilistic and non-deterministic factors. Probabilistic factors include path selection, vehicle destruction and path destruction while non-deterministic factors include path traveling time, occurrence time of disaster, selection of available vehicles [20] etc. This model can be used to analyze the critical properties by varying different RSLD parameters.

In the proposed model, `S` and `D` represent the total number of sources and destinations, `s` represents a specific source while `d` represents a specific destination with values ranging 1 to `S` and 1 to `D`, respectively. The overall model consists of two modules: `Source_P_Destination` and `Source_S_Destination`. The first represents primary destinations and the latter corresponds to secondary destinations of a source `s`. The inputs of the model are described in Algorithm 4.1. The working of our RSLD model is divided in two kinds of main activities, i.e, pre-disaster and post-disaster activities.

5.1 Pre-disaster

The pre-disaster activities include the coverage of RSLD schemes that are meant to materialize before the disaster occurrence, e.g., destination selection. In the proposed methodology, we use the minimum distance from the sources as the foremost criteria for destination selection [20]. The original map of the affected area is used to calculate the distance from each source to the destination, which is then used to determine the primary destination, i.e., the nearest destination for a source, and the secondary destination.

5.2 Post-disaster

Post-disaster activities include the coverage of events that are meant to materialize after the disaster occurrence, e.g., the affected area identification. The disaster event is categorized into rush hours (R), working hours (W) and non-working hours (N) based on its occurrence time [20]. The disaster time `T_D` is selected non-deterministically in our model as shown in Algorithm 4.1.

To proceed further, the transportation time of all the paths from the source to the destination is calculated. The modeling of this step in PRISM is performed by calculating the normal transportation time by dividing the distance between the source `s` and its all possible destinations, with `J` paths, with the average speed of the vehicle, as shown in Algorithm 4.1.

The next step is to check the path availability based on the damages caused by a disaster event, e.g., landsliding and path destruction. As shown in Algorithm 4.1, if the path with the minimum transportation time is available then it is selected for transportation, otherwise next available shortest path is opted.

To proceed further, the transportation resources are chosen, i.e., the number of vehicles meant for transporting medical supplies from source to destination. The RSLD model keeps an update regarding the status of vehicles while sending medical supplies on a selected path from source to destination and vice versa. On detection of a vehicle destruction, the model recomputes the number of vehicles and the destination demand. Upon demand fulfillment the target of the model gets accomplished, otherwise the next alternate source for the destination is selected based on the minimum distance criteria. These set of activities will continue until the destination demand is fulfilled. As shown in Algorithm 4.1, the vehicle selection activity is performed according to the number of primary destinations, i.e., the vehicles are distributed equally. In case of one primary destination, vehicles are distributed according to its demand, as shown in the Vehicle Selection part of Algorithm 4.1. The selected vehicles `veh_s_Dd` carrying medical supplies are transported to the destination accordingly. Afterwards, the vehicle destruction along-with demand fulfillment of destination is checked. Based on above output, the remaining demand of destinations `RD_d`, remaining capacity of sources `RC_s`, and remaining vehicles `RV_s` are computed. In case of vehicle destruction, the remaining demand of the destination `RD_d` and remaining vehicles `RV_s` are updated accordingly, as shown in the Vehicle Destruction part of Algorithm 4.1. If no vehicle destruction occurs, then only the total number of available vehicles `V_s` are updated. Similarly, vehicle destruction from a destination to a source is monitored and the total number of available vehicles `V_s` are updated. Afterwards, if the remaining demand of the destination `RD_d` is greater than 0 and the remaining source capacity `RC_s` or remaining number of vehicles are consumed then destination `d` selects the secondary source located at the shortest distance. Otherwise, the destination selects the same source for demand fulfillment. The destination demand is completed if the remaining demand `RD_d` becomes 0.

Chapter 6

Formal Verification of RSLD

We have proposed the verification framework for the functional verification and performance analysis of RSLD. The same is exhibited in Fig. 6.1.

