USAR simulation system: ~~presenting~~ spatial strategies ~~in~~ for agent~~s'~~ task allocation under uncertain conditions

Navid Hooshangi[1] , Ali Asghar Alesheikh[2] , Mahdi Panahi[3,4], Saro Lee[4,5]

1 Assistant Professor, Department of Surveying Engineering, Arak University of Technology, Arak, Iran,Postal code 3818146763

2 Professor in geospatial information science, Faculty of Geodesy and Geomatics Engineering, K.N. Toosi University of Technology, Tehran, Iran

3 Division of Science Education, Kangwon National University, College of Education, # 4-301, Gangwondaehakgil, Chuncheon-si, Gangwon-do 24341, South Korea

4 Geoscience Platform Division, Korea Institute of Geoscience and Mineral Resources (KIGAM), 124, Gwahakro Yuseong-gu, Daejeon 34132, Korea

5 Department of Geophysical Exploration, Korea University of Science and Technology, 217 Gajeong-ro Yuseonggu, Daejeon 34113, Korea

Correspondence: Ali Asghar Alesheikh (alesheikh@kntu.ac.ir.) and Saro Lee (leesaro@kigam.re.kr)

ABSTRACT

Task allocation ~~in~~ under uncertain~~ty~~ conditions is a key problem for agents attempting to achieve harmony in disaster environments. ~~This paper presents an agent-based simulation to investigate tasks allocation through the consideration of appropriate spatial strategies to deal with uncertainty in urban search and rescue (USAR) operations.~~This paper presents an agent-based simulation to investigate task allocation considering appropriate spatial strategies to manage uncertainty in urban search and rescue (USAR) operations. The proposed method is based on the contract net protocol (CNP) and implemented ~~is presented in~~over five phases: ordering existing tasks considering intrinsic interval uncertainty, finding a coordinating agent, holding an auction, applying allocation strategies (four strategies), and implementing ~~implementation~~ and ~~observation of~~observing the real environmen~~tal uncertainties~~. Applying allocation strategies is the main innovation of the method. –The methodology was evaluated in Tehran's District 1 for 6.6, 6.9, and 7.2 magnitude earthquakes. The simulation ~~started~~ began by calculating the numbers of injured individuals, which ~~was~~ were 28,856, 73,195~~28856, 73195~~, and 111,463~~111463~~ people for each earthquake, respectively. ~~The~~ Simulations were performed for each scenario for a variety of rescuers (1000, 1500, and 2000 rescuers). In comparison with the ~~contract net protocol (~~CNP~~)~~, the standard duration ~~time~~ of rescue operations ~~in~~ with the proposed approach exhibited ~~includes~~ at least 13% ~~of~~ improvement~~-~~, with a maximal improvement ~~and the best percentage~~ of ~~recovery was~~ 21%. Interval uncertainty analysis and ~~the~~ comparison of the proposed strategies showed that ~~an increase in~~increased uncertainty ~~has~~ le~~a~~ds to increased ~~an increase is~~d rescue time for the CNP~~ of 67.7 hours,~~ and ~~for~~ strategies ~~one~~ 1 to ~~four~~4 ~~an increased rescue time of 63.4, 63.2, 63.7, and 56.5 hours, respectively~~. The time increase was less with ~~in~~ the uniform distribution strategy (~~S~~strategy 4) ~~was less~~ than with the other strategies~~rest~~. The ~~Considering~~ consideration of strategies in the task allocation process, especially spatial strategies, ~~resulted~~ facilitated both ~~resulting in the~~ optimization and increased flexibility of the allocation. It also improved ~~as well as~~ conditions for fault tolerance and agent-based cooperation stability in the USAR simulation system.

Keywords: USAR operations; Agent-based simulation; Disaster Environments; Task allocation; Interval uncertainty; Spatial strategies.

1. Introduction

Preparation to manage deal with an earthquake crisis requires by an optimal and appropriate correct management is absolutely necessary. Agent b-based modeling of search and rescue (SAR) operations after an earthquake is a good choice model for decision making, compared to with traditional computational approaches (Hooshangi and Alesheikh, 2018). Multi-Multi-agent systems (MASs) consist of several automatic and autonomous agents which that coordinate their activities to achieve a target (Crooks and Wise, 2013;Sabar et al., 2009). Multi-agent systemsMASs are suitable for the modeling and simulation of complex systems (Mustapha et al., 2013). They allow the division of divide the system into subdivisions (agents) and the modelling of the relationships among these agentsmodel the relationship between them (Uno and Kashiyama, 2008). The utilization use of multi-agent systems is necessary in for disaster management (Hawe et al., 2015;Grinberger and Felsenstein, 2016). Importantly, multi-agent systemsMASs can be used to implement various scenarios of search and rescue SAR operations, as well as distributions of and facilities, distribution in the crisis area (Crooