Evaluation of Disaster Response System Using Agent-Based Model With Geospatial and Medical Details

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***Abstract*—Many disasters have occurred around the world and have caused sizable damage. A disaster, called a mass casualty incident (MCI), generates a large number of casualties that overwhelm the capacity of local medical resources, and the disaster responses to the MCI requires many interactions among the disaster responders. To evaluate the efficiency of the disaster responses against MCIs, this paper proposes an agent-based model describing the cooperations among the responders during the overall process in the disaster responses from transporting patients to their definitive care. In particular, the proposed model includes geospatial details, such as the road network and the location of hospitals around the disaster scene, and medical information, such as the distribution of medical resources and transporting units, in the region of interest to discover the key factors of the disaster response system that customized to the target region. The case study in this paper presents that the proposed approach was applied to describe a disaster response system and illustrates how the additional details are utilized to analyze the disaster response system. We expect that the proposed method can provide comprehensive insights to a disaster response system of interest, and it can be used as groundwork for improving the disaster response system.**

***Index Terms*—Agent-based model, disaster response system, geospatial and medical details, mass casualty incident (MCI).**

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I. INTRODUCTION

THE scale of urban disasters varies from small incidents (e.g., a house fire and a car accident) to serious disasters (e.g., massive transit accidents and building collapse). During the serious disasters, massive casualty incidents (MCIs), emergency medical services (EMSs), such as personnel and equipment, are overcome by the number and severity of casualties [1]. Recently, MCIs have been observed around the world, such as the 911 attacks in 2001 and the Haiti earthquake in 2010, and there have been several reports that MCIs caused by natural and man-made disasters had brought about 2.6 billion casualties in the 2000s [2], [3].

While a formal declaration of an MCI is usually made by an officer or chief of the agency in charge, such as the Federal Emergency Management Agency (FEMA) in the U.S., it can be declared by the first unit arriving at the disaster scene. Once an MCI is declared, various responders, such as ambulances, firefighters, police officers, and hospitals, are deployed for the rescue, and the rescue mission is managed by an incident command system to establish a unified command to run all aspects of the MCI [4]. When an MCI is declared, the first arriving responder will check the condition of victims at the disaster scene; based on the triage result, victims will receive a temporary medical care for stabilizing their condition, and then they will be transported to a hospital for receiving definitive care.

Due to the imbalance of disaster victims and responders, the victims are keen to be distinctively situated with little systematic support. Such situations dictate that the victims and the responders follow their instincts as well as drilled routines in hopes that the combination of such behavior mechanisms will result in fewer casualties and damages to our society. Prior to the disasters, we can prepare ourselves and our society to mitigate the challenge by establishing disaster response policies as well as deploying necessary logistical supports in advance. Having said that, our question is how to measure the quality and the quantity of our preparedness against unforeseen MCIs.

The evaluation of the preparedness might be qualitatively made by subject-matter experts, and these experts opinions matter most in the real world because they know the field and events from the past. Also, historic data provide us with scenarios to prepare for the conventional disasters. However, what if we have to prepare ourselves for unconventional disasters that have never been observed in the real world? Preparing for such unseen disasters requires guidance

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beyond expert opinions and historic data because the events are yet unchartered. One feasible way to mitigate this difficulty is artificially to generate the potential disasters and to model and simulate our preparedness for the virtual disasters to measure our performance. This approach of modeling and simulation (M&S) has been widely used to explore unnoticed situations in various fields, such as biology [5], urban-growth [6], military [7], and economics [8].

The M&S approach is also not new to the field of disaster management; rather, it is frequently utilized in the disaster response field [9]–[14]. However, many simulation models in the field are limited to considering one perspective of disasters. For instance, fire spread models, flooding models, and bombing models from [12] and [13] included the geospatial characteristics of disasters and provided in-depth representations about how the spatial distributions of resources and damages would evolve over time. These models leaned toward regional modeling, and physical and spatial modeling of disasters. While looking at the big picture and regional hypothetical situations, they did involve the details of modeling disaster response operations; in other words, they were keen to anticipate the effect of the disasters in terms of the number of casualties, but they may not shed light on the storyline of how the casualties are rescued, delivered, and stabilized with details of medical operations. In contrast, the models containing medical backgrounds decide their scopes of in-hospital activities, e.g., operations in the emergency department (ED) [15], [16]. Frequently, these models deliver the hospital as an abstract process and the victims as an object to be processed. This is quite understandable because there exist protocols for handling patients in the ED, and modelers assume that the personnel in the ED follow the protocols. These medical simulators were often either very specific as to the level of surgical operations on patients or very location-oriented as to the scope of the emergency rooms or hospital operation rooms (ORs).

This paper introduces an agent-based model describing the EMS in an MCI situation; in particular, the model contains the geospatial and medical details associated with the MCI situation so as to fill the gap between prehospital delivery and in-hospital care over the course of the disaster response. Authors who are experts in the disaster and the emergency medicine have noticed communication problems between the personnel in the prehospital and in-hospital settings, and their experience reveals that prehospital care, triage, and transportation decisions have the utmost impact on the victims' remaining care. This would not be solved only by optimizing either rescue and transportation or hospital care. In spite of their conjecture, the logs of prehospital and in-hospital care are separately maintained, one by the fire department and related services and the other by the hospital administration, so it is difficult to generate convincing arguments from the separated and incomplete log data on rarely or unseen disasters. Therefore, we were motivated to build a simulation model that encompasses the whole operation of the EMS, in disaster scenarios, from the rescue of the victims at disaster scenes to the definitive treatment of the victims in hospitals.

Our model starts from the declaration of an MCI at the disaster scene, and the model simulates the prehospital care (e.g., the rescue operation, triage process, transportation of victims) and the in-hospital care (e.g., care in the ED, and the potential diversion and transfer of victims). This simulation scenario includes the geospatial elements of transportation and the deployments of key resources, such as ambulances and hospitals, as well as the in-hospital care elements, i.e., the number of ORs, number of ED doctors, number of X-ray rooms, etc. Moreover, the protocols and practices in the transportation and hospital care are modeled and implemented, such as the field triage rules, disaster response team operation procedures, the operation priorities in the ED, and transportation priorities. This model enables us to investigate the overall procedure of the EMSs in an MCI situation.

The proposed model was applied to evaluate the disaster preparedness of Gangnam District in Seoul, South Korea. We incorporated the geospatial and medical details on the target region and conducted virtual experiments with varying these details. From the experimental results, we discovered that the quality of ambulances (standardized coefficient in linear regression: −0.12) and number of X-ray rooms, doctors, and ORs (standardized coefficient: −0.11, −0.22, and −0.64) in hospitals are significantly important factors for better disaster preparedness in the target region. Also, we performed the in-depth analysis on disaster response systems using the micro-level information from the proposed agent-based model. Specifically, we defined micro-level performance measures on the prehospital and in-hospital phases, and these performance measures provided us explicit insights for the future disaster response systems of the target region.

II. Related Works

Many research papers have been conducted for improving disaster responses, and mathematical and M&S techniques are applied to analyze and optimize the responses. This section introduces some of the papers and shows the distinctiveness of the proposed model with the previous ones.

A. *Mathematical Models for Disaster Responses*

Mathematical models handling disaster situations are based on optimization techniques, such as linear programming, mixed integer linear programming (MILP), and multicommodity network flow model, and these models have been utilized to develop evacuation processes and identify optimized response network structures. For example, Barbarosoğlu and Arda [17] proposed a two-stage stochastic programming model to plan the transportation of vital first-aid commodities to disaster areas during emergency response, and Chien and Korikanthimath [18] investigated the relationship between delay and evacuation time and found the optimal number of evacuation stages through their mathematical models. Shahparvari *et al.* [19] and He *et al.* [20] discovered optimized evacuation processes through a multiobjective optimization model and an MILP model, respectively.

To improve the efficiency of disaster responses, geospatial features need to be considered. For example, to reduce the transportation time to hospital, the responders decide their transportation route considering the road network and the

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hospital locations around disaster scenes. While most of the previous works often neglected or abstracted geospatial features, some recent works incorporated the geospatial factors into their mathematical models; Yi and Özdamar [21] developed a mixed integer multicommodity network flow model for coordinating logistics support and evacuation operations in disaster response activities, and Chiu and Zheng [22] proposed the cell transmission model based on linear-programming for emergency response in disaster situations, and the proposed model considered geospatial features, such as length, speed limit, and number of lanes of roads.

While geospatial features are relevant with the prehospital delivery, medical resources, such as the number of doctors and medical equipment, will affect the in-hospital care. Several research papers utilized the medical features as constraints in their mathematical models; for instance, Na and Banerjee [23] proposed an MILP and minimum-cost flow model called the triage-assignment-transportation model, and the model decides the routing strategy of evacuation considering disaster situations and medical resources. Caunhye *et al.* [24] formulated a mathematical model with several medical features, such as treatment and triage capacity, which provides the optimized disaster response supply chain for faster casualty transportations.