The major components of verification framework are RSLD modeling and performance parameters. The factors involved in RSLD modeling are sources, destinations and paths, as described in the previous two sections. After modeling a set of functional properties based on the working description of the given RSLD scheme is identified. The functional properties ensure the precise and accurate working of RSLD schemes. These properties are represented by the LTL operators that are available in the PRISM model checker. The PRISM model checker provides quantitative information about these properties, which can play a vital role in developing effective RSLD schemes.The RSLD performance parameters are used to analyze the impact of varying probability of path destruction, number of destinations, expected time and vehicle destruction, on the demand fulfillment of a destination. The sub-attributes of vehicle destruction are number of lost vehicles and the probability of vehicle destruction. The transportation of medical supplies from source to destination require available paths and vehicles and it depends on

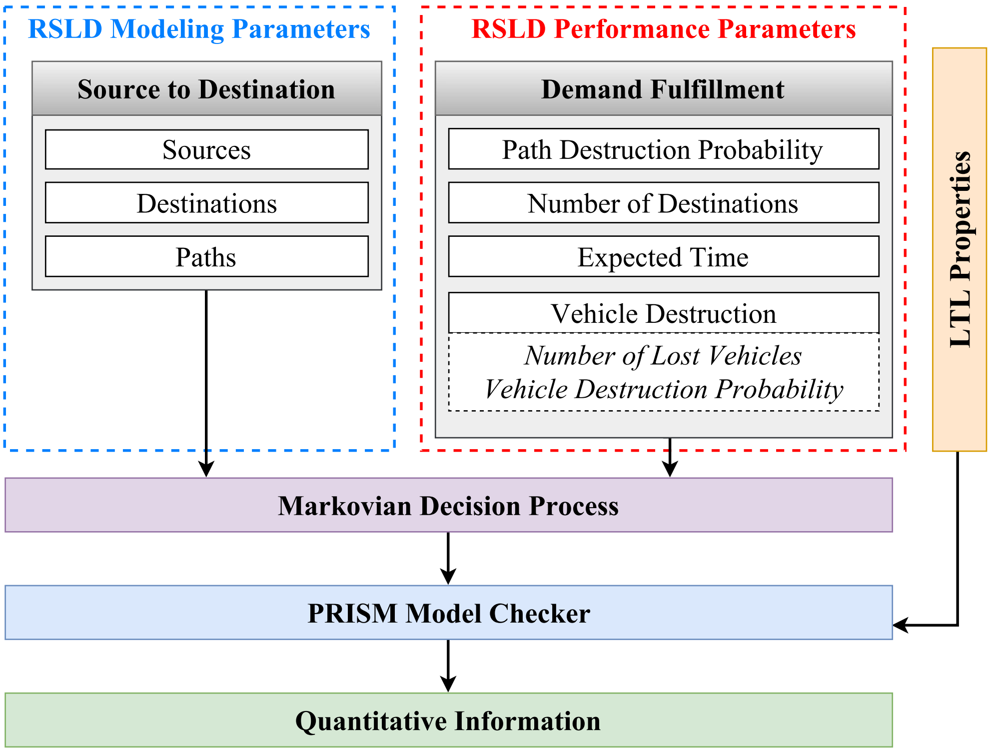


Figure 6.1: Verification Framework

a highly vulnerable transportation system which make it a critical parameter in the analysis. Demand fulfillment is analyzed with respect to varying number of destinations instead of number of sources to study the capability of a source to fulfill the demand of multiple destinations.

We now provide a set of properties to formally analyze the functionality of scenarios with respect to sources and destinations. For instance, probability of eventually fulfilling destination demand is exhibited by LTL property:

$$P =?[F \;\; RD\_d \;\; = 0 \;\; \& \;\; var\_d\_n \;\; = 1] \tag{6.1}$$

where `RD_d` represents the total demand of destination `d` with an associated flag `var_d_n`. The destination `d` varies from 1 to `D` and `n` corresponds to the number of primary destinations of source `s`. This property evaluates the probability of demand fulfillment of a destination `d` with respect to a source. Property 6.1 corresponds to demand fulfillment of destination `d` when `RD_d` becomes 0 and `var_d_n` updates its status to 1. Property 6.1 can also be used for the verification of demand fulfillment of primary and secondary destinations.

