International Journal of
Geo-Information

MDPI

Article

Developing an Agent-Based Simulation System for Post-Earthquake Operations in Uncertainty Conditions: A Proposed Method for Collaboration among Agents

Navid Hooshangi and Ali Asghar Alesheikh *

Geospatial Information Science, Faculty of Geodesy and Geomatics Engineering, K.N. Toosi University of Technology, Mirdamad Cross, ValiAsr Avenue, No.1346, 9967-15433 Tehran, Iran; navid.hooshangi@yahoo.com

* Correspondence: alesheikh@kntu.ac.ir; Tel.: +98-912-159-7191

Received: 19 October 2017; Accepted: 11 January 2018; Published: 15 January 2018

Abstract: Agent-based modeling is a promising approach for developing simulation tools for natural hazards in different areas, such as during urban search and rescue (USAR) operations. The present study aimed to develop a dynamic agent-based simulation model in post-earthquake USAR operations using geospatial information system and multi agent systems (GIS and MASs, respectively). We also propose an approach for dynamic task allocation and establishing collaboration among agents based on contract net protocol (CNP) and interval-based Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methods, which consider uncertainty in natural hazards information during agents' decision-making. The decision-making weights were calculated by analytic hierarchy process (AHP). In order to implement the system, earthquake environment was simulated and the damage of the buildings and a number of injuries were calculated in Tehran's District 3: 23%, 37%, 24% and 16% of buildings were in slight, moderate, extensive and completely vulnerable classes, respectively. The number of injured persons was calculated to be 17,238. Numerical results in 27 scenarios showed that the proposed method is more accurate than the CNP method in the terms of USAR operational time (at least 13% decrease) and the number of human fatalities (at least 9% decrease). In interval uncertainty analysis of our proposed simulated system, the lower and upper bounds of uncertain responses are evaluated. The overall results showed that considering uncertainty in task allocation can be a highly advantageous in the disaster environment. Such systems can be used to manage and prepare for natural hazards.

Keywords: natural hazards; multi-agent systems; USAR operation simulation; coordination; geospatial information systems

1. Introduction

Natural hazards such as earthquakes cause large-scale casualties, injuries and the destruction of housing in residential areas [1,2]. Nowadays, smart systems with acceptable coherence and flexibility are essential. Using simulators allows for the analysis of different strategies in dealing with crises and optimizes the decision-making, while ultimately minimizing losses [3]. Applying an agent-based simulation model to earthquake search and rescue operations can be a good alternative to traditional decision-making methods.

Multi agent systems (MASs) making it possible to simulate building demolition, damage to urban infrastructure, injuries, search and rescue teams [4]. MASs deal with complex systems by emphasizing the interaction between agents and dividing the system into sub-sectors of the environment and other actors [5]. Task allocation plays an important role in coordinating an MAS within a set of agents [6,7].

Appropriate allocations are critical for the efficient implementation of tasks undertaken in natural hazard environments. Proposing a proper approach to consider uncertainty in task allocations plays an important role in decision-making with regard to urban search and rescue (USAR) operations in crisis-stricken areas [8].

Earthquakes involve specific conditions and origins of uncertainty, which should be considered in USAR task allocation [9]. In traditional USAR models for disaster environments, task allocation is based on consistent information about the environment [7], while USAR is generally on a large scale and involves many uncertainties [10]. Assuming coordination in environments with no uncertainty is essentially an unrealistic scenario [11]. One of the major problems regarding the planning of rescue operations concerns uncertain conditions, which have considerable influence on initial planning and operationalizing a plan. Despite the findings of various projects, no solution has been found, which meets the various and important needs of task allocation in natural disaster environments in real-time [12]. In task allocation, each agent encounters different risks, which must be considered in the decision-making process. Therefore, in the context of task allocations, each agent should consider uncertainties in their decision-making process [13].

The present study pursues two main objectives. The first is to develop a dynamic agent-based simulation model for USAR operations after an earthquake. The agent-based simulator system is based on the simulation of a 6.6 magnitude earthquake in Tehran's District 3 to observe the performance of a search and rescue operations system. The developed system provides a tool, which, by illustrating the search and rescue operations involved, can predict the collaboration of existing agents in order to plan and make decisions at critical moments. The second objective is to provide a method for task allocation by combining the on contract net protocol (CNP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to establishing collaboration among agents, while taking uncertainty in environmental information into account.

The main innovation of this research is to present a method that is appropriate to measure the uncertainties in post-earthquake USAR operations for task allocation and collaboration among agents using the interval-based TOPSIS method. On the other hand, given that most of the developed methods of collaboration are studied in laboratory conditions, a real simulation is used for allocation in the current study and the performance of the proposed method is examined in the form of a real simulation in order to consider the appropriateness of the proposed method with included application.

The paper is organized as follows. Previous studies on earthquake-related USAR and theoretical insights are provided in Section 2, with reference to geospatial information system (GIS) analysis and building damage assessment and task allocation methods, all of which were employed in the present study. In Section 3 the case study is presented. Section 4 is dedicated to an explanation of the proposed methodology in four sub-steps, while the results obtained from computer simulations of USAR operations are summarized in Section 5. Lastly, the conclusion to this research is presented in Section 6.

2. Previous Studies on Earthquake-Related USAR

2.1. Agent-Based Simulated Systems

Crisis management, supply chain and collective behavior surveys are some of the simulations performed in a wide variety of disciplines. Some of studies conducted in the field of agent-based simulation in disaster management are presented in Table 1.

Table 1. Agent-based simulations conducted in disaster management.

Obvious Point	Objective	Result	Ref.
Providing a new modeling framework for combining agent-based simulation and various sources of spatial data such as volunteered geographic information	Using Web 2.0 technology to combine resources in post-quake operations	A spatial agent-based sample model was created using crowd-sourced GIS and other existing resources to study post-earthquake events.	[14]
Combining macro and micro models to increase the speed of the optimal evacuation program	Determining how to evacuate people during an earthquake	Improving macro model of efficient evacuation from parts of the road network by increasing the details of micro models.	[15]
Providing an innovative approach to resolving future earthquake problems	Synchronization of three factional groups in earthquake operations	7.5–24% progress of outputs in the case of agents' coordination.	[16]
Combining a population allocation algorithm with a bottom-up and top-down procedures simulation	Assessing the welfare impacts of urban disasters	Micro scale results suggest that physical destruction leads to a zero-sum game within the housing market.	[4]
Proposing a framework to reflect the dynamic dimension of organizational structures and policies within the simulation	Natural disaster modeling involving complex Systems	An agent-based methodological framework for complex systems (supply chain, natural disaster) is created.	[3]
Providing a link between people, socio-cultural information and relevant humanitarian relief organizations	Modelling a disaster response	Results show clear differences in the effectiveness of different aid center configurations.	[14]
Minimizing the latest hospital arrival times to enable resources for a two-site incident to be effectively allocated	Optimal resource allocation in emergency response	Such an application supports the use of an agent-based simulation as a tool to aid emergency responses.	[17]

Simulation is one of the major applications of agent-based systems. Simulation provides the decision makers with a prototype or framework, which can support decision-making, complex behavior observation in processes, and the estimation of optimized strategies in the relevant field. By implementing different working groups as smart agents, the models allow decision-making and collaboration among agents. Simulation models provide efficient solutions for analyzing the complexity of interactions and urban processes and can be used in planning and policymaking [18]. In the studies presented in Table 1, few researchers have addressed how agents interact in disaster environments. For many reasons, the utilization of MASs is appropriate in crisis management [4]. They are suitable for finding optimal strategies for widespread incidents and crisis management. MASs have a high level of potential for disaster relief, from first aid to understanding the situation of individuals. Researchers can implement various scenarios of relief and distribution facilities in the same environment through a new attitude to crisis management [14]. Most of these studies failed to investigate uncertainty in decision-making and establishing collaboration among agents. Environmental preparation and the manner of assigning important tasks are essential in the field of agent-based simulation for search and rescue operation after an earthquake. In the following, the studies undertaken in the field of preparing an earthquake simulation environment and the methods for task allocation to support cooperation among agents are addressed.

2.2. Preparation of an Earthquake Environment

Preparing the earthquake environment requires the creation of a scenario for the earthquake and estimating the vulnerability of buildings and individuals. In this context, GIS are becoming more and more important in natural hazard management systems and graphically present disaster-relevant data [10,19]. GIS-based mapping is used to identify the ranking of parameters for the evaluation of seismic hazards and loss scenarios in earthquake-prone areas [20]. Systems such as GISs have allowed decision-makers to analyze earthquake data on multiple scales and formulate various perspectives [21].

These models give a picture of the scale and spatial distribution of an earthquake in terms of its impact on infrastructure.

A study on the building vulnerability assessment of earthquakes shows that each earthquake network is strongly connected [20]. Karimzadeh et al. (2017) developed a GIS-oriented hybrid site condition map for an earthquake damage assessment, which is compatible with Iranian buildings, soil and geological parameters [19]. A combination of MCDM methods and GIS-representing capabilities is one of the most commonly applied techniques for building vulnerability assessments [22]. Grigoratos et al. (2016) proposed simplified fragility and exposure models for Palestine, based on local field surveys and data collection. The outcome of this study has enabled the assessment of earthquake risk in cities [23]. Monteiro et al. (2016) propose a web-based platform for an integrated seismic risk assessment in the city of Nablus for the reduction of potential losses. The results of the study identified regions that are more vulnerable to earthquakes, as well as provided future rapid loss assessments on a regional scale [24]. Mansouri et al. (2008) describe a methodology for modeling and estimating the severity and spatial distribution of human loss, based on the Hazus earthquake model in Iran, in which they used a GIS platform to represent spatial results [25]. Here, we have used the International Institute of Seismology and Earthquake Engineering of Iran's human loss model and GIS spatial analysis to graphically present seismic hazard maps and human loss in District 3 in Tehran. This model's results are compatible with Tehran buildings especially District 3.