There have been many comments that both geospatial and medical information are critical to analyzing disaster damages and leading the success in disaster responses [25]–[27]. We have reviewed several research papers about disaster responses, but most of the papers had a tendency of focusing on one of those factors. Only Na and Banerjee [23], to our best knowledge, noted that geospatial considerations will be incorporated into their model in their further work. One reason of this scarcity might be that it is hard to formulate mathematical models considering various factors simultaneously.

B. Simulation Models for Disaster Responses

While mathematical models for disaster responses aimed at optimizing evacuation polices and disaster response networks, simulation models were applied to analyzing disaster situations and discovering better alternatives to mitigate disaster damages [28]. Various simulation models, such as probabilistic [29], [30] and queuing [31] models, have been introduced, but most of the simulation models are formed as agent-based models because the organization structure and policy in disaster responses have to be taken into account to simulate a real emergency activity [32], [33].

Agent-based models for disaster responses have been developed to discover efficient disaster plans and better decision making in disaster situations by focusing on human behaviors [34]–[38]. For example, Pluchino *et al.* [34] introduced an agent-based model for pedestrians' evacuation using belief-desire-intention model [39] which is used to describe human practical reasoning process. Teo *et al*. [35] considered the importance of social capital from past disasters and integrated the social capital to their agent-based model.

Some agent-based models had geospatial and medical features, so more practical solutions are provided. For example, March proposed an agent-based models using geographic information system (GIS) for improving short-term disaster management activities. Also, Bae *et al.* [14] and Montz and Zhang [40] developed their agent-based models depicting bombardment and hurricane evacuations using GIS. Contrary to the details on the geospatial features, they were based on critical assumptions, such as infinite medical supplies. One research covered both geospatial and medical features in an agent-based model, yet the features were not from the real data.

Details on the geospatial and medical features are critical to understand and analyze disaster response systems, so the previous works incorporated such data on their models. However, their data utilizations were confined from the following perspectives.

1) The geospatial features were described using abstracted or synthetic data.
2) The demand and supply of medical resources was not considered within the disaster medical procedures.
3) The previous works did not consider both geospatial and medical features concurrently.

This paper proposes an agent-based model where disaster responders are cooperated to rescue victims in an MCI situation, and this cooperation would be conducted within the considerations of the geospatial information around the disaster scene (e.g., road network and location of hospitals), and the medical details about the prehospital care (e.g., triage and transportation with the limited resources) and in-hospital behaviors (e.g., hospital processes and capacity).

III. Model Development

The proposed model includes various responders and environmental aspects in MCI situations, and they are closely related with geospatial and medical details in the disasters. This section: 1) introduces the disaster scenario that the proposed model considered; 2) enumerates which features are considered, how and why as well; and 3) illustrates how the selected features are constructed as an agent-based model.

A. Disaster Response Scenario and Victim Profile

We hypothesized a disaster scenario where an MCI occurs in a crowded convention center in Gangnam region. Our disaster scenario starts from an event of MCI in any case of a large-scale fire, gas leak, or building collapse that would decide the configuration of hypothetical victim profiles in our model. Furthermore, this approach enables us to abstract the cause and the progress of the disasters, and we build more detailed models on the EMS perspective.

Responding to the MCI, the central agency, called the emergency management agency (EMA), controls the overall disaster response mission. Fig. 1 represents the process of the disaster response that our model describes. The procedure consists of three phases: 1) *before MCI*; 2) *prehospital delivery*; and 3) *in-hospital care*.

When receiving an emergency call about mass casualties, the EMA declares an MCI, which occurs in the before MCI phase. In the prehospital delivery phase, the EMA dispatches

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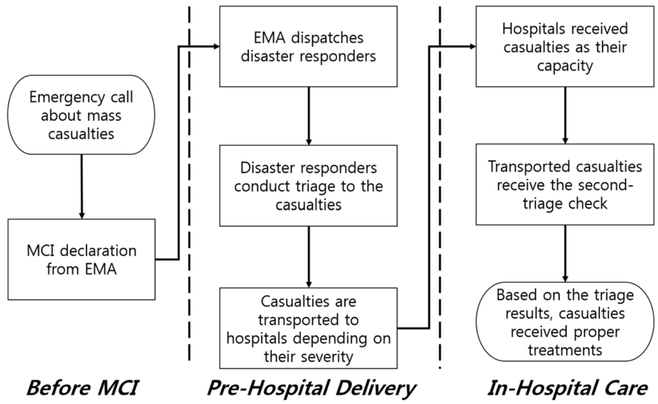

Fig. 1. Disaster response procedure for the hypothesized MCI.

disaster responders, such as ambulances for transporting casualties to hospitals and medical resources for emergency treatment of severely injured casualties. Arriving responders first conduct a triage test to check the status of casualties. If any emergent patients, i.e., red and black triaged patients, are identified, they are transported immediately; otherwise, the responders would move around to search and test other casualty. After delivering all the emergent patients, the responders transport the remainders, which were relatively slightly injured. However, each hospital has limitations on its capacity; some of them might be go to find another hospital, which is called a diversion case.

When the casualties arrive at the hospitals, the in-hospital care phase begins. The arriving casualties go through the second triage test because the triage results from responders at the disaster scene might be in error due to their limited skills and equipment. Based on the second triage test and additional scanning, such as X-rays, the casualties that requires definitive care, such as operations and receive appropriate treatments. However, due to the limited number of doctors and ORs, some casualties might be sent to another hospital for the faster treatment, which is called a transfer case.

In the disaster response procedure, several decision-making points would exist, such as how to efficiently distribute casualties to hospitals for less diversion cases and how to efficiently deploy medical resources in hospitals for less transfer cases. Such issues should be investigated under the overarching disaster response procedure; in other words, these issues are considered from both prehospital and in-hospital perspectives. Moreover, due to the insufficient resources compared to the number of casualties from an MCI, disaster responders are not well coordinated, but tend to save casualties autonomously, and the success of the rescue would be significantly affected by the road network and the volume and location of medical resources. Hence, we proposed an agent-based model describing the overall disaster response procedure with geospatial and medical details.

The victim profile that we used is created by the subject-matter experts among the authors. This dataset describes 2013 individual victim types specifying the cause of the injury, the implicit survival rate curve, the requirement of surgery, the usual number of X-rays taken, the number of sutures needed, and the triage difficulty. Fig. 2 shows the descriptive statistics of the victims. Each victim has an evaluation on the seriousness of his or her injury: *black*, *red*, *yellow*, and *green*. This follows the triage method named *Simple Triage and Rapid Treatment* [41], [42]. Black means that the victim is dead or about to die, and red means that the victim will die unless he or she receives medical care immediately. Yellow and Green mean that the victim will be alive without immediate care. Our victim profile holds a predetermined and true designation of this triage result, but our simulated responders will conduct a triage check to victims with an error probability for illustrating their limited resources at MCIs.

B. Modeled Features in MCI Situation

The presented simulation model aims at generating the disaster victim care from rescue to definitive care. This simulation scope requires including the field entities and the in-hospital resources at the same time. The modeled field entities related to prehospital delivery are listed below.

1) *Victims* are the casualties who require medical care at the disaster scene. Their vital signs as well as their implicit survival rate curve are modeled, but the vital sign and curve are not visible to the disaster responders in the simulation. The behavior of the victims is described in Section III-C.
2) *Ambulances* are the entities that transport the victims to the hospital where, the victims receive the definite care that terminates their status as victims. The modeled ambulances are categorized into three different types, those with a level 1 emergency medical technician (EMT) licensed by the government, those with a level 2 EMT, and the para-medical transporter that has no medical expertise. These different levels of ambulances have different abilities in treating and triaging victims.
3) Disaster Medical Assistance Teams (DMATs) are the entities responding to the disaster scene. The DMATs consist of ED doctors and nurses who are able to correctly triage victims and provide basic medical assistance to them.
4) *Field EMS* consists of a truck and the assigned personnel that responds to the scene with a much slower speed than other responders because of the medical resources on board. Despite its slow response, once deployed, the field EMS becomes the center of the triage and the treatment on the scene with much higher throughput compared to the DMAT.
5) *Hospitals* are the ultimate emergency medical resource where victims can receive correct triage and proper treatments, such as X-rays and operations if needed. Once the victims get the treatments, they will reach the safe state.
6) *EMA* is the agent in charge of managing the MCI situation, similar to the FEMA in the U.S. Specifically, the EMA takes in the disaster situation through the emergency calls and communications with the responders, and it commands the responders to save more casualties.

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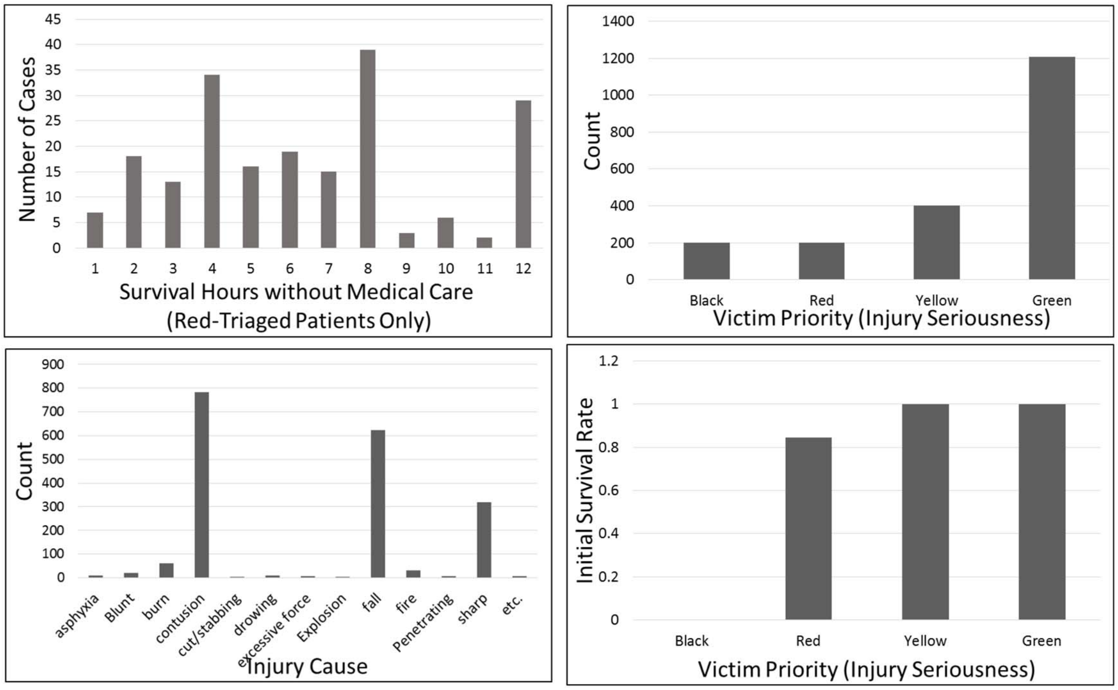

Fig. 2. Descriptive statistics of the victim profiles created by the subject-matter experts.

However, given the considerable volume of information about MCIs, the EMA does not always provide the optimal instructions to the responders.

The following is a list of in-hospital care resources. These are resources deployed to each hospital, and the resource amounts are different by the hospital size and its disaster preparedness level, which is assessed and designated by the National Emergency Medical Center (NEMC) in South Korea. By law, the level of disaster preparedness dictates the amount of resources to be maintained by hospitals.

1) *Beds* are the fundamental resources limiting the number of patients to be admitted to a hospital. Beds basically refer to monitored beds that victims with serious injuries can use.
2) *ED doctors* are the resources to splint and suture the critical wounds. They provide care to the victims prior to the surgical operations if needed. If victims do not require operations, they are treated definitely by the ED doctors.
3) *X-ray rooms* are the resources to identify and assess the critical injury. For this objective, various resources, such as an ultrasonar scanner, CT, etc., are used in the ED, but our subject-matter experts acknowledge that the X-ray rooms are the bottleneck of the ED operation because monitored beds have ultrasonar scanners, and CT is not as frequently used as X-rays in disasters responses.
4) *ORs* are the ultimate resources to stabilize the victims who need surgery. Hospitals have a limited number of ORs, and the numbers are differentiated by their levels and sizes.

The environmental features in the proposed model mainly originates from the traffic aspect (i.e., road network) around the disaster region. This paper experiments a disaster in the Gangnam region, where the road network is dense and complex. Based on the simulation scenario, our road network environment includes both main avenues and lanes where the responders can move. The road network consists of road segments and junctions, and the average speed of the road segments is collected from the National Transport Information Center in South Korea [43]. Our traffic information is collected by assuming that the disaster occurred at 5:00 P.M. on Friday, which is the busiest hour and in the busiest district of South Korea [14].

C. Model Description

This section describes the proposed model, called the EMS simulator (EMSSim), integrating the entities introduced in Section III-B. EMSSim is developed by large-scale, dynamic, extensible, and flexible (LDEF) formalism [44] and its corresponding simulation environment. LDEF formalism is a variant of the dynamic structured DEVS formalism [45]. Specifically, LDEF formalism consists of two elements, a *behavioral model* for describing a part of the system behavior and a *dynamic structural model* for representing the system structure, which can be changed during the simulation execution. We utilized LDEF formalism for the following reasons.

1) To clearly present the structure and the behavior of our model.
2) To incrementally compose and develop the simulation models.

1) Model Composition and Structure: The proposed model is hierarchically composed with multiple agents, i.e., disaster responders, and environments, i.e., geospatial features (see Fig. 3). EMSSim is the highest-level hierarchy model

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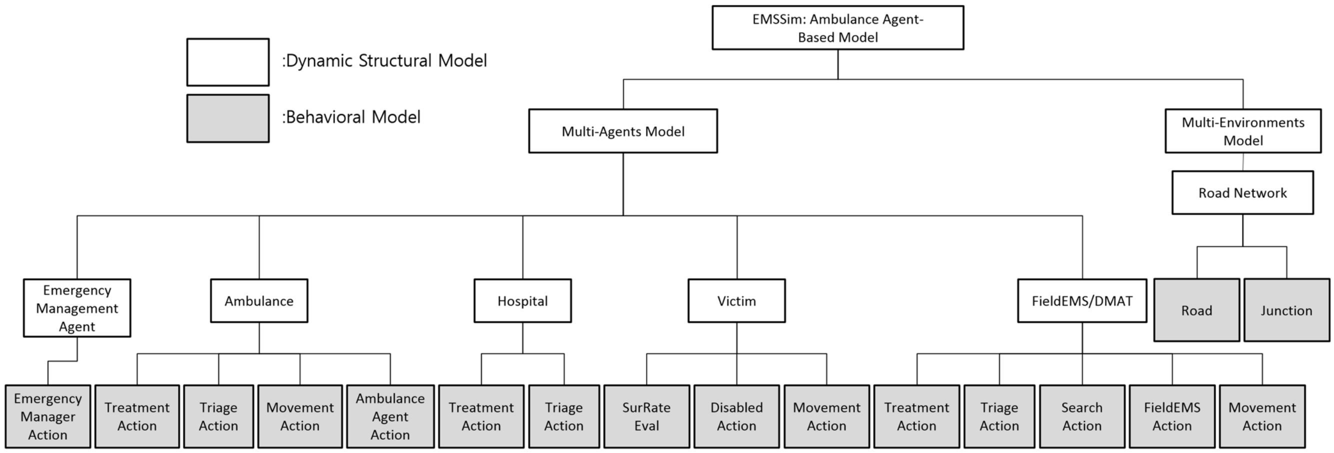

Fig. 3. Hierarchical structure of the proposed model, EMSSim.