It is quite important in the case of disasters to meet the destination demand within a certain time. This makes the expected time a vital parameter in assessing the performance of RSLD schemes. Keeping it in view, we have proposed another property which evaluates the probability of destination demand fulfillment with respect to the expected time.

$$\begin{gathered} P =?[F \;\; RD\_d \;\; = 0 \;\; \& \;\; var\_d\_n \;\; = 1 \;\; \& \\ estimatedtime\_Dd <= expectedtime\_Dd] \end{gathered} \tag{6.2}$$

Property 6.2 corresponds to the demand fulfillment of destination within expected time when `RD_d` is set to 0, `var_d_n` updates the status as 1 and the estimated or computed time of demand fulfillment `estimatedtime_Dd` is less than or equal to the expected time `expectedtime_Dd`. Expected time is computed by taking into account the best and the worst case scenarios of the given RSLD scheme and the estimated time is the approximate time computed by number of steps involved in hospital demand fulfillment in PRISM. Best case scenario is when there is no path and vehicle destruction and warehouse has maximum capacity for hospital's demand fulfillment and worst case scenario is when there is only one path available having maximum transportation time, vehicles also get destruct on the way or the warehouse has not enough capacity to fulfill its hospitals demand.

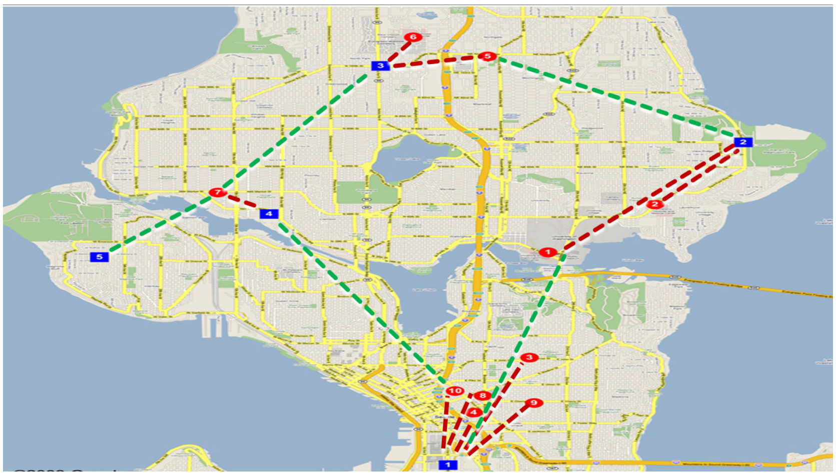
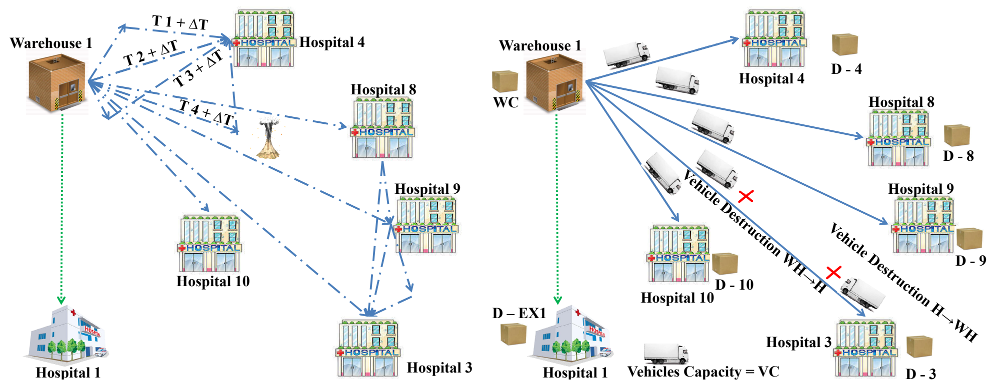


Figure 6.2: Seattle Map with hospitals and warehouses

6.1 RSLD in Seattle,USA

For illustration purposes, we applied the proposed RSLD model on a real world scenario, as shown in Fig. 6.2 for RSLD. We used the occurrence probabilities of different disasters from a previous work, on analyzing RSLD in Seattle [20]. The probabilities of having a disaster in Seattle is considered to be 0.4 [20]. The disaster onset probability is further divided into three different probabilities, based on its occurrence time, i.e., probability of having a disaster during working (`TD = 1`), rush (`TD = 2`) and nonworking hours (`TD = 3`) are 0.275, 0.175 and 0.55, respectively [20].