2.3. Task Allocation Methods

Task allocation include assigning a number of workers (resources) to supply the requirements needed for a number of tasks (consumers), so that the overall desire can be maximized [26,27]. There are several methods for task allocation, including auction-based, community-based, optimization and learning methods. A summary of the methods for each group is given in Table 2.

Table 2. A classification of task allocation methods.

Classification	Available Methods	Description
Auction-based	CNP [1], Norm-based CNP M+ protocol [28]	- In these approaches, each agent suggests a cost for undertaking work. The auctioneer reviews the suggestions and assigns the work in line with the best suggestion. - This is the most popular solution for solving MRTA which has been tested more than other methods.
Consensus-based	CBAA [2], CBBA [3], HRCA [4] [29]	- This is a kind of decentralized allocation approach which gives a group of agents the opportunity to converge in terms of environmental awareness and task allocation in different network topologies. - The methods are time-consuming and require the exchange of a huge amount of data.
Optimization Approaches	GA [5], ACO [6], Max Min, Tabu search [30]	- In this approach, the allocation problem is formulated as a definite optimization problem which is solved by using linear and nonlinear programming methods.
Learning-based	CBR [13], LA-CBR	- The utilization of learning techniques, in order to provide superfluous rules and a higher degree of authority and priority to manage the behavior of agents plays an effective role in allocation.

[1] Contract Net Protocol; [2] Consensus-Based Action Algorithm; [3] Consensus-Based Bundle Algorithm; [4] Heterogeneous robots consensus-based allocation; [5] Genetic; [6] Ant colony optimization.

As indicated in Table 2, many methods have been presented for task allocation. Scientific activity in this area remains a serious challenge for researchers. Several studies used the CNP as a subset of auction-based methods. This study presents an approach and extension in order to include in CNP, which was selected because of its simplicity, applicability and popularity.

2.4. Approaches to Applying Uncertainties in Task Allocation

As a term and a concept, 'uncertainty' involves different definitions and origins [31]. Probabilistic, fuzzy, rough set and interval are some methods with which to work with data that includes uncertainty. Methods based on the theory of probability and fuzzy logic being more common. Probabilistic models use different probability distribution functions and statistics for modeling. Fuzzy sets are based on calibrating concepts and linguistic ambiguities. Rough sets are new mathematical tools to deal with uncertainty and incomplete information. In interval modeling, uncertain parameters are represented by interval parameters, which are valued in intervals. A proper method should be chosen in order to consider uncertainty, which is appropriate to each area and activity. The present study used an interval method to interfere with the uncertainty in the assignment of tasks. In an interval method, the availability of interval information concerning quantities is essential for modeling [32]. Unlike probabilistic and fuzzy methods, there is no need for the interval approach to determine or assume possible distributions (in random programming) or membership functions (in fuzzy programming), as working with interval data is simpler than other methods [33].

Various studies have been undertaken in the field of uncertainty modeling in task allocation. A fuzzy genetic—TOPSIS method was used for agents' decision-making and the determination of the decisions' weights in the modeling of linguistic variables in disabled people who were rescued during an earthquake [9]. Uncertainty about the existence of tasks, agent performance, the relationship between tasks and the effect of a task was mapped by using a genetic algorithm for the task allocation of a task with five sub-tasks. This meant that these various uncertainties, along with probabilistic reasoning, were used in calculating the utility function to perform the tasks. Uncertainty in operating sensors of agents was considered by the auction method in order to find alarms in different rooms. Four strategies were evaluated on the basis of robots' coordination and commitment. The results revealed no special optimal strategy [34]. Hooshangi and Alesheikh (2017) provided a VIKOR interval-based approach to reflect the uncertainty in agents' decision-making during task allocation. Their work was evaluated in a 20×20 km environment. The results indicated an improvement in the accuracy of task allocation between agents.

The interval-based TOPSIS, VIKOR and ECLECTRE decision-making methods were developed to illustrate the real situations of the multi-criteria decision-making process [11]. This study provides an interval-based TOPSIS approach to reflect the uncertainty in the agents' decision-making during task allocation. TOPSIS is a multi-criteria decision analysis method, in which the standard ranking of the options is based on how close they are to a target alternative and a far-from-worst condition. A comparative analysis of MCDM methods is illustrated their similarity and some differences [35]. In TOPSIS vector normalization is used to eliminate the units of criterion functions. The TOPSIS method is suggested if the decision-maker is seeking optimization of the decision and the risk level is very important [35]. This approach has hardly been applied in previous research on assigning tasks among agents.

3. Case Study and Data

In order to assess the capability of the presented approach, it has been applied to estimate the seismic risk in District Three in the city of Tehran, the capital and political center of Iran. District 3 located in north of Tehran, has an area of around 208 km/m^2 and has a population of over 314,112. It is located in Zone 39N UTM (Figure 1).

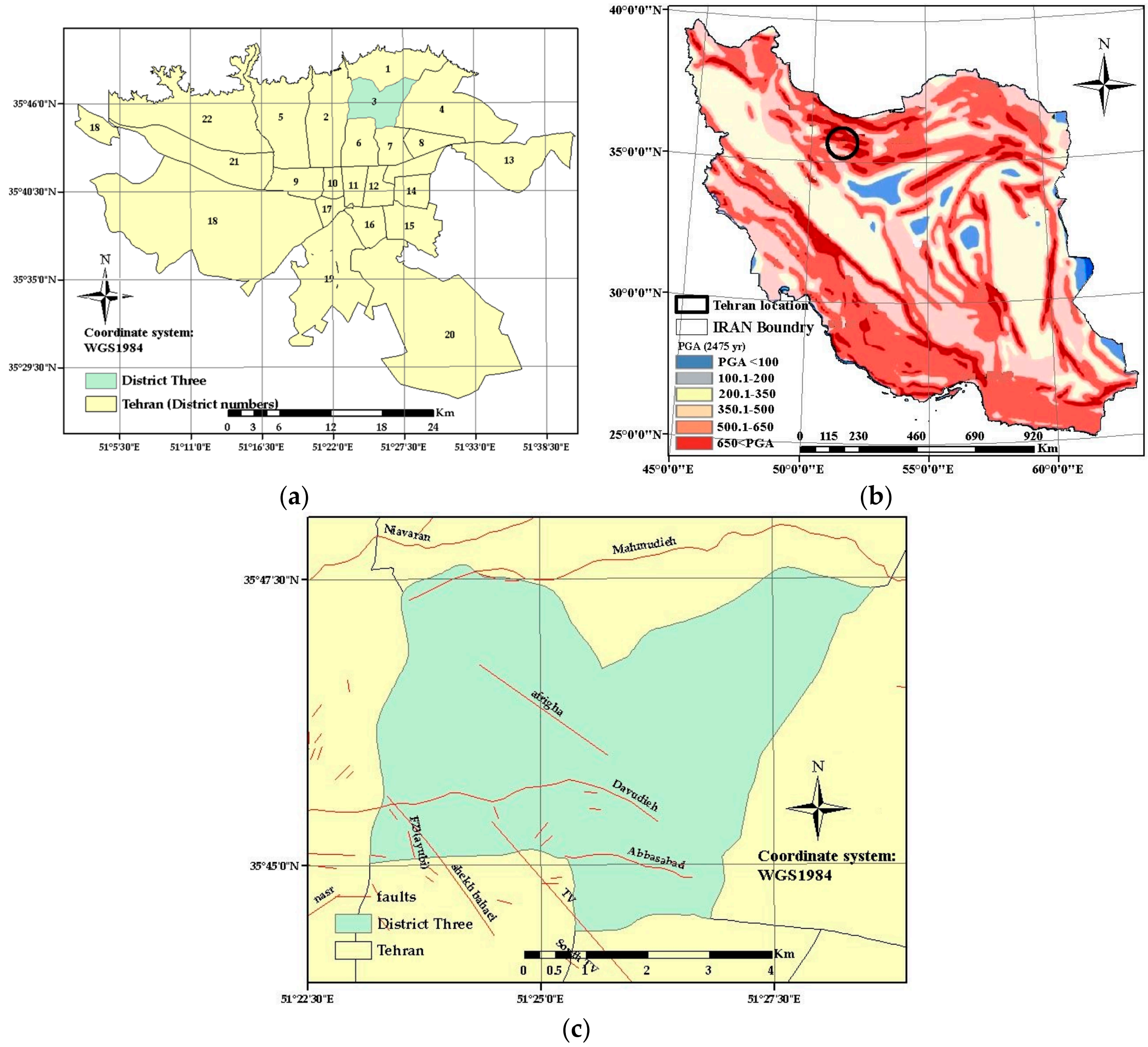


Figure 1. Location of case study: (**a**) location of District 3, Tehran, (**b**) peak ground acceleration map of Iran for a return period of 2475 years [36] and approximate location of Tehran, (**c**) location of faults in District Three of Tehran.

Iran is considered to be the seismic region of the world (Figure 1). Tehran, as the capital of Iran, is located on multiple faults. Besides the vulnerability of structures in Tehran, the rapid growth of urbanization has increased the vulnerability of most districts [37]. A major portion of District 3 has a semi-rural fabric. The building's type in this area is fully compatible with the model used to calculate the vulnerability of buildings and the number of injured people. As shown in Figure 1, District three is a highly seismic area. The proposed methodology can be implemented for all other areas, if data is available. Seismologists believe that a strong earthquake may occur in the near future in Tehran, which is home to millions of inhabitants, [37]. The Niavaran Fault is one of the city's biggest faults which located in North of Tehran. This fault has a length of 43 km. The recent earthquake in Tehran had a magnitude of less than 4.6 on the Richter scale. The last major earthquake in Tehran (as high as 6.5) was in 1830. The magnitude of the earthquakes predicted by the International Institute of Seismology and Earthquake Engineering of Iran is 7.2 for the North Tehran fault and 6.6 for the Niavaran faults on the Richter scale. This difference in severity is due to the difference in the length of the faults. New research shows that there is more evidence of activity along the Niavaran Fault, compared to the North Tehran Fault [38]. For this purpose, the Niavaran Fault scenario is selected.