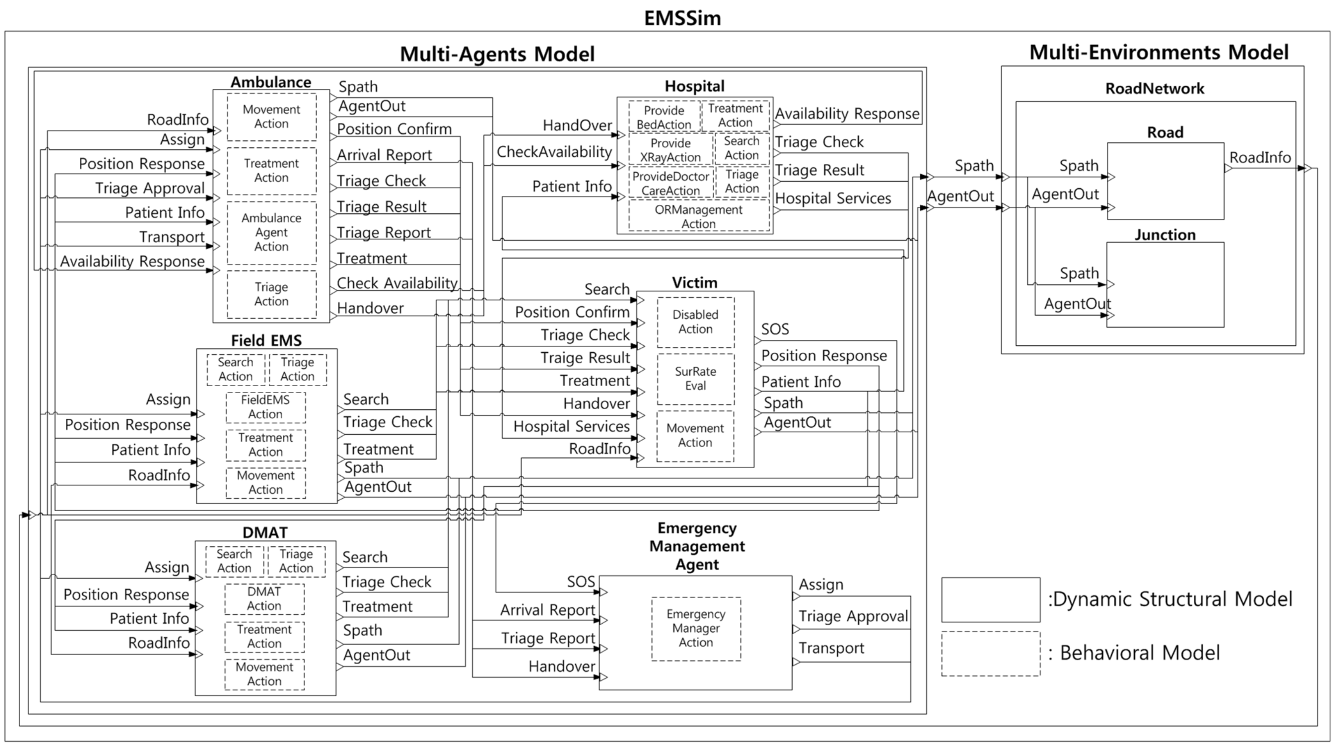

Fig. 4. Coupling relations among disaster responders and environments in EMSSim.

that consists of the multiagents model and the multienvironment model. The multiagents model includes the responders (i.e., EMA, ambulances, field EMS, DMAT, and hospitals) as well as the victims. Each responder exhibits different behavior characteristics, so the associated model reflects such diversity through the various compositions of action models; for example, Field EMS and DMAT are responsible for identifying victims, so they have the search action while the ambulances do not have the search action. Additionally, a hospital does not move to the scene, so the movement action is not involved. On the other hand, the medical actions, such as triage and treatment, are common behaviors performed by all of these medical responders, so they are included in all responder models. Having said that, the behavior of the common model in different responders can be varied by different model parameters. The victim has the SurRate behavioral model that calculates the survival curve of the agent, and the behavior determines when the victim will die. Fig. 4 represents the coupling relations among components in EMSSim to enable the model hierarchy. We used the DEVS diagram notations [46] to show a more transparent view of the model designs.

2) Model Behaviors: Components in EMSSim simulate interactions via messages through the dynamic coupling structures, and the fundamental drivers of the simulation progress are its behavioral models (e.g., atomic model in DEVS), which corresponds to the leaf node of the model hierarchy. Such notion comes from the concept of DEVS formalism where

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TABLE I
BEHAVIORAL MODELS IN EMSSIM AND THEIR FUNCTIONS

Responders	Behavior	Explanation
Emergency Management	Emergency Manager Action	Managing the overall disaster response procedures
Ambulance	Ambulance Action	Conducting triage check and transportation by EMA orders
Victim	SurRate Eval Action	Describing the change of survival rate of the victim over time
	Disabled Action	Requesting rescue and describing the immovable state by the injures
FieldEMS and DMAT	FieldEMS /DMAT Action	Conducting triage checks and providing treatments to victims at the disaster scene
	Search Action	Identifying victims at the disaster scene
Common	Triage Action	Describing a triage check to victims
	Treatment Action	Providing treatments to victims
	Movement Action	Moving to the destination through the road network

the atomic model is only able to generate and consume timed events with state transition and time advance functions.

EMSSim contains various behavioral models that are interconnected through the coupling relations of the associated dynamic structural models, and the composition of the behavioral models represents the behavior of the responders. Table I briefly presents a list of the behavioral models and their functions. Among them, this section presents the model diagrams of three representative behavior models, such as emergency management action, disabled action, and ambulance agent action. These models are selected because their interactions are tightly linked with each other, and they play an important role during the disaster response. Fig. 5 represents three DEVS diagrams about the three behavioral models.

Events that are generated from or consumed by the behavioral models are forwarded from the coupling structure in Fig. 4, and the event exchanges proceed as the simulation progresses. Because it is difficult to regenerate the progress and the interaction between the models, we provided our design for the sequential message exchanges in Fig. 6.

D. Model Parameters

Table II provides the list of simulation parameters and our parameter settings for the virtual experiment design of this paper. We only varied some of the listed parameters. Additionally, some parameters are collected from the real world and from the subject-matter experts, and they are not going to be changed unless the experiment hypothesizes that such changes are enabled in reality; the bold parameters indicate that they are used as experimental variables in the following experiments.

One of key features in EMSSim is representing the change of the survival rate of the victims. The idea of generating and utilizing victim profiles was introduced in the past works from various fields [47]–[49]. However, the previous models did not provide the mathematical formulation of the individualized survival curve, which we introduce here.

The death of a victim is caused by four main factors: hemorrhage shock (hours to die without any treatment), asphyxia (minutes or an hour to die without any treatment), a mixed cause of hemorrhage shock and asphyxia, and a mixed cause of hemorrhage shock and traumatic brain injury. We differentiated the curve shape according to the causes of death, and the method calibrates the logistic function to show the part of the curve. The logistic curve can represent quick death by the asphyxia, sudden death by traumatic brain injury, and the continual and constant decrement by the hemorrhage. Fig. 7 represents the shape of the logistic functions and the correspondence of the used parts. By utilizing this originating function of the survival rate, each victim profile has a calibration of the curve shape by setting its own logistic function parameters (e.g., k, L, t_0, and y_0)

$$\text{SurvivalRate}(t) = \frac{L}{1+\exp(k(t-t_0))} + y_0 \qquad (1)$$

where t = simulation time, and others (e.g., k, L, t_0, and y_0) are function parameters to be calibrated for the victim profiles.

IV. CASE STUDY: MCI IN GANGNAM REGION

This section introduces a case study using the EMSSim. The case study hypothesized an MCI occurred at Korea World Trade Center, a famous multipurpose conventional center in Seoul, at 5.00 P.M. of Friday. In the following sections, the disaster scenario, the performance measures, and the experimental design applied to the case study are illustrated.

A. Disaster Scenario and Key Performance Indicator

The case study was designed to evaluate the disaster response system of Gangnam District. The Gangnam region is a metropolitan district with a population density of over 24 070 people per km^2 when including floating populations. In the Gangnam District, there are five major hospitals with EDs: four local emergency medical centers and one local emergency medical institution, and 20 ambulances are distributed within nine EMS base stations and the five major hospitals. Details about the are of interest in the case study are presented in Table III.

To measure the efficiency in the disaster response, we suggested a performance measure, called preventable death ratio (PDR). PDR is the fraction of the expected number of dead patients who would not be dead if definitive care was immediately given [see (2)]. It is calculated with the ratio of "the expected number of survived patients" to "the expected number of patients who would be survived if a definitive care is provided." Hence, lower PDR would indicate more efficiency of the disaster response system

$$\begin{aligned}\text{PDR}(\%) &= \frac{\sum_{i=0}^{N}\left(P_0^i - P_f^i\right)}{\sum_{i=0}^{N} P_0^i} \times 100\\ &= \left(1 - \frac{\sum_{i=0}^{N} P_f^i}{\sum_{i=0}^{N} P_0^i}\right) \times 100 \qquad (2)\end{aligned}$$