Seattle contains five warehouses represented by square boxes and ten hospitals represented by circles, as shown in its map in Fig. 6.2. Each warehouse selects a set of primary hospitals ranging from `1` to `5` and a secondary hospital ranging from `1` to `2` on the basis of shortest distance. Warehouse `1` has five primary hospitals, i.e., `3`, `4`, `8`, `9` and `10` and a secondary hospital `1` as shown in Fig. 6.3a. Warehouse `1` has multiple available paths to connect with a hospital. The transportation time for different available paths between warehouse `1` and hospital `4` are labeled as `T1`, `T2`, `T3` and `T4`. After disaster occurrence, the path transportation times `T1`, `T2`, `T3` and `T4` are updated, based on the occurrence time of the disaster, i.e., working, rush and non-working hours, to `T1+ΔT`, `T2+ΔT`, `T3+ΔT` and `T4+ΔT` where `ΔT` represents the change in time as shown in Fig. 6.3a, and it's value is different for different paths. Similarly, the post-disaster transportation times against all other hospitals are computed.



(a) Path Selection after disaster (b) Vehicle Selection and Destruction

Figure 6.3: Case Study: Scenario

Warehouse `1` checks the availability of all active paths and the paths having minimum transportation time are selected for shipping relief supplies to the respective hospitals. Fig. 6.3b depicts a scenario of vehicle selection and its destruction from warehouse to hospital `(WH→H)` and from hospital to warehouse `(H→WH)`. `WC` is the warehouse capacity, `VC` is the vehicle capacity, `D-EX1` is the demand of secondary hospital 1 and `D-3`, `D-4`, `D-8`, `D-9`, `D-10` are the demands of the corresponding primary hospitals. In Fig. 6.3b, the paths between the warehouse and hospitals with minimum transportation time are shown. Vehicles available at warehouses are assigned to all primary hospitals and relief supplies are transported on the pre-selected paths. Thereafter, we perform for vehicle destruction check to update the status of vehicles along with the demand of hospitals.

To verify the demand fulfillment property of any primary hospital, e.g., Hospital `3` of Warehouse `1`, we modified the generic Property 6.1 as follows:

$$P =?[F \ \ rem\_H3 = 0 \ \ \& \ \ var\_ID\_1 \ \ = 1] \tag{6.3}$$

where `rem_H3` is the remaining demand of hospital 3 and `var_ID_1` is its associated flag. The same property is used for the verification of demand fulfillment of other primary and secondary hospitals of Warehouse `1`. Warehouse `1` depending upon its capacity will fulfill the demand of its secondary hospital if secondary hospital's demand is not fulfilled by the assigned warehouse and the demand of its all primary hospitals is met. Similarly, we used Property 6.1, to verify the demand fulfillment of all the primary hospitals by adding hospitals in the property as follows.

$$\begin{aligned} &P =? \ F \ \ [rem\_H3 = 0 \ \ \& \ \ var\_ID\_1 \ \ = 1 \ \ \& \ \ rem\_H4 = 0 \ \ \& \\ &var\_ID\_2 \ \ = 1 \ \ \& \ \ rem\_H8 = 0 \ \ \& \ \ var\_ID\_3 \ \ = 1 \ \ \& \ \ rem\_H9 \ \ = 0 \ \ \& \\ &var\_ID\_4 \ \ = 1 \ \ \& \ \ rem\_H10 = 0 \ \ \& \ \ var\_ID\_5 \ \ = 1] \end{aligned} \tag{6.4}$$

The above property is used for verifying the demand fulfillment of primary and secondary hospitals of other warehouses i.e., 2,3,4 and 5. The proposed model can be used to obtain very interesting insights about the given RSLD by varying the probability of vehicle and path destruction, the number of hospitals, warehouses and vehicles. We have used PRISM version 4.3 with 64-bit Windows 7 and PC 8 GB RAM, default maximum path length (10000), confidence (0.01) which is 99% confidence level, number of samples (100000) and simulation method CI (Confidence Interval) for the verification of the properties. The probability of error or the probabilistic bound for each of the verified property is approximately 0.004.

In order to analyze the RSLD for the given case study, we computed the fulfillment probability of hospital demand against path and vehicle destruction probability by using property described above. For example, Figs. 6.4a and 6.4b depict the demand fulfillment probability of primary hospitals (`3`, `4`, `8`, `9` and `10`) for the scenario consisting of one warehouse and six hospitals (five primary and one secondary hospital) against the probabilities of vehicle and path destruction, respectively.