In the current study, a GIS system was used for data preparation, data entry in software and the creation of an environment for simulation. There are two important parts in preparing the environment to simulate search and rescue operations, such as simulating the earthquake-damaged environment and the dispersion of agents. The basic data used in the application are block maps, population, distance from fault, building material, agents' location, buildings' year of construction and building height. The primary location of the injured agent is based on building damage, while population loss assessments and the location of the search agent group, the rescue group and medical groups were randomly generated in four vector maps.

4. Methodology

The steps for creating and implementing a proposed simulation system are summarized in Figure 2.

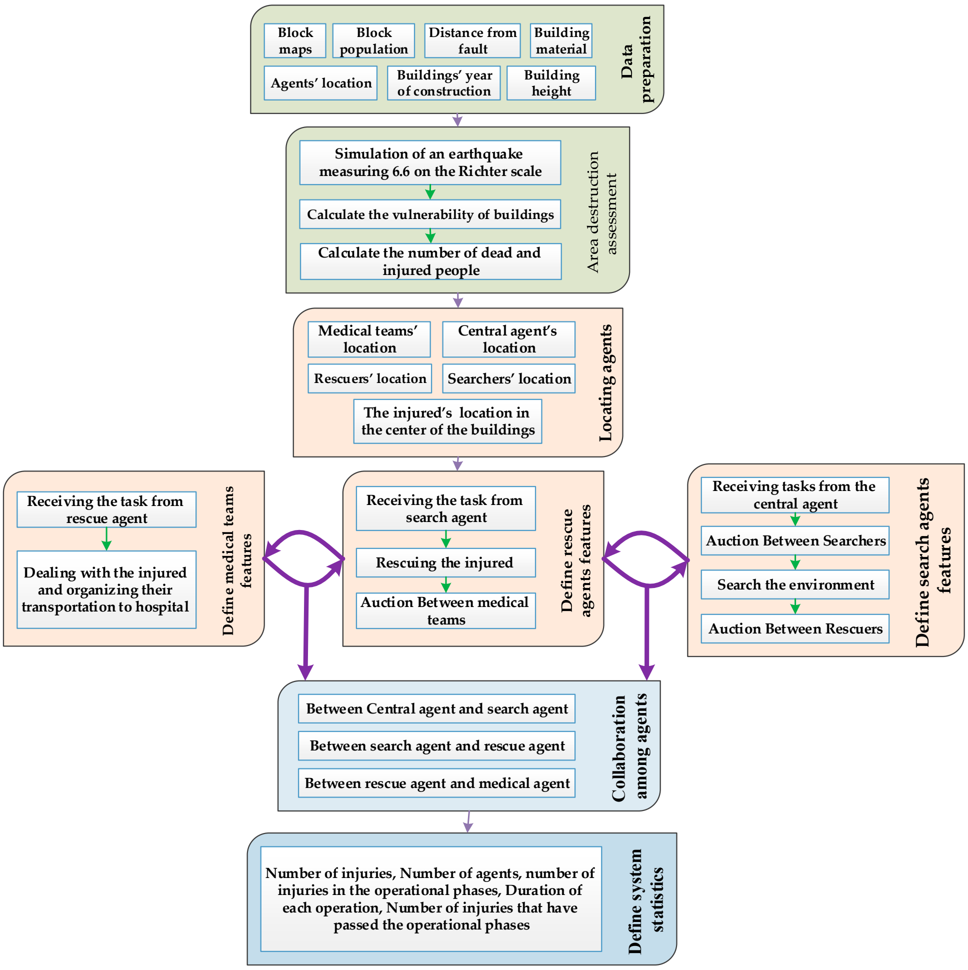


Figure 2. Implementation steps of the simulated search and rescue operations system after an earthquake.

This study requires the implementation of three main parts. The first step consists of preparing the data in the ArcGIS environment and calculating the damage rate of the area, simulation of the agent-based system which include locating the agents in the environment, defining their characteristics and, ultimately, implementing the proposed method for collaboration between agents and specifying statistics in order to obtaining the status of the system and assessing the capability of the proposed method. The methods used to implement each section are described below.

4.1. Building Damage Assessment

The purpose of this section is to predict the vulnerability of the buildings and the number of injured people in an earthquake. This paper uses a methodology that was applied during a research project at the International Institute of Seismology and Earthquake Engineering of Iran. The model was developed during a collaborative project between the Japan International Cooperative Agency (JICA) and the Center for Earthquake and Environmental Studies of Tehran (CEST). It is a local project in Iran and is known as the JICA project. The output of this plan is presented in Mansouri et al. (2008). The model is also used in [39,40].

JICA model provides a structural vulnerability estimation at four levels of failure (slight, moderate, extensive and complete). According to characteristics of buildings and the magnitude of an earthquake in the buildings' location, each building can be placed within a level of failure [25]. The methodology has four major stages: namely, seismic hazard assumption as an input, building inventory development, building and human vulnerability function developments and implementations, and, finally, the production of results in a GIS. The inputs of the model are building material, building height, a building's year of construction, distance from the fault, and parcel maps and fragility curves. To calculate the number of injured people, building population was used.

After the earthquake in Bam, a human vulnerability model was also developed using structural damage vulnerability and collected data on human-structural mortality. In order to implement the model, it is sufficient to know the population living on a construction site at the time of the earthquake. Using the results obtained while estimating the structural damage, the number of dead, injured and uninjured people is calculated. For human vulnerability, Equation (1) is used [25]:

$$\begin{bmatrix} Uninjured \\ Injured \\ Dead \end{bmatrix} = \left(\frac{Population}{Buildings}\right) \begin{bmatrix} -0.073 & 1.040 & 0.650 \\ 0.071 & 0.047 & 0.062 \\ 1.001 & -0.087 & 0.289 \end{bmatrix} \begin{bmatrix} Slight \\ Moderate \\ Extensive + Complete \end{bmatrix} \quad (1)$$

Based on the above formula, human casualties are calculated at three levels (uninjured, injured and dead). For each building block, the number of damaged buildings is entered into the formula.

4.2. Simulation of the Agent-Based System

Based on the scenario of a simulated system, the earthquake first occurs in a definite position and with definite severity. Buildings damage and the number of injured people are simulated. In an actual search and rescue operation, there is no accurate information on damaged buildings, the number of injuries, injury rates and other environmental parameters. Initially, the central agent prioritizes tasks based on information obtained from the environment and assigns each task to the nearest agent to injure. The relevant agent establishes an auction among the other nearby search teams and selects the most appropriate group. After visiting and searching the environment, if the selected group finds an injured individual, they try to choose the most appropriate group among the rescue agents by using tender and decision-making uncertainties and assign the rescue of the injuries to that group. The selected rescuer moves to the environment and rescues people from the rubble, as well as chooses the best medical team from among the existing teams through a tender for primary medical care, before the rescued are transferred to the hospital or service centers.

In the present study, with regard to previous studies [8,9,11] and expert advices in post-earthquake search and rescue (SAR), various uncertainties were regarded in each stage of the assignment of tasks or collaboration. Table 3 lists common uncertainties in the tasks prioritizing and the uncertainties in each stage of task allocation and cooperation. Decision-making weights in the tasks prioritizing and task allocation can be directly chosen by the decision maker, or by using methods such as pair-wise comparisons in AHP. In this case, weights were calculated on the basis of expert's opinions by Analytic hierarchy process (AHP). An AHP defines a set of criteria and sub-criteria arranged in a hierarchy in order to make pairwise comparisons and find the weights of the criteria or decision alternatives.

Table 3. The reflected uncertainties for task prioritizing and uncertainties involved in each stage of task allocation and collaboration between agents.

Phase	Uncertainty	Description
Uncertainties for task prioritizing	**Number of injuries**	In the natural hazards, the exact number of injured persons in each region is not identified.
	Severity of the victims' injuries	Prior to attending the location, there is merely a prediction of the environment and the severity of injury is not accurately known.
	Duration of operation	The time required for SAR operations at the environment depends on various factors and it is difficult to determine it accurately. The approximate amount is specified as an interval.
	Infrastructure priorities	In the disaster environments, the locations have different applications and priorities for SAR operations, for example, the hospitals are of a higher priority.
Uncertainties involved in each stage of task allocation and collaboration	**Agent energy**	Operation in any location reduces the agent's energy, the energy reduction for each agent cannot be measured precisely.
	Route status	The agent should pass a distance to attend the injured persons place. This route has different conditions. In this study, we used the Euclidean distance.
	Task runtime by an agent	Each agent estimates the time of operations based on the parameters presented. The parameters are different from the operation time of the central agent. This factor is calculated by the agent and according to its characteristics.
	Risk level for agent	Attending in the natural hazards is dangerous for each agent, such as falling rubble and explosions. Each agent must calculate any amount of risk of every task.
	The remaining time of the task	If the agent is busy in doing something, the time needed to complete the task is sent to the tenderer as an interval parameter.

The proposed multi-agent system consists of five groups including independent agents, injured agent, central agent, search agent, rescue agent and medical team. These agents are independent entities which can move and assess the environment and examine the status of their neighbors. Each agent represents a physical entity of search and rescue operations, which includes one or more planning and decision-making functions. These agents (except for the injured agent) are independent and rational which can communicate with each other and have full authority in declaring their parameters for participating in tender in interval form. All five used agents are spatial, which means that they are distributed over a geo-referenced environment and have two-dimensional locations. In the present study, preventing injuries involves the cooperation between four types of agents. Collaboration between different agents is required to complete the search and rescue operation among the various agents present in the environment. Each of the agents has a specific task as follows:

Central agent: Sorting the tasks in order of priority, determining the nearest search agent, evaluating the different subgroups of search agents, announcing the assigned task to the nearest rescue agents.

Search agents: Responsible for the environment search and finding the traumatized agents, holding a searcher allocation auction (sending the proposed task to the subgroups of search agents, receiving bids from the subgroups of search agents), sending the group qualification and order for the agents to the searcher auctioneer, responsible for the rescuer find auction, sending the work errors to the responsible search agent.

Rescue agents: Responsible for rescuing injuries from the debris, identifying the feature intervals and announcing them to the coordinator agent, responsible for medical find auction, sending the work errors to the responsible search agent.