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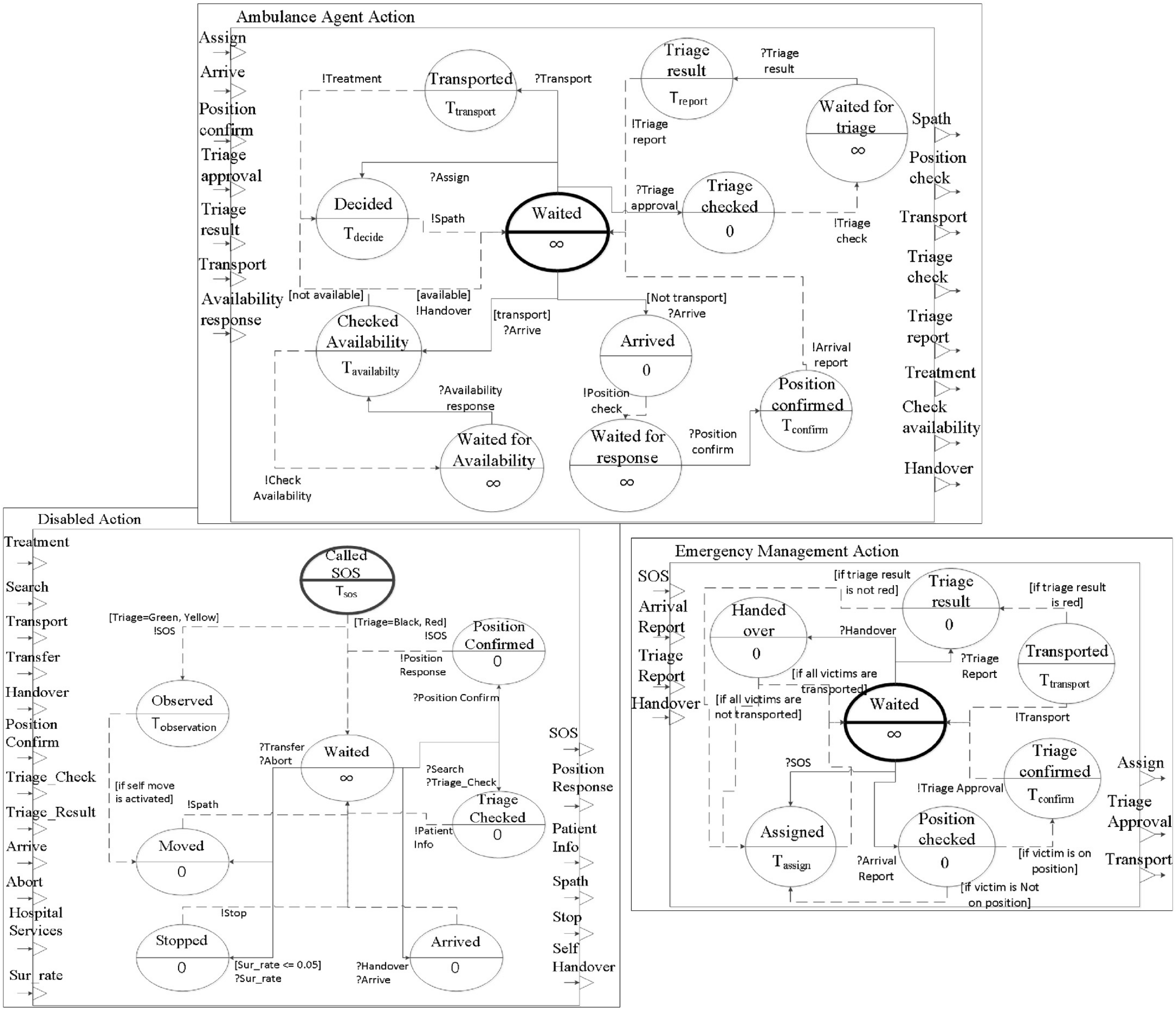

Fig. 5. State transition diagram of three action models: emergency management action, disabled action, and ambulance agent action. The diagrams follow the notation of the DEVS atomic model formalism.

where N = total number of victims, P_0^i = initial survival probability of victim i, and P_f^i = final survival probability of victim i.

Applying statistical methods to the simulation results, It is possible to find key factors to the performance measure. However, the simulation results are difficult to present why these factors are identified in the simulation scenario. Such interpretations are invaluable because they can provide further insights to establish the future disaster responses of the target region. This paper presents such an analysis, called in-depth analysis, on the simulation scenario.

The in-depth analysis was conducted using the micro-level information from the simulation model, such as sojourn time of medical processes and average number of dead patients in a hospital. The EMSSim was designed by the integration of patient and hospital components, so it is easy to obtain the micro-level information through the components logs, which is one reason why we utilized the agent-based model approach.

B. Experimental Design

The experimental variables are selected from the model parameters, particularly, considering the prehospital and in-hospital phases. For the prehospital phase: 1) the number of ambulances; 2) ratio of level 1 EMTs in ambulances; and 3) number of DMATs were selected. In particular, the proposed model assumes that level 1 EMTs have more accuracy in disaster response operations, such as triage, treatment, and hospital selection, than level 2 EMTs. The DMAT is organized with doctors and nurses from major national hospitals. It conducts a triage test of multiple victims and provides a treatment to stabilize victims' status.

For the in-hospital phase: 1) the maximum capacity of hospital admission; 2) the number of X-ray rooms; 3) the number

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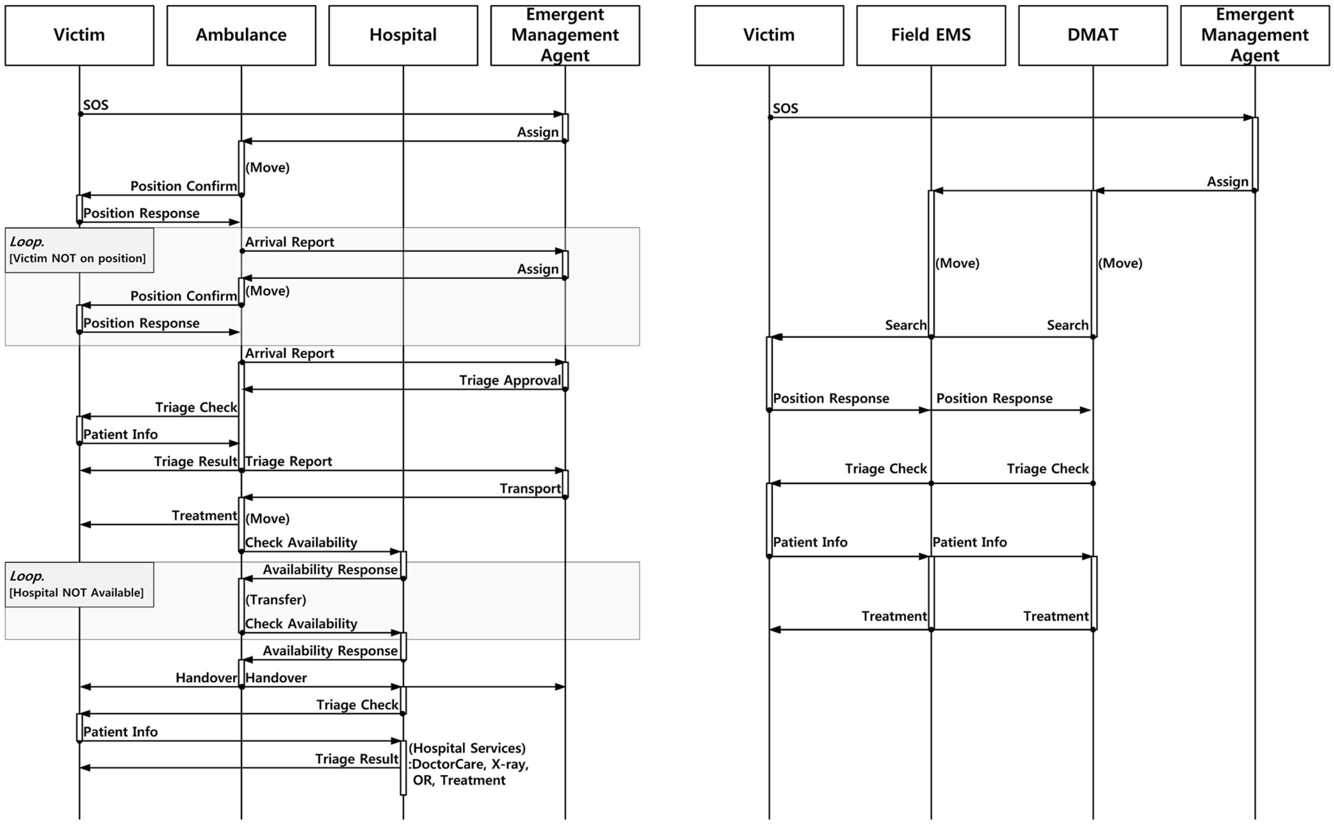

Fig. 6. Sequential diagrams about the event exchanges over the simulation execution. Left: the first phase of the simulation rescues the victims from the scene through the interactions between victims, ambulances, and EMA. At the final stage of the transportation, the hospital interacts with the ambulances and the victims. Right: in the middle of the rescues, the field EMS and the DMAT provide the search, the triage, and the treatment to the victims, and they also deliver information to the EMA.