The graph in Fig. 6.4a exhibit a decreasing trend in hospital demand fulfillment probability with respect to an increase in the probability of vehicle destruction assuming no path destruction. Moreover, we also change the hospital demand, i.e., Hospital `3` has the maximum demand (4) and Hospital `10` has a minimum demand (1), to analyze its impact on the demand fulfillment probability. We can thus deduce that with the increase in hospital demand, the impact of vehicle destruction increases. Similarly, for the same scenario, the probability of hospital demand fulfillment decreases with an increase in path destruction probability assuming no vehicle destruction as shown in Fig. 6.4b.

We also analyzed the hospital demand probability within expected time for the same scenario. For illustration of the effect of expected time on demand fulfillment, the demand fulfillment of a single hospital, i.e., Hospital `3` of warehouse `1` is plotted against the probabilities of path and vehicle destruction by varying expected time. The required time or the expected time is the time stated by respective hospitals to meet their corresponding demands. The values of expected time are selected based on the best and worst cases of hospital demand fulfillment time. In Fig. 6.5a, the demand fulfillment of

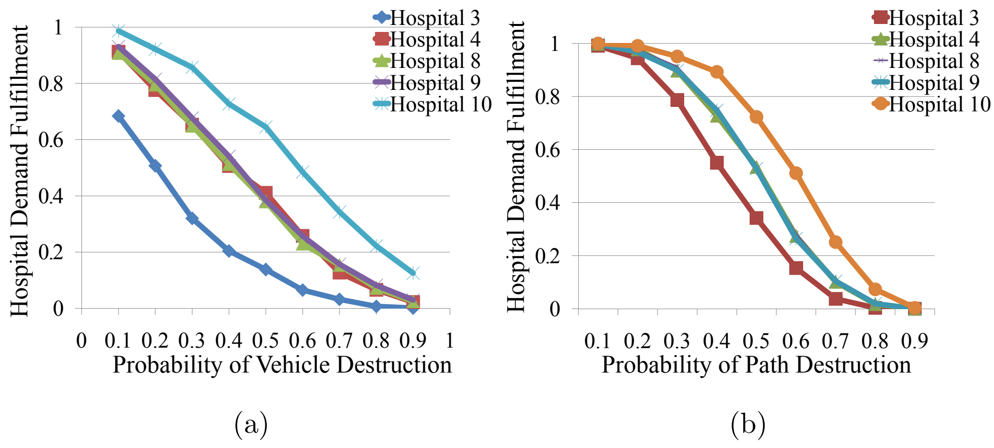
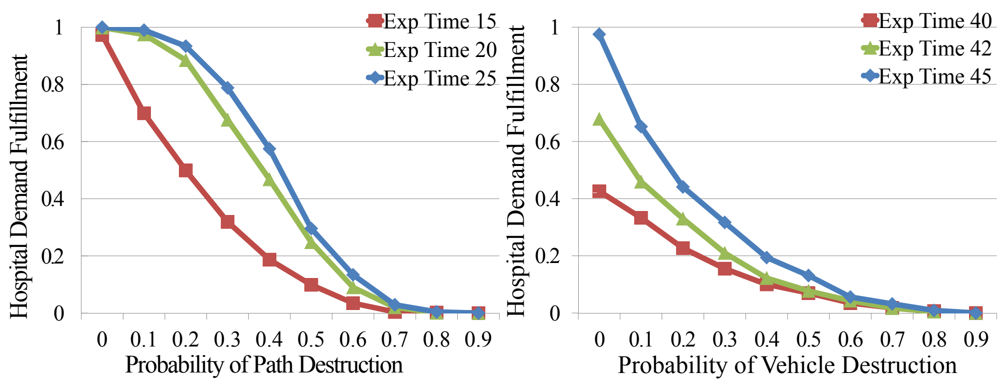


Figure 6.4: Demand fulfillment of Hospitals Vs Probability of Vehicle and Path Destruction

a hospital within a expected time of 15, 20 and 25 units is observed based on the probability of path destruction with no vehicle destruction. The slope of the curve for expected time equal to 15 is higher as compared to the other two until the region where the probability of path destruction becomes 0.3, afterwards the blue and green lines exhibits a larger slope. This trend enables a disaster manager to route its vehicle on potentially safe paths (to avoid vehicle destruction) in case of having strict constraints on the required time and route remaining vehicles on alternate paths to efficiently fulfill the demand.