Medical agents: Responsibility for providing medical services and transferring injured to hospital, Identifying the features intervals and announcing to the coordinator agent, Sending the work errors to the responsible search agent.

Injured agents: Residing in the environment, this is not smart, changing the critical condition. In the simulator systems, the use of more maps and parameters leads to more accurate results. However, in many conditions, utilizing more criteria and parameters only complicates the problem. Therefore, the current study tried to simulate the performance of the search group, rescue group and the medical team in order to model the earthquake environment. Two main issues should be taken into consideration when designing agent-based simulations in the form of search and rescue operations. The first is related to preparing the simulation environment damaged by the earthquake while the second is concerned with designing agents and establishing the relationships among the agents. In this study, the model presented by the Japan International Cooperation Agency (JICA) and the Center for Earthquake and Environmental Studies of Tehran (CEST) studies was used to simulate the earthquake environment. We use the output functions to estimate the amount of damages considering that it is suitable for buildings in Iran. A developed method is used to establish cooperation among agents. In the following, the methods used to simulate the earthquake environment and the proposed method for establishing cooperation among the agents is described.

4.3. Proposed Task Allocation Method

The proposed approach in the present study is not specific to a particular phenomenon and subject, but due to the included uncertainties, it is appropriate to search and rescue operations after an earthquake. In the current study, a method is presented with regard to environmental uncertainties when assigning tasks and establishing collaboration between agents. The proposed method can be used for task allocation and collaboration between agents. Figure 3 illustrates the process of assigning a set of tasks to a set of agents, despite the presence of uncertainty in the information. The proposed method is general and depends on the interaction between two agents, A and B. In this case, Agent A is assumed to have a set of tasks, as well as wanting to select a set of Agents B for these tasks.

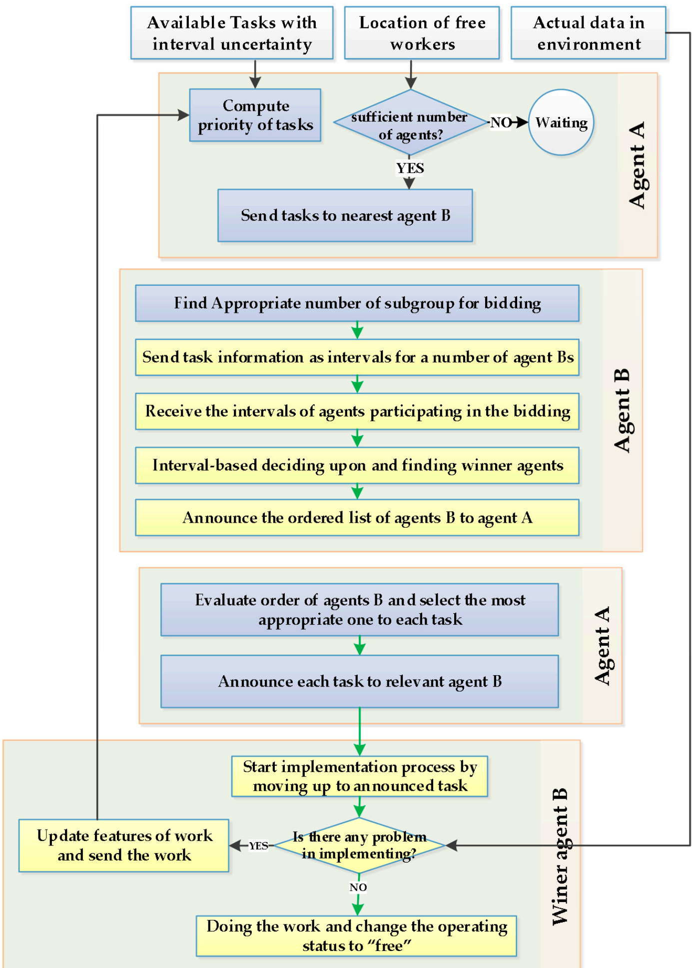


Figure 3. The process of assigning a set of tasks to a set of agents despite uncertainty in the information.

It is assumed that the environment consists of a set of tasks (uncertain and exact characteristics of tasks) and agents dispersed across it. The proposed method is described in the following steps.

4.3.1. Sorting the Tasks and Determining the Auctioneer

Initially, central agent as Agent A, with a set of tasks, prioritizes the existing tasks. Usually, the tasks should be performed in the order of priority. In natural hazards, the priority given to saving an injured person depends on different factors. Four parameters (number of injuries, severity of the victims' injuries, duration of the operation and infrastructure priorities) are defined for each task in interval form. Earthquake prediction models are used to create the initial task list. Considering the fact that there is no accurate information about the number of injuries, the severity of injuries, the duration of operations and the infrastructure priorities, after obtaining the value for each of the characteristics, the numbers are converted into intervals in terms of expert opinions. In this study, using the International Institute of Seismology and Earthquake Engineering of Iran model, the number of victims was calculated in each block (a number such as X was calculated). Then, in order to create interval values and simulate uncertainty in the environment of the data (for example, 30% uncertainty in the information), the first and second values of the interval were created randomly between [X, X + 30%X] and [X − 30%X, X]. In this phase, those tasks that receive a higher score from the interval-based TOPSIS method are performed before other tasks. The weight of parameters of number of injuries, severity of victims' injuries, duration of operation and infrastructure priorities in TOPSIS method were considered 0.35, 0.2, 0.31 and 0.14, respectively.

After the ordering of the tasks by central agent (Agent A), the closest searcher agent (Agent B) is chosen as the auctioneer. Central agent then sends a message to the auctioneer about the work features. Searcher agent (Agent B) tries to conduct a tender for each job because the overhead of the information decreases in this case. On the other hand, the uncertainty decreased in the communications, due to the proximity of the agent to the disaster environment.

4.3.2. Selecting the Sub-Group Agents of the Tender

There are two important factors to consider when selecting individuals for the subgroup conducting the tender: the spatial distance and the absence of free agents for search and rescue operations. Each task should be assigned to the agents at a proportional distance. Failure to observe this hint results in excessive movement of forces and wasted operational time, as well as disturbing the uniform distribution of agents. Therefore, the spatial condition should be defined for agents of the subgroups and agents participating in a tender at a specified distance (e.g., 1 km from their place duty). On the other hand, in crisis-stricken environments, the number of duties is always more than the number of individuals in a search and rescue team. Thus, there are always no free agents in the region to participate in the tender. Accordingly, the tasks are performed by search agents over a long period of time, while the tasks are not allocated to rescue agents until they become free from duty. In order to solve this problem, the free condition is not defined as Boolean for agents. In other words, if there is no free agent in the tender area, the tender is held among the agents that are not free and require a period of time to complete their duties. In this circumstance, the agents winning the tender have less time to finish their duty and are superior in terms of certain parameters such as agent energy, route status, task runtime by agents and risk level for agents. In this study, for the purpose of holding any tender, a distance of 1 km for each task was considered as a range for selecting agents. First of all, this represents an attempt to assign tasks to free agents within this range of 1 km. If there is no free agent, allocation is performed between the busy agents.

4.3.3. Auction Phase

In this phase, the CNP algorithm is used, in which uncertainty is reflected. A CNP is an important coordination technique for assigning tasks and sources of establishing collaboration among agents. The four steps of a CNP are as task(s) recognition, task(s) announcement, receive offers and allocate tasks. After receiving work features, Agent B holds the tender and announces the task to the subgroup agents, which are B types. Each agent in the subgroup estimates the level of risk, energy reduction, the route condition and the task runtime, according to the characteristics of the assigned task, such as its location, and sends the corresponding interval to the coordinating agent. Then, searcher agent (Agent B) sorts the agents for the requested task and identifies the priorities using the interval-based TOPSIS method. The weight of decision—making parameters, the level of risk, energy reduction, the route condition and the task runtime, in TOPSIS were considered 0.22, 0.24, 0.18 and 0.36, respectively.

Since each of the subgroup agents may be a subgroup or a coordinating agent in another group, the answers should be sent to central agent (Agent A). Therefore, each nearest agent sends the priority of the agents along with the estimated time needed to perform a task, to central agent (Agent A).

4.3.4. Evaluating the Results of the Tenders and Selecting the Most Appropriate Agent

The central agent (Agent A), after obtaining all the coordinator agents' lists, assigns high-priority tasks to agents that have given the best estimate for the job. Then the central agent eliminates that task and agents from all lists, and continues to allocate tasks with existing free agents. After that the allocation process continues by assigning low-priority tasks, while the other remaining tasks are gradually allocated. Therefore, the allocation process continues by assigning low-priority tasks, while the other remaining tasks are gradually allocated. According to this strategy, searcher agent (Agent B) provides local optimality, while the central agent (Agent A) is responsible for global optimality.

4.3.5. Implementation and Observation of Environmental Uncertainties

Each of the uncertainties included in the decision-making process can be reflected in the real environment while performing the tasks. With this assumption, the working environment of the agents must be simulated in USAR operation by the central agent. In the working environment, there is only one number for each parameter of task. In this research, a random number is chosen to model the working environment in a range of numbers [X − 30%, X + 30%].

After beginning the task, the agent observes the difference between the uncertainties that are presented from their point of view and in the working environment. In some cases, the uncertainties are located within an anticipated domain and not affecting the results. In other cases, one should select between accepting the delay and rescheduling. For example, the agent estimates a time interval (15–21) to reach the injured person for a certain task and wins the auction. In the working environment, the agent's arrival time may not occur within the estimated interval. In this case, the agent may refuse to perform the task due to the complexity of the working environment. Therefore, the uncertainties are updated and the task is sent back to the central agent, which considers the new uncertainties of the environment for reallocation. Various conditions are established for the agent that reallocates the tasks, if the working environment is different from its prediction. For example, the agent can refuse to perform the task if, among the eight parameters on which their decision was-based, three items have a margin of 5% and/or four items are out of the interval range. Otherwise, the task is ended by accepting the delay in the process.