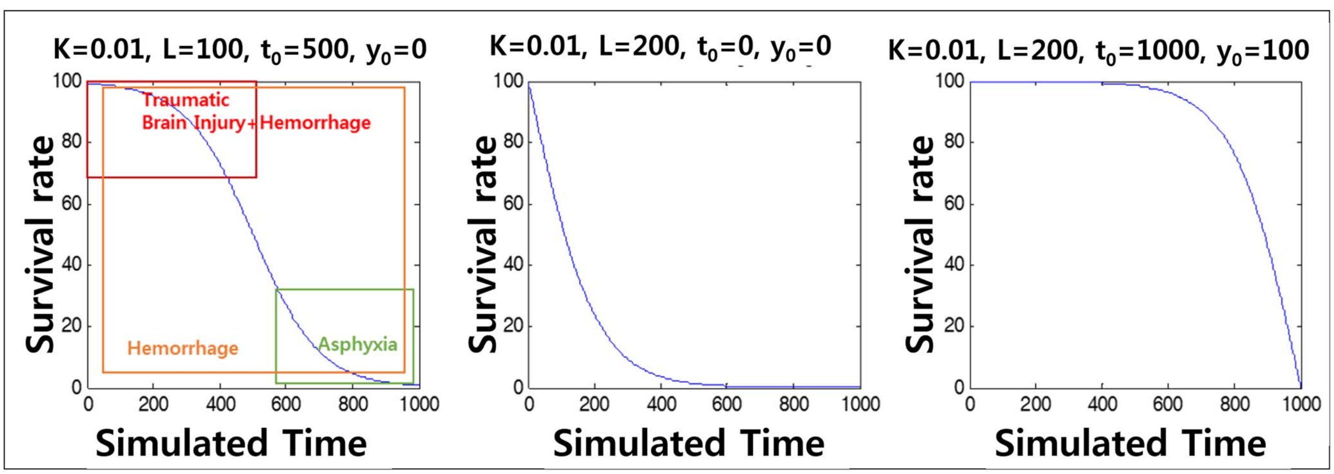

Fig. 7. Original function of the survival rate curves. A part of the logistic curve shape is used to represent the survival rate change by an injury type. Additionally, individual victims have their own shape parameters, which are k, L, t_0, and y_0, to calibrate the individualized curve.

of ED doctors; and 4) the number of ORs were considered. the maximum capacity of hospital admission is determined based on the number of beds in the ED of each hospital, and the number was provided by the NEMC in South Korea. Table IV represents the experimental design based on the selected variables.

We considered seven variables and their alternatives in the experimental design, so evaluating their effectiveness to the performance measure requires 1458 cases by the full-factorial design. The full factorial design generally provides significant insights from statistical analyses but, in this case, it costs considerable time and resources at the same time. Hence, we applied the fractional factorial design to our design of experiments. Specifically, we adopted L18 orthogonal array with 18 rows and 8 columns for the experimental setting. The values of each column indicate the level of each experiments variable. Since we only have seven factors (experimental variables), the last column is ignored. Orthogonal arrays have been

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TABLE II
MODEL PARAMETERS USED IN EMSSIM. THE VALUES OF THE MODEL PARAMETERS ARE DETERMINED BY THE CORRESPONDED VALUES IN THE REAL WORLD, SURVEY FROM SUBJECT-MATTER EXPERTS, AND MEASURES FROM THE SIMULATION EXECUTION (BOLD PARAMETERS ARE USED AS EXPERIMENTAL VARIABLES IN THE FOLLOWING EXPERIMENTS

Model	Parameter	Value	Implications
Multi-Agents Model	**Num. of ambulances**	Varied in the experimental design	Number of ambulances in the simulation
	Num. of hospitals	Real world	Number of hospitals in the simulation
	Num. of field EMS	Real world	Number of Field EMS in the simulation
	Num. of DMAT	Varied in the experimental design	Number of DMAT in the simulation
	Num. of victims	80 victims	Number of victims in the simulation (Black: 10, Red: 20, Yellow: 30, and Green: 20)
Multi-Environments Model	Target region	Gangnam, Seoul	Region of interests in the simulation
	Disaster scene	WTC conevention, Seoul	Center coordinate of the disaster a source point and a radius of disaster scene in the target region
Victim Agent	Current position	Random around the disaster scene	Current coordinate of the victim from the geographical perspective
	Used victim profile	From the subject-matter experts	Index of the victim profile used to generate the simulated victim from 2013 victim profile cases
Ambulance Agent	Initial position	Real world data	Initial coordinate of the ambulance in the simulation
	Ratio of level 1 EMTs	Varied in the experimental design	Ratio of level 1 to level 2 EMT (level 1 : level 2) in the ambulance
	Prob. of treatment success	From the subject-matter experts	Probability of the success on the interventions by the ratio of level 1 EMTs
	Prob. of triage success	From the subject-matter experts	Probability of the correct triage test by the ratio of level 1 EMTs and the victim case
FieldEMS and DMAT Agent	Initial position	Real world data	Initial coordinate of the ambulance in the simulation
	Search radius	From the subject-matter experts	Radius of search, treatment and triage
Hospital Agent	Location	Real world data	Geographical coordinate of the hospital
	Max. capacity of hospital	Varied in the experimental design	Number of patients that the hospital maximally afford to take care
	Num. of ED doctors	Varied in the experimental design	Number of emergency department (ED) doctors in the hospital
	Num. of X-ray rooms	Varied in the experimental design	Number of X-ray rooms in the hospital
	Num. of ORs	Varied in the experimental design	Number of operation rooms (ORs) in the hospital

widely used for experimental design, especially in Taguchi method [50]. Although the orthogonal array designs are criticized for its limitation in the calculation of interactions between factors, but it still provides enough representation to identify key factors among experimental variables. Summing up the arrays of same level of a factor makes the effects of other factors stack up to zero under the additive effect model assumption. Comparing average values of each level, key parameters that have the most effect on the performance can be inferred. The reduced experimental design using L18 orthogonal array is shown in Table V. Each experiment set is replicated 15 times.

V. RESULT ANALYSES

Based on the simulation results from the above experimental design, the effectiveness of the experimental variables on PDR is investigated. The following section observes the variation of PDR related to the experimental variables, and provides statistical analyses and meta-modeling analysis to the simulation results.

A. *Performance Analysis*

Fig. 8 represents the differences of PDR caused by varying the conditions of medical and transportation resources. The largest and smallest value of PDR from the 18 experimental cases were calculated as 50.5% and 24.6%, respectively. They indicate that the experimental variables in the worst and the best case were fairly distinct: the input factors were set as the lowest quality for the worst configuration (experiment set 1); on the other hand, the best configuration (experiment set 3) had the maximum number of medical resources and the ambulances while the other two factors (i.e., ratio of level 1 EMTs and DMATs) were set as the lowest level (see Table VI).

Fig. 9 represents the effects plot of each experimental variable. As shown in Fig. 9, ratio of level 1 EMTs, the number of X-ray rooms, the number of ED doctors, and the number of ORs seem to have negative correlations to PDR. These experiment results shown in Figs. 8 and 9 imply that the efficiency

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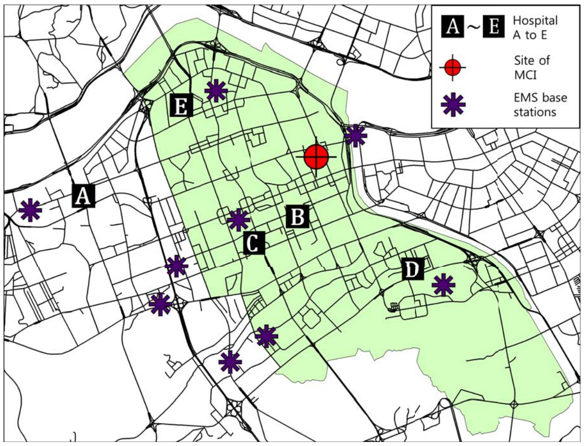
TABLE III
SUMMARY OF TARGET AREA AND MCI INFORMATION

	Gangnam district of Seoul city
Characteristics	Metropolitan district
Area	39.55 km^2
Emergency medical centers (total 5 centers)	4 local emergency medical centers 1 local emergency medical institution
Ambulances (total 20 units)	10 ambulances in nine EMS base stations 2 ambulances in each hospital
MCI Cite	Korea World Trade Center
MCI Time	Friday, 5 pm
Victims in MCI	Overall 80 victims (Black:10, Red:20, Yellow:30, Green:20)



of the disaster management would be altered by the conditions of resources and operations.

We conducted an additional experiment with the optimal setting of the experimental variables (the optimal column in Table VI), which is set as the best levels of each factor determined by marginalized average PDR. We see that the PDR was increased by applying the combination of the best levels (23.8%), which is the best performance within the simulation results. Also, this result implies that our fractional factorial design is sufficient to identify main factors of the disaster response system.

B. t-Test and Meta-Modeling Analysis for PDR

To statistically see the effectiveness and the robustness of the experimental variables, t-test and meta-modeling analyses were performed. Specifically, t-test was performed to check whether PDR values evaluated from the simulation results were significantly different, and meta-modeling with linear regression analyses was conducted to evaluate to identify the key factors as well as their influence power and robustness.