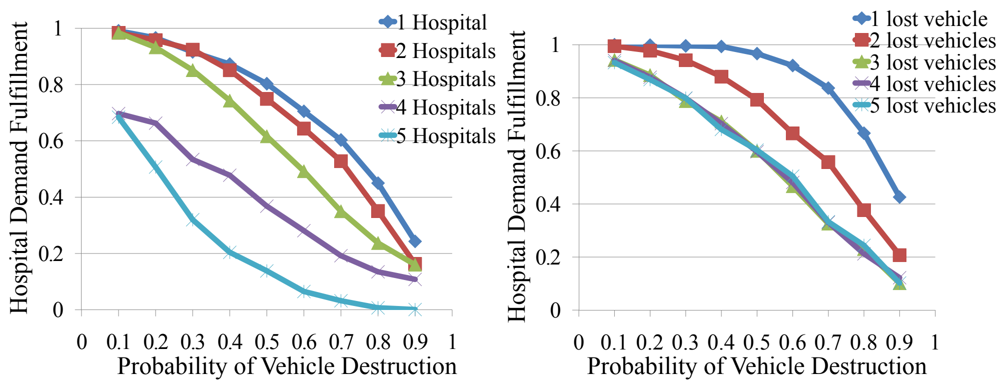
Fig. 6.5b, shows the relationship of the demand fulfillment of Hospital 1 with an expected time of 40, 42 and 45 units. All the curves exhibit a decreasing trend in hospital demand fulfillment with respect to an increase in probability of vehicle destruction assuming the safe path. This experiment indicates that a curve with a larger expected time has more probability of demand fulfillment and a larger value of slope as compared to a curve with a smaller expected time. This trend enables a disaster manager to route the mechanically fit vehicles (to avoid vehicle destruction) to hospitals having



(a) (b)

Figure 6.5: Demand fulfillment of a Hospital V Probability of Path and Vehicle Destruction with in expected time

larger expected time and route the remaining vehicles to hospitals having smaller expected times to efficiently fulfill the demand.



(a) (b)

Figure 6.6: Demand fulfillment of Hospital Vs Probability of vehicle destruction w.r.t number of hospitals and number of vehicles lost

We also analyzed the effect of the number of served internal hospitals and number of lost vehicles on the probability of demand fulfillment. Fig. 6.6a exhibits a decreasing trend in hospital demand fulfillment with respect to an increase in probability of vehicle destruction for different number of served hospitals ((`1-5`) by Warehouse `1`. It is evident from the graph that the demand fulfillment of the hospital decreases with an increase in the number of serving hospitals for a specific value of probability of vehicle destruction, because of resource sharing, i.e., capacity and number of vehicles at a warehouse. Similarly, Fig. 6.6b shows a decreasing trend in hospital demand fulfillment with respect to an increase in the number of lost vehicles and probability of vehicle destruction.

RSLD scheme comprises of a large number of random variables, that is why it produces gigantic database of scenarios. This complexity is tackled in the SP models by using Monte Carlo simulations. The SP model reduces the total number of scenarios by using the method of sample average approximation. On the other hand, the proposed analysis method either provides a complete analysis if all the paths are analyzed otherwise a probabilistic bound on the analysis error is provided, which is one of the distinguishing features of statistical model checking compared to simulation. The usage of a formal model for the analysis is another feature that makes statistical model checking superior than traditional simulation based analysis. A number of random factors have been incorporated by our methodology, i.e., location of warehouse and inventory level, path destruction and vehicle destruction. All of these factors, to the best of our knowledge, have not been incorporated simultaneously in any existing RSLD management scheme.

Chapter 7

Conclusions

7.1 Summary

This paper presents a generic methodology and verification framework to model and verify any given RSLD scheme and analyze its effectiveness during different natural disaster scenarios. We primarily utilize statistical model checking to analyze the impact of critical and uncertain parameters, such as path and vehicle destruction. The proposed analysis enables the disaster manager to opt a proactive approach in accomplishing the hospitals demands in varying scenarios. In order to illustrate the usefulness of the proposed methodology, we used it to analyze a real-world RSLD scenario based in Seattle. The analysis results demonstrate the effectiveness of the proposed methodology.

7.2 Future Work

The methodology can be used to formally analyze other domains of natural disaster management such as emergency evacuation.

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