The proposed method can be used to establish cooperation between two agents, A and B, on a task, in which Agent A has a task and wants to assign this task to Agent B, as shown in Figure 3. In this case, given that there is only one duty, there is no need to arrange tasks. Therefore, the first step removed and the interval auction is held to establish cooperation between agents.

4.4. System Evaluation

An appropriate simulator system should provide an instantaneous control of the system. Thus, the statistics should be considered to reflect the system's momentum status. As shown in Table 4, in the developed search and rescue simulator system statistics were defined for each of the available agents in order to obtain the result of the simulation process and the capability of the proposed method at any moment.

Table 4. Defined statistics for various agents.

Agent	Defined Statistics
Central agent	The number of assigned tasks The number of injured agents in the phase of the search The number of injured agents in the phase of rescue The number of injured agents in the medical phase The duration of a search and rescue operation The number of completed search and rescue operations
Searcher	The number of agents engaged in the search task The duration of the commenced search operations The distance traveled by the search agents The duration between completing two search tasks
Rescuer	The number of agents engaged in the rescue task The duration of the rescue operations started The distance traveled by the rescue agents The duration between completing two rescue tasks
Medical team	The number of agents engaged in the medical task The duration of the medical operations started The distance traveled by the medical agents The duration between completing two medical duties

Due to the complex nature of the phenomena modeled by the agents, the validation of the designed agent-based models has always been regarded a challenge for researchers in this field. Given that there are no ground data on task allocation and cooperation between rescue teams in USAR operations, an evaluation of the proposed method with ground data is not possible. The simulation of the interaction between the agents is an evaluation method.

In multi agent systems, there is no fixed criterion for all agents. Reducing the casualties and the timing of the conclusion of an operation are considered as the main objectives in rescue simulation systems. According to recent studies [6,9,11], two performance criteria of profitability were mentioned in order to focus on the performance of the proposed methods, including the number of fatalities and the rescue time. In this study, the proposed method was evaluated by numerical simulation and a comparison with the CNP algorithm. In order to examine the effect of uncertainty, the CNP method involved in two assumptions. At first, we ran the model by assuming accurate decision-making parameters and at second assuming with uncertainty.

5. Results and Discussion

Expert opinions show that the most probable earthquake intensity in the District 3 municipality of Tehran is, on average, 6.6 on the Richter scale. This severity represents the seismic intensity of the Niavaran Fault in the study area. Figure 4 shows the vulnerability of buildings.

Building vulnerability is classified into four classes. The vulnerability grade has a direct influence on building damage. Buildings with no damage or with a damage grade of "Slight" are habitable (7027 buildings, 334 blocks), buildings with a damage grade of "Moderate" can be used to a limited extent (11,046 buildings; 525 blocks), buildings with a damage grade of "Extensive" are not safe (7111 buildings; 338 blocks), and buildings with damage grades of "Complete" have been destroyed (4881 building; 232 blocks). An earthquake (dependent on ground type) could leave 16% (buildings classified to a "Complete" grade) of buildings in District 3 of Tehran permanently and 24% of buildings temporarily out of use (buildings with a damage grade of "Extensive"). Furthermore, 40% of citizens could temporarily be left without a home and possibly needing rescue, medical care and rehousing. The number of injured and deceased people calculated for this scenario (6.6 Richter) are 17,238 and 22,435. The injured, central, search and rescue agents and the medical team are placed in the environment using the information stored in the Access database and the SQL functions. The injured agents are dispersed in the environment in accordance with the computational process of model presented by the International Institute of Seismology and Earthquake Engineering of Iran. The number of injuries was calculated for each block and included in the center of the relevant block. Search, rescue and ambulance agents were randomly distributed in the environment.

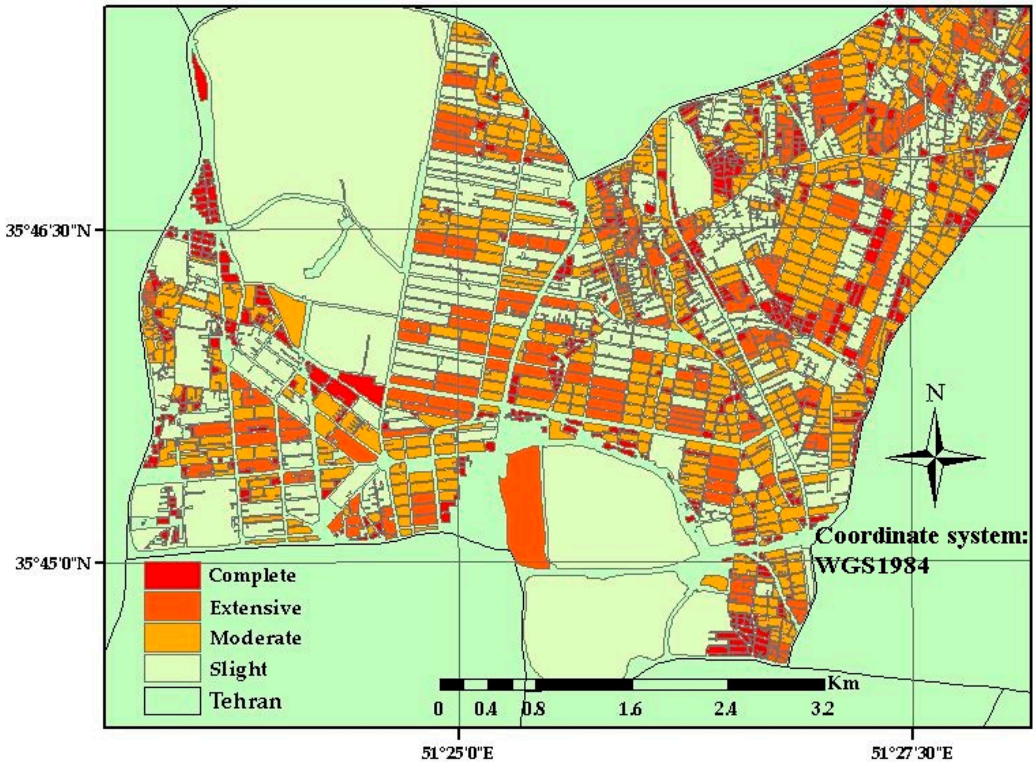
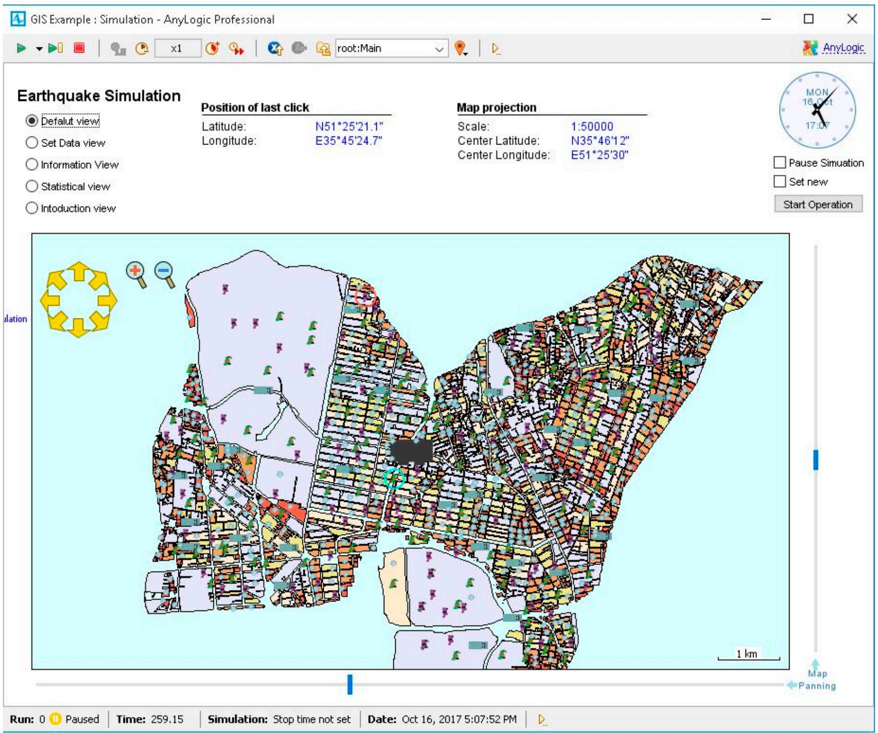


Figure 4. Four structural vulnerability levels in District 3, Tehran.

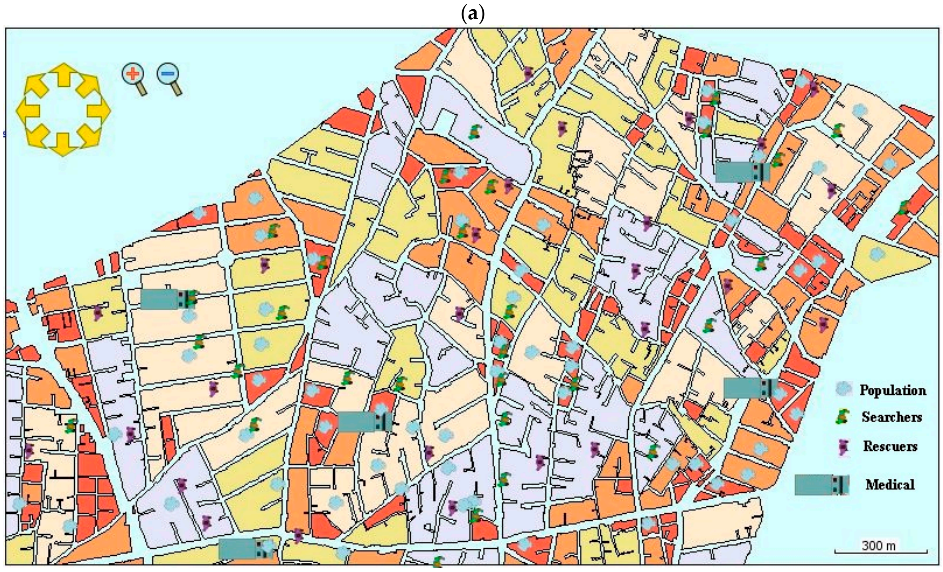
The successful implementation of MASs largely depends on the availability of appropriate technology, i.e., programming languages, software libraries and software production tools, in order to implement related concepts. AnyLogic software was used to implement this system, which allows the utilization of GIS data. In the current implementation, each agent plays the role of a team; that is, considering the regarded capabilities, each agent can be considered as an equivalent to a group in the real world. Further, in order to avoid the enhancement of the number of agents and the complexity of the environment and the aggravation of the calculations, a citizen agent is regarded as being equal to a population living in a block. In order to start the process of a search and rescue operation, the search agent first collaborates with the central agent in order to obtain the task of the environment. The central agent assigns tasks to the search agents after prioritizing the tasks and selecting the responsible agent for the tender.