Table VII presents the results of t-test with t-stats of the experimental variables and their p-values. The results represent that while the prehospital variables did not make any significant difference on PDR, the number of ED doctors and the number of ORs significantly decreased PDR when they were increased (i.e., negative t-stats with p-value under 0.05), which is similar to Fig. 9 and Table VI.

Meta-modeling results with the standardized coefficients and p-value of the experimental variables are summarized at

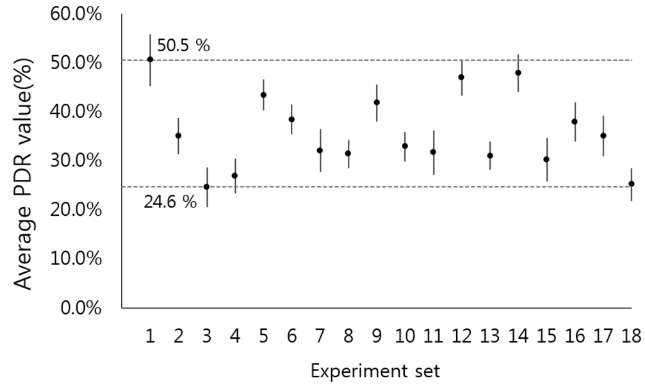


Fig. 8. Average PDR over the experiment sets. Bar indicates 95% confidence interval and dotted line represents the lowest and highest value.

Table VIII. According to the absolute values of standardized coefficient, key factors are enumerated in descending order as the number of ORs (−14.281), the number of ED doctors (−4.877), and ratio of level 1 EMTs (−2.687) to the number of X-ray rooms (−2.485). This result indicates that by controlling the key factors we can mitigate PDR from the target disaster response.

Based on the identified the key factors and their influence power, it seems that the quantity of medical resources and quality of transportation resources is critical to reducing PDR from the hypothesized MCI scenario. In particular, according to the size of the coefficients, the medical resources are more important, so we can see that reducing the processing time in the in-hospital phase is a prior task to mitigate damages from an MCI in Gangnam district.

C. In-Depth Analysis: From Geospatial and Medical Perspectives

The in-depth analysis was performed for investigating the reasons of the key factors to PDR from the micro-level view. The following sections introduce: 1) the recorded measures during the simulation execution that are correlated with the performance measure and 2) the in-depth interpretations from the geospatial and medical perspectives given in the target region.

1) Correlation Analysis Between Statistics and Performance Measure: Since the EMSSim describes the overall procedure of disaster response at the micro-level (with agents), we calculated the additional statistics related to the disaster response process. For example, the sojourn time of suture and splint processes, which are provided by ED doctors in hospitals, can be measured by aggregating the waiting and the operation time for the processes of each victims in the simulation. To filter out processes that are significantly related to the PDR, the Pearson correlation analysis between the PDR and the simulation statistics was performed. Then, we selected the five top simulation statistics considering the absolute value of the correlation coefficient (see Table IX).

The correlation results are consistent with the meta-modeling analyses; it represents that the factors about the in-hospital process are critical to the efficiency of the disaster responses system. For reference, the sojourn time in the

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TABLE IV
EXPERIMENTAL DESIGN FOR THE EMSSIM: VARYING EXPERIMENTAL VARIABLES FROM THE PREHOSPITAL AND THE IN-HOSPITAL PHASES

Experimental variables	Variation cases	Implications
Pre-hospital phase		
Ratio of level 1 EMTs	0.4, 0.6, 0.8 (3 cases)	Ratio of level 1 to level 2 EMTs in each ambulance
Num. of ambulances	10, 20, 30 (3 cases)	Number of dispatched ambulances during the simulation
Num. of DMATs	1, 2 (2cases)	Number of dispatched DMATs during the simulation
In-hospital phase		
Max. capacity of hospital	200, 250, 300 (%) × Number of beds in ED of each hospital (3 cases)	Maximum number of patients that can be admitted to each hospital
Num. of X-ray rooms	50, 100 (real world), 150 (%) × Number of X-ray rooms of each hospital (3 cases)	Number of X-ray rooms in each hospital
Num. of ED doctors	50, 100 (real world), 150 (%) × Number of ED doctors of each hospital (3 cases)	Number of ED doctors in each hospital
Num. of ORs	2, 3, 4 (3cases)	Number of ORs of each hospital
Total cases	1458 cases	$3 \times 3 \times 2 \times 3 \times 3 \times 3 \times 3 = 1458$ cases
Reduced cases	18 cases	Reduced cases by the orthogonal array method (Each case is replicated 15 times)

TABLE V
DETAILS ABOUT THE ORTHOGONAL ARRAY USED IN REDUCING THE EXPERIMENTAL DESIGN

Experiment Set	Ratio of level 1 EMTs	# of Ambulances	# of DMATs	Max. capacity of admission	# of X-ray rooms	# of ED doctors	# of ORs
1	0.4	10	1	200 %	50 %	50 %	2
2	0.4	20	1	250 %	100 %	100 %	3
3	0.4	30	1	300 %	150 %	150 %	4
4	0.6	10	1	200 %	100 %	100 %	4
5	0.6	20	1	250 %	150 %	150 %	2
6	0.6	30	1	300 %	50 %	50 %	3
7	0.8	10	1	250 %	50 %	150 %	3
8	0.8	20	1	300 %	100 %	50 %	4
9	0.8	30	1	200 %	150 %	100 %	2
10	0.4	10	2	300 %	150 %	100 %	3
11	0.4	20	2	200 %	50 %	150 %	4
12	0.4	30	2	250 %	100 %	50 %	2
13	0.6	10	2	250 %	150 %	50 %	4
14	0.6	20	2	300 %	50 %	100 %	2
15	0.6	30	2	200 %	100 %	150 %	3
16	0.8	10	2	300 %	100 %	150 %	2
17	0.8	20	2	200 %	150 %	50 %	3
18	0.8	30	2	250 %	50 %	100 %	4

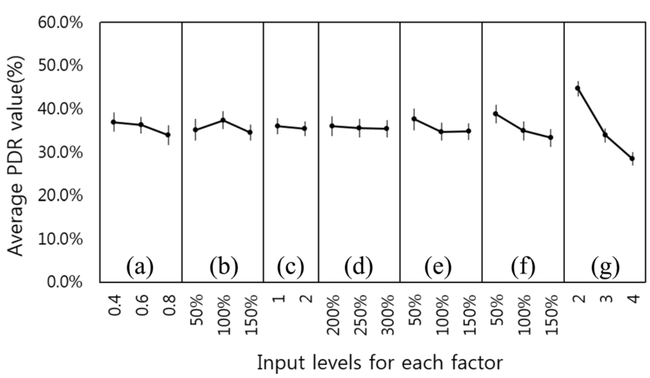

Fig. 9. Effects plot of each factor. (a) Ratio of level 1 EMTs. (b), (c), and (e)–(g) Number of ambulances, DMATs, X-ray rooms, ED doctors, and ORs. (d) Maximum capacity of hospital admission. Bar indicates 95% confidence interval.

simulation statistics represents the sum of the waiting and operation time.

2) Meta-Modeling Analyses on Simulation Statistics: Based on the correlation results, we developed linear regression models for the top five statistics to discover key experimental variables to the statistics. Table X represents the standardized

TABLE VI
VALUES OF THE EXPERIMENTAL VARIABLES IN THE OPTIMAL, BEST AND WORST RESULTS CASES

Experimental variables	Optimal	Best	Worst
Pre-hospital phase			
Ratio of level 1 EMTs	0.8	0.4	0.4
# of ambulances	150 %	150 %	50 %
# of DMATs	2	1	1
In-hospital phase			
Max. capacity of admission	300 %	300 %	200 %
# of X-ray rooms	100 %	150 %	50 %
# of ED doctors	150 %	150 %	50 %
# of ORs	4	4	2
Average PDR	23.8%	24.6%	50.5%

coefficients and their p-values calculated from the regression models.