Figure 3 displays the method of assigning these tasks, in which the central agent plays the role of Agent A, while the search agent has assumed the role of Agent B. At each stage, the search agents, which are responsible for the tender, based on their own rule-based logic and interval-based TOPSIS analysis, choose the most appropriate search agent for the specified tasks.

The search agents are initially in a ready state. They begin their search process when they win a tender and a task is assigned to them. The relevant agents move along the central line of the road and use the Dijkstra algorithm to find the shortest path. Dijkstra's algorithm is a well-known algorithm for finding the shortest paths in road networks. It turns out that one can find the shortest paths from a given source to all points in a graph at the same time [41]. In AnyLogic software, agents use the Dijkstra algorithm to traverse the path between two points. After reaching the desired location, in relation to the actual data, they start to save the casualties (operation phase). However, after referral to the region, the agents may find a significant difference between the information expressed in the tender and the actual information. In this case, as well as informing the central agent, they may refuse to do the work, which may not be possible given the operational capability of the group. Different conditions can be defined for such a situation. After finding the first injured person, they look for rescue agents for the injured person using the contract net. How this cooperation works is in the "Proposed Method" section. Based on Figure 3, A and B are search and rescue agents, respectively. Therefore, they inform the groups in the operational area and wait for a response from the relevant groups. Then, they consider the results and find the most suitable rescuer group and award the rescuing task to the relevant group in the form of a message, before moving on to the next task. The final simulation environment is as shown in Figure 5.



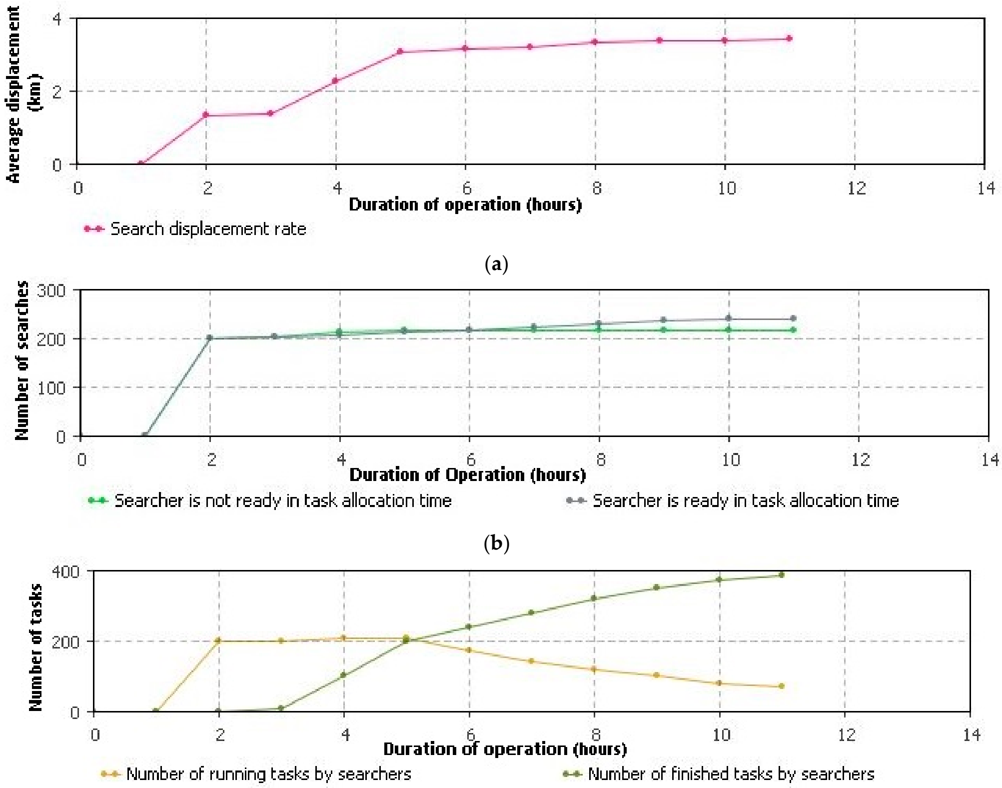
(**a**)



(**b**)

Figure 5. An overview of simulated system: (**a**) a view of USAR simulator, (**b**) Distribution of agents during the rescue and search process.

In the search and rescue simulator environment, adding a specific team to a specific location is possible if the latter exists on the map. Users can observe the position and tasks of the agents by clicking on each agent. Pages are included to enable continuous observation of the statistics for each agent. The rescue system should have the capabilities to display the best-possible information and status of the agents involved in the operation. At this stage, some facilities are added to the proposed system. Statistics are defined in order for each agent to follow the search and rescue operations. Figure 6 demonstrates a sample of the statistics defined for the search agent. In addition, the statistics are defined for the overall process of operations.



(c)

Figure 6. Instantaneous statistics for search agents at moment t_1, (**a**) the distance traveled by the search agents, (**b**) ready search agents during the operations, (**c**) the number of injuries in the search phase or passed the phase.

Then, the rescuer groups change their status to a task-performing status and begin the rescue procedure, before selecting the most suitable medical team to handle the injured. After performing their job, they change their status to the ready state.

The ratio of success between the proposed method and the traditional CNP method is compared on different scales. The application of allocation methods, the size of the agent team, and the number of tasks are three main causes of complexity [11]. The qualitative evaluation of the proposed algorithms is necessary in order to examine their capabilities in relation to different scales of agents [42]. The scalability of algorithms is investigated through the implementation of each method per different amounts of each scenario, with the number of agents increasing in each scenario.

Table 5 indicates the results of the system when run for different numbers of each agent. The results were achieved by carrying out each scenario 500 times. The computational time of the proposed method was less than 2 s for a scenario with 300 rescue and search agents and 70 medical teams. In other words, the proposed method runs, at most, for 2 s. Due to the low computational time, this time was not included for different scenarios.

Table 5. A comparison of the CNP and the proposed method.

No.	Number of Searchers	Number of Rescuers	Medical Teams	CNP		Proposed Method	
				Duration of USAR (Hour)	Number of Fatalities	Duration of USAR (Hour)	Number of Fatalities
1	200	200	40	110.5	3135	89.3	2598
2	200	200	55	92.5	2952	61.6	2382
3	200	200	70	75.8	2784	53.7	2146
4	200	300	40	93.3	2798	79.6	2392
5	200	300	55	77.6	2341	55.8	2105
6	200	300	70	57.9	2335	49.2	2057
7	200	400	40	97.8	2570	77.4	2295
8	200	400	55	72.7	2275	54.2	2016
9	200	400	70	63.8	2560	48.5	1991
10	300	200	40	71.4	2358	58.1	2068
11	300	200	55	53.2	1959	43.4	1699
12	300	200	70	45.7	1902	37.0	1509
13	300	300	40	60.0	2345	52.1	2007
14	300	300	55	44.0	1756	37.3	1540
15	300	300	70	41.8	1785	33.7	1461
16	300	400	40	55.3	1974	46.0	1732
17	300	400	55	37.3	1799	32.6	1431
18	300	400	70	36.0	1582	30.1	1402
19	400	200	40	45.6	1968	39.0	1570
20	400	200	55	35.2	1627	30.0	1390
21	400	200	70	35.0	1592	25.9	1327
22	400	300	40	43.5	1567	33.2	1420
23	400	300	55	31.7	1404	24.5	1222
24	400	300	70	29.1	1269	23.1	1124
25	400	400	40	42.0	1421	31.1	1282
26	400	400	55	31.5	1290	24.5	1159
27	400	400	70	26.3	1186	22.1	1054

As indicated in Table 5, with the increase in the number of search, rescue and medical teams, the duration of the rescue operation and the number of fatalities in both the proposed and the traditional CNP models are reduced. Therefore, the smallest number of fatalities and shortest duration of operations relate to the 27th scenario. In the proposed method, the duration of the search and rescue operations for different scales is at least 4.2, at most 30.9 and on average 11.6 h less than the duration in the case of the traditional CNP method. Thus, the average results for different scales indicate that reflecting uncertainty in task assignment improves the time of search and rescue operations by at least 13% and, on average, 20%. The number of fatalities in the proposed method decreased for different scales by at least 131, at most 638 and, on average, 302 individuals, respectively. Therefore, the proposed approach may perform better than the traditional CNP method, while the evaluation of the proposed method is superior for all evaluation parameters. The results demonstrate a significant degree of success in reducing the time spent on performing assigned tasks, as well as the number of fatalities, due to the uncertainty. The results indicate the importance of uncertainty and the need to address uncertainty in task assignments.

Uncertainty analysis was performed for each scenario. Uncertainty analysis plays an important role in model development and evaluation. It is necessary for defining the uncertainty bounds of model outputs [43,44]. There are various methods for analyzing uncertainty, which are mostly in the area of probable uncertainties. Monte Carlo method is one of them [43] that rely on repeated random sampling to obtain numerical results. In interval uncertainty, it is usually impossible to obtain the distribution of uncertain parameters and also, considering time progresses of probabilistic uncertainty analysis, the overestimation of the bounds will increase. Limited studies have been done on the interval uncertainty analysis. In this study, a proposed method by Lan and Peng (2016) was used for the interval uncertainty analysis [45].

In our model, the duration of rescue operations depends on task prioritization and outputs of each action in each stage. The final model used to calculate the duration of UARA operation can be defined as Equation (2):

$$T(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8) = A(x_1, x_2, x_3, x_4) + B(x_5, x_6, x_7, x_8) \tag{2}$$

The variables x_1 to x_8 are number of injuries, severity of the victims' injuries, duration of the operation and infrastructure priorities, energy, route status, task runtime by agents and risk level for agents, respectively. A and B are functions of prioritization and bidding. In the simulated system, task prioritization takes place $n + 1$ times (n is the number of tasks that cannot be performed in step 5 of the proposed method and re-added to the list) also, $T + n$ bidding will be held (T is total number of available tasks). Based on this information, Equation (2) can be represented as follows:

$$T(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8) = \sum_{n=1}^{n+1} \alpha_n(x_1, x_2, x_3, x_4) + \sum_{w=t}^{n+t} \beta_w(x_5, x_6, x_7, x_8) \tag{3}$$

Equation (3) is dynamically executed in the simulated system, until the duration of USAR operation is estimated. Based on Lan and Peng (2016) proposed interval uncertainty analysis, the Chebyshev points used. In Chebyshev formula (Equation 4), m collocation points on interval [0, 1], can be constructed using the following points [45]:

$$number_i = \left\{ \begin{array}{cc} 0.5 \times \left[1 - \cos\left(\frac{\pi(i-1)}{m-1}\right)\right] & for\ j = 1,\ if\ m = 1 \\ 0.5 & for\ j = 1,\ if\ m = 1 \end{array} \right\} \tag{4}$$

Using Equation (4), for each of the decision-making parameters in phase 1 and 5 of our proposed method, the numbers in the intervals are selected and the simulation continues. This technique presents a range of different outputs that may occur for each simulation. The results for 500 runs of each scenario are shown in Figure 7.

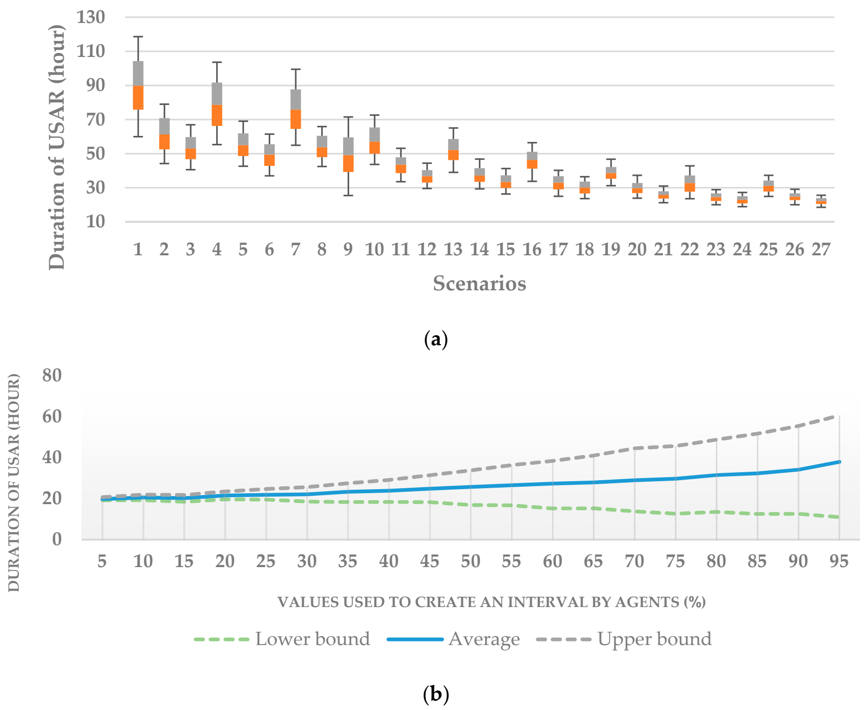


Figure 7. Uncertainty analysis of the proposed method in USAR operations, (**a**) for 27 simulated scenarios, (**b**) for different values in determining intervals on the 27th scenario.

As shown in Figure 7a, for scenario 27, the interval of results for duration of USAR operation is the lowest. This means that the length of the interval has a direct relation to the operating time. The reason for this can be found in Equation (3). Based on this formula, fewer task allocation lead to less operational time. Because the fewer task allocation causes less uncertainty in the simulated dynamic system. In step 3 of the proposed method, the agents use the [X, X + 30%X] and [X − 30%X, X] to estimate the bounds. In Figure 7b the results were obtained for different values instead of 30%. This analysis was applied to the 27th scenario. The graph shows that with the increase of uncertainty percentage of agents, the duration of USAR operation increases. This increase is due to the number of incorrect allocation.

In a limited number of studies, uncertainty in decision-making has been taken into account. Sang (2013) investigated rescue and search operations for disabled people during an earthquake, in which the fuzzy concept was used in order to interfere with linguistic uncertainties [9]. Fuzzy methods are highly dependent on fuzzy membership functions. Most of the research in this area has examined the proposed methods in a laboratory environment [11,26,27]. Experimenting the USAR operation on real scale to observe the uncertainties and their impact is very difficult and costly. Previous studies used square-shaped environment [26,27]. Injured persons, who should be rescued by rescue agents in the random initial position, were randomly distributed in an environment, which every side had a length of 2 km up to 20 km. investigating the proposed methods in simulated environments or real environments can be a more appropriate approach than testing in laboratory environments. According to previous studies, considering uncertainty in task allocation and cooperation between agents, as well as evaluating them in simulated UASR operations, was the main innovation of this research.

6. Conclusions

In the present study, a spatial simulation model for simulating post-earthquake USAR operations and modeling processes, as well as interactions related to natural hazards, was developed. The system provides a user-controlled toolkit to examine the interactions between search and rescue groups. The results of the current research enable appropriate decisions to be made in order to deal with the crisis during an earthquake or the simulation of earthquake conditions. Based on the results, in order to solve the problem of MASs coordination, using the CNP along with uncertainty, in order to coordinate and assign tasks among agents, can improve the behavior of the system. In addition, significant results were obtained in the field of establishing coordination among the agents of MASs.

Numerical results show that the proposed method is better than the CNP in terms of the duration of USAR operations (11.6 h on average) and the number of fatalities (302 individuals on average). Comparing the results of the proposed method and the CNP showed that taking uncertainty in task allocation into account improved the duration of the rescue operations by 20%. Also, decreased the number of fatalities by 15%. Therefore, the proposed approach showed a better performance than the traditional CNP method.

Although post-earthquake operations are difficult to manage and predict, the results of the present study indicated that the method of managing and coordinating is largely predictable, while some improvements can be made by identifying the important influential agents and using a model with a high adaptability to the conditions. Further, the results of the study illustrated that the agent-based modeling, as a low to high mode, can effectively simulate some of the behaviors of various human groups and, by obtaining results, display a general trend of social phenomena, such as cooperation during search and rescue operations. Although chaotic situation modeling can vary according to different factors, such as urban amenities, social culture and seasons, the proposed model can also be considered for chaotic situations involving higher levels of uncertainty (for example, 50% instead of 30%). It should be noted that, at higher rates, the proposed model simplifies the real environment and cannot fully model the chaotic situation.

In addition, the GIS proved its capabilities as an appropriate context for preparing the environment of agents, modeling their behavior and analyzing the results obtained from their activities. The model developed in the present study is flexible, due to having multiple and effective parameters for adapting to the environment, and can be used in other areas by considering its favorable results. Using the simulation of USAR operations can be a good alternative to traditional decision-making methods because these systems can model decision-making members, along with their interaction, as well as model the participation of different groups in decision-making. The characteristics of these systems can be attributed to their high ability to combine and consider incompatible time-spatial and behavioral complexities.

Some cases arising from the results and limitations of this study can be investigated in future research. These include: research to propose a method for interval uncertainty analyses by focusing on reducing the number of executions in dynamic simulations, evaluation of proposed method by calculating road blockages, using logic tree and fuzzy logic in order to address weighting techniques, applying the proposed method in an area where ground data exist (for example, a transportation system, simulation of a gate assignment problem), and focusing on the modeling of a chaotic situation.

Acknowledgments: This research was partially supported by a grant from the Iran national science foundation (Grant number 94012866).

Author Contributions: Navid Hooshangi and Ali Asghar Alesheikh conceived and designed the experiments.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Vecere, A.; Monteiro, R.; Ammann, W.J. Comparative analysis of existing tools for assessment of post-earthquake short-term lodging needs. *Procedia Eng.* **2016**, *161*, 2217–2221. [CrossRef]
2. El-Anwar, O.; El-Rayes, K.; Elnashai, A. Optimizing large-scale temporary housing arrangements after natural disasters. *J. Comput. Civil Eng.* **2009**, *23*, 110–118. [CrossRef]
3. Mustapha, K.; McHeick, H.; Mellouli, S. Modeling and simulation agent-based of natural disaster complex systems. *Procedia Comput. Sci.* **2013**, *21*, 148–155. [CrossRef]
4. Grinberger, A.Y.; Felsenstein, D. Dynamic agent based simulation of welfare effects of urban disasters. *Comput. Environ. Urban Syst.* **2016**, *59*, 129–141. [CrossRef]
5. Uno, K.; Kashiyama, K. Development of simulation system for the disaster evacuation based on multi-agent model using GIS. *Tsinghua Sci. Technol.* **2008**, *13* (Suppl. 1), 348–353. [CrossRef]
6. Liu, L.; Shell, D.A. Tackling Task Allocation Uncertainty via a Combinatorial Method. In Proceedings of the 2012 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR), College Station, TX, USA, 5–8 November 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 1–6.
7. Nourjou, R.; Hatayama, M.; Tatano, H. Introduction to Spatially Distributed Intelligent Assistant Agents for Coordination of Human-Agent Teams' Actions. In Proceedings of the 2012 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR), College Station, TX, USA, 5–8 November 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 251–258.
8. He, Y.H.; Pan, M.C.; Xu, W.; Zou, Y.B. Research of allocation for uncertain task based on genetic algorithm. In *Advanced Materials Research*; Trans Tech Publications: Zurich, Switzerland, 2014; pp. 324–329.
9. Sang, T.X. Multi-Criteria Decision Making and Task Allocation in Multi-Agent Based Rescue Simulation. Ph.D. Thesis, Saga University, Saga Prefecture, Japan, 2013.
10. Fiedrich, F.; Gehbauer, F.; Rickers, U. Optimized resource allocation for emergency response after earthquake disasters. *Saf. Sci.* **2000**, *35*, 41–57. [CrossRef]
11. Hooshangi, N.; Alesheikh, A.A. Agent-based task allocation under uncertainties in disaster environments: An approach to interval uncertainty. *Int. J. Disaster Risk Reduct.* **2017**, *24*, 160–171. [CrossRef]
12. Olteanu, A.; Pop, F.; Dobre, C.; Cristea, V. A dynamic rescheduling algorithm for resource management in large scale dependable distributed systems. *Comput. Math. Appl.* **2012**, *63*, 1409–1423. [CrossRef]