In the case of the average number of dead patients in a hospital before an operation (AND-IHBO), gauged as the highest correlation, ratio of level 1 EMTs (in the prehospital phase); the number of ED doctors and ORs (in the in-hospital phase) are identified as the significant experimental variables (i.e., p-value under 0.05). The result show that the number of OR is the most critical factor to AND-IHBO (the highest absolute value of the standardized coefficient), which is quite acceptable

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TABLE VII
t-TEST RESULTS FOR DIFFERENT INPUT LEVELS OF EACH FACTOR TO PDR (BOLD FIGURES INDICATE THAT THEIR p-VALUES ARE UNDER 0.05)

Pre-hospital phase								
Factor	Ratio of level 1 EMTs		Factor	# of ambulances		Factor	# of DMATs	
Level	0.6	0.8	Level	100%	150%	Level	2	-
0.4	-0.398	-1.933	50%	1.452	-0.427	1	-0.483	-
0.6	-	-1.713	100%	-	-1.882	-	-	-

In-hospital phase										
Factor	Max. capacity of admission		Factor	# of X-ray rooms		# of ED doctors		Factor	# of ORs	
Level	250%	300%	Level	100%	150%	100%	150%	Level	3	4
200%	-0.271	-0.329	50%	-1.756	-1.782	**-2.548**	**-3.687**	2	**-8.796**	**-13.499**
250%	-	-0.053	100%	-	0.034	-	-1.063	3	-	**-4.780**

TABLE VIII
STANDARDIZED COEFFICIENTS OF THE LINEAR REGRESSION MODEL FOR PDR (BOLD FIGURES INDICATE THAT THEIR p-VALUES ARE UNDER 0.05)

Experimental variables	Preventable Death Ratio
Pre-hospital phase	
Ratio of level 1 EMTs	**-0.12**
Num. of ambulances	-0.03
Num. of DMATs	-0.03
In-hospital phase	
Max. capacity of admission	-0.02
Num. of X-ray rooms	**-0.11**
Num. of ED doctors	**-0.22**
Num.of ORs	**-0.64**
Adjusted R^2	0.466

because AND-HBO would be increased when the waiting time for OR is increased due to the shortage of ORs.

The result about the average sojourn time of an operation (ASTO) is significantly affected by the number of ambulances and all variables in the in-hospital phase. We note that the operation processing time is invariant among the experimental cases; in other words, ASTO would be totally varied by the waiting time of operation process. In this sense, the number of OR with the highest coefficient value is a predictable result. Increasing the number of ED doctors and X-rays make the processing time of the preoperation processes, such as suture and splint, and X-ray, so they eventually lead to the increase of ASTO. Also, the effect from increasing the number of ambulances can be conjectured similar as the ED doctor and the X-ray cases.

One counter-intuitive observation might be the inverse relationship between the maximum capacity of hospital and ASTO. This result can be interpreted from the medical details in the target region, especially the transfer rules: when there is no available ORs, the required patients would be transferred to other hospitals, and the admission to a hospital is determined by the hospital capacity, which reflects the hospital policy from the subject-matter experts. Hence, when the maximum capacity of hospital admission decreases, with the higher probability, the more patients would wait in the first hospital due to the failure in the admission to other hospitals.

The average sojourn time of suture and splint process in the hospital C (ASTS-HC) presents the direct relationship with the prehospital phase but the inverse relationship with the in-hospital phase. The most interesting result about ASTS-HC is about the maximum capacity of hospital admission, and it should be investigated from the geospatial perspective (see Table III): the hospital C is not one of the nearest hospitals from the disaster scene, but the second one. Therefore, the maximum capacity of the nearest one (i.e., hospital B in the figure) varies the number of victims in the hospital C and eventually affects to ASTS-HC. Inversely, the case of the average sojourn time of suture and splint process to red patients (ASTS-R) illustrates the inverse relationship with the maximum capacity. It can be interpreted as that increasing the maximum capacity promotes more congestion in the nearest hospital.

Finally, the ratio of level 1 EMTs is identified as the only significant variable to the average transporting time of red patients (ATT-R). We note that especially ATT-R presents the negative correlation with the performance measure, which means more patients would be dead if red triaged patients arrived faster. It is also relevant with the geospatial and the medical characteristics in the target region; in Gangnam district, the nearest located hospital from the disaster scene is the lowest level hospital which is unable to handle seriously injured patients (red patients). If the ratio of level 1 EMTs is increased, the probability that red patients are sent to proper hospitals, i.e., hospitals that can handle red patients, would be increased. To put it briefly, increasing the ratio of level 1 EMTs would extend the transporting time of red patients but improves their outcomes at the same time.

VI. DISCUSSION

This section presents several discussions about this paper. This paper applies agent-based modeling approach for describing disaster response systems because it provides an explicit way to incorporate micro-level data, such as agent behaviors and environmental details, to an ABM. Such incorporated micro-level information could provide a guidance of the simulation result analysis.

While the needs for understanding and analyzing complex systems, such as socio-economic and disaster response systems, have been increased, they are known to be difficult to model system behaviors as a whole [51]. ABM is considered as an alternative way because it describes system behaviors with the integration of multiple agents (i.e., bottom-up approach). Specifically, agents are developed a component of a target system (e.g., ambulance in a disaster response system), and, by the combination of their behaviors and interactions, the system behavior would be simulated.

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TABLE IX
TOP FIVE STATISTICS HAVING THE HIGHEST ABSOLUTE VALUE OF PEARSON'S CORRELATION COEFFICIENTS WITH p-VALUE UNDER 0.01

Phase	Statistic	Coefficient
In-hospital	Average number of dead patients in a hospital before an operation (AND-IHBO)	0.807
In-hospital	Average sojourn time of an operation (ASTO)	0.451
In-hospital	Average sojourn time of suture and splint process in the hospital C (ASTS-HC)	0.307
In-hospital	Average sojourn time of suture and splint process to Red patients (ASTS-R)	0.294
Pre-hospital	Average transporting time of Red patients (ATT-R)	-0.268

TABLE X
STANDARDIZED COEFFICIENTS FROM THE REGRESSION MODELS FOR FIVE TOP RANKED STATISTICS
(BOLD FIGURES INDICATES THEIR p-VALUES ARE UNDER 0.05)

Experimental variables	AND-IHBO	ASTO	ASTS-HC	ASTS-R	ATT-R
Pre-hospital phase					
Ratio of level 1 EMTs	**-0.113**	0.036	-0.057	**-0.115**	**0.283**
Num. of ambulances	0.086	**0.132**	**0.196**	**-0.091**	-0.063
Num.of DMATs	-0.003	-0.041	0.028	0.016	-0.006
In-hospital phase					
Max. capacity of admission	-0.043	**-0.162**	**-0.272**	**0.187**	-0.001
Num. of X-ray rooms	-0.061	**0.088**	0.006	0.018	-0.003
Num. of ED doctors	**-0.188**	**0.158**	**-0.649**	**-0.668**	-0.017
Num. of ORs	**-0.612**	**-0.729**	**-0.111**	-0.005	0.062
Adjusted R^2	0.421	0.601	0.538	0.490	0.064

The micro-level description helps us to understand and analyze complex systems. When the system behaviors are generated, the transition logs of agents can provide the clues of the system behaviors. The micro-level description in ABM could provide the individual histories over the simulation execution. One example is the in-depth analysis in this paper (see Section V-C). The in-depth analysis interpreted the causes of the system performance with geospatial and medical details in the EMSSim, and these interpretations were conducted by analyzing the simulation logs about the histories of agent behaviors. Such micro-level interpretations can suggest the diagnosis that is fitted to a target system, so they would be utilized for shedding light on the future direction of the target system.

Agents in the EMSSim are designed to be responded to the external stimulus (e.g., requests from other agents) based on their own rules, which means they are reactive agents. Similar as this paper presents, the reactive agents are appropriate to illustrate what will occur if the present keeps. Hence, this approach has been used to analyze target systems. However, we may have another interests on proactive agents that attempts to plan ahead to predict the future states. While the current version of the EMSSim does not consider proactive agents, it offers a basis for the extension of proactive agents: we separate an agent model and its behaviors using LDEF formalism, which means it is possible to replace the current reactive action component with new proactive action component. This is one of the advantages from applying formalism to the ABM development [44].

VII. CONCLUSION

M&S techniques have been applied to analyze and optimize disaster response systems. In MCI situations, many disaster responders should manage a large number of victims with limited resources, so it is important to efficiently coordinate the cooperations among the responders. Having said that, those interactions are closely related with resources and facilities around the disaster scene. However, most previous works evaluated the disaster response systems without considering the key factors related with the disaster resources, such as the geospatial and medical details around the disaster region.

This paper proposes an agent-based model describing both prehospital and in-hospital processes during the disaster response. In particular, we made an effort to incorporate geospatial and medical details in the proposed model for the customized analysis of the target region. The case study provided in this paper presents the results of an analysis of the disaster response system in the Gangnam region, and it shows how the additional factors are utilized to find more suitable interpretations for the target region. We expect that the proposed model will be applied to test the disaster response system of other regions with the ease of resetting its model parameters, and the analysis results of the simulation results would be utilized as the groundwork for improving the disaster response system of interests.

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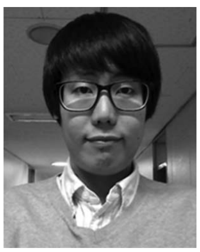

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