13. Kwon, O.; Im, G.P.; Lee, K.C. Mace-SCM: A multi-agent and case-based reasoning collaboration mechanism for supply chain management under supply and demand uncertainties. *Expert Syst. Appl.* **2007**, *33*, 690–705. [CrossRef]
14. Crooks, A.T.; Wise, S. GIS and agent-based models for humanitarian assistance. *Comput. Environ. Urban Syst.* **2013**, *41*, 100–111. [CrossRef]
15. Anh, N.T.N.; Zucker, J.D.; Du, N.H.; Drogoul, A.; An, V.D. Hybrid equation-based and agent-based modeling of crowd evacuation on road network. In Proceedings of the Eighth International Conference Complex System, Quincy, MA, USA, 26 June–1 July 2011; pp. 456–466.
16. Edrissi, A.; Poorzahedy, H.; Nassiri, H.; Nourinejad, M. A multi-agent optimization formulation of earthquake disaster prevention and management. *Eur. J. Oper. Res.* **2013**, *229*, 261–275. [CrossRef]
17. Hawe, G.I.; Coates, G.; Wilson, D.T.; Crouch, R.S. Agent-based simulation of emergency response to plan the allocation of resources for a hypothetical two-site major incident. *Eng. Appl. Artif. Intell.* **2015**, *46*, 336–345. [CrossRef]
18. Fecht, D.; Beale, L.; Briggs, D. A GIS-based urban simulation model for environmental health analysis. *Environ. Model. Softw.* **2014**, *58*, 1–11. [CrossRef]
19. Karimzadeh, S.; Feizizadeh, B.; Matsuoka, M. From a GIS-based hybrid site condition map to an earthquake damage assessment in Iran: Methods and trends. *Int. J. Disaster Risk Reduct.* **2017**, *22*, 23–36. [CrossRef]
20. Deyasi, K.; Chakraborty, A.; Banerjee, A. Network similarity and statistical analysis of earthquake seismic data. *Phys. A Statist. Mech. Appl.* **2017**, *481*, 224–234. [CrossRef]
21. Kwan, M.-P.; Lee, J. Emergency response after 9/11: The potential of real-time 3D GIS for quick emergency response in micro-spatial environments. *Comput. Environ. Urban Syst.* **2005**, *29*, 93–113. [CrossRef]
22. Panahi, M.; Rezaie, F.; Meshkani, S. Seismic vulnerability assessment of school buildings in Tehran city based on AHP and GIS. *Nat. Hazards Earth Syst. Sci.* **2014**, *14*, 969–979. [CrossRef]
23. Grigoratos, I.; Dabeek, J.; Faravelli, M.; Di Meo, A.; Cerchiello, V.; Borzi, B.; Monteiro, R.; Ceresa, P. Development of a fragility and exposure model for Palestine—Application to the city of Nablus. *Procedia Eng.* **2016**, *161*, 2023–2029. [CrossRef]
24. Monteiro, R.; Ceresa, P.; Cerchiello, V.; Dabeek, J.; Meo, A.; Borzi, B. Towards Integrated Seismic Risk Assessment in Palestine—Application to the City of Nablus. In Proceedings of the 7th European Congress on Computational Methods in Applied Sciences and Engineering (ECCOMAS Congress 2016), Crete, Greece, 5–10 June 2016; pp. 5987–5998.
25. Mansouri, B.; Hosseini, K.; Nourjou, R. Seismic Human Loss Estimation in Tehran using GIS. In Proceedings of the 14th World Conference on Earthquake Engineering, Beijing, China, 12–17 October 2008.
26. Lee, H.; Al-yafi, K. Centralized Versus Market-Based Task Allocation in the Presence of Uncertainty. In Proceedings of the 2010 International Conference on Control Automation and Systems (ICCAS), Gyeonggi-do, Korea, 27–30 October 2010.
27. Rahimzadeh, F.; Khanli, L.M.; Mahan, F. High reliable and efficient task allocation in networked multi-agent systems. *Auton. Agents Multi-Agent Syst.* **2015**, *29*, 1023–1040. [CrossRef]
28. Botelho, S.C.; Alami, R. M+: A Scheme for Multi-Robot Cooperation through Negotiated Task Allocation and Achievement. In Proceedings of the 1999 IEEE International Conference on Robotics and Automation, Detroit, MI, USA, 10–15 May 1999; IEEE: Piscataway, NJ, USA, 1999; pp. 1234–1239.
29. Di Paola, D.; Naso, D.; Turchiano, B. Consensus-Based Robust Decentralized Task Assignment for Heterogeneous Robot Networks. In Proceedings of the 2011 American Control Conference, San Francisco, CA, USA, 29 June–1 July 2011; IEEE: Piscataway, NJ, USA, 2011; pp. 4711–4716.
30. Kmiecik, W.; Wojcikowski, M.; Koszalka, L.; Kasprzak, A. Task Allocation in Mesh Connected Processors with Local Search Meta-Heuristic Algorithms. In Proceedings of the Asian Conference on Intelligent Information and Database Systems, Hue City, Vietnam, 24–26 March 2010; Springer: Berlin/Heidelberg, Germany, 2010; pp. 215–224.
31. Bradley, R.; Drechsler, M. Types of uncertainty. *Erkenntnis* **2014**, *79*, 1225–1248. [CrossRef]
32. Liang, J.; Chin, K.; Dang, C.; Yam, R.C. A new method for measuring uncertainty and fuzziness in rough set theory. *Int. J. Gen. Syst.* **2002**, *31*, 331–342. [CrossRef]
33. Sayadi, M.K.; Heydari, M.; Shahanaghi, K. Extension of VIKOR method for decision making problem with interval numbers. *Appl. Math. Model.* **2009**, *33*, 2257–2262. [CrossRef]

34. Matarić, M.J.; Sukhatme, G.S.; Østergaard, E.H. Multi-robot task allocation in uncertain environments. *Auton. Robots* **2003**, *14*, 255–263. [CrossRef]
35. Opricovic, S.; Tzeng, G.-H. Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *Eur. J. Oper. Res.* **2004**, *156*, 445–455. [CrossRef]
36. Hamzehloo, H.; Alikhanzadeh, A.; Rahmani, M.; Ansari, A. Seismic hazard maps of Iran. In Proceedings of the 15th World Conference on Earthquake Engineering, Lisbon, Portugal, 24–28 September 2012.
37. Hosseini, K.A.; Hosseini, M.; Jafari, M.K.; Hosseinioon, S. Recognition of vulnerable urban fabrics in earthquake zones: A case study of the Tehran metropolitan area. *J. Seismol. Earthq. Eng.* **2009**, *10*, 175–187.
38. Meghdad, S. Strong Ground Motion Prediction of Future Large Earthquake from Niavaran Fault in Tehran, Iran by Finite Fault Method. In Proceedings of the 15th World Conference on Earthquake Engineering, Lisbon, Portugal, 24–28 September 2012.
39. Vafaeinezhad, A.; Alesheikh, A.; Hamrah, M.; Nourjou, R.; Shad, R. Using GIS to Develop an Efficient Spatio-Temporal Task Allocation Algorithm to Human Groups in an Entirely Dynamic Environment Case Study: Earthquake Rescue Teams. In Proceedings of the International Conference on Computational Science and Its Applications, Seoul, Korea, 29 June–2 July 2009; pp. 66–78.
40. Rasekh, A.; Reza Vafaeinezhad, A. Developing a GIS Based Decision Support System for Resource Allocation in Earthquake Search and Rescue Operation. In Proceedings of the International Conference on Computational Science and Its Applications, Salvador de Bahia, Brazil, 18–21 June 2012; pp. 275–285.
41. Chen, Y.-Z.; Shen, S.-F.; Chen, T.; Yang, R. Path optimization study for vehicles evacuation based on Dijkstra algorithm. *Procedia Eng.* **2014**, *71*, 159–165. [CrossRef]
42. Badreldin, M.; Hussein, A.; Khamis, A. A comparative study between optimization and market-based approaches to multi-robot task allocation. *Adv. Artif. Intell.* **2013**, *2013*, 256524. [CrossRef]
43. Inam, A.; Adamowski, J.; Prasher, S.; Albano, R. Parameter estimation and uncertainty analysis of the Spatial Agro Hydro Salinity Model (SAHYSMOD) in the semi-arid climate of Rechna Doab, Pakistan. *Environ. Model. Softw.* **2017**, *94*, 186–211. [CrossRef]
44. Albano, R.; Craciun, I.; Mancusi, L.; Ssole, A.; Ozunu, A. Flood damage assessment and uncertainty analysis: The case study of 2006 flood in Ilisua basin in Romania. *Carpathian J. Earth Environ. Sci.* **2017**, *12*, 335–346.
45. Lan, J.; Peng, Z. Interval uncertainty analysis using CANDECOMP/PARAFAC decomposition. In *Model Validation and Uncertainty Quantification, Volume 3, Proceedings of the 34th IMAC, a Conference and Exposition on Structural Dynamics 2016*; Atamturktur, S., Schoenherr, T., Moaveni, B., Papadimitriou, C., Eds.; Springer International Publishing: Cham, Switzerland, 2016; pp. 73–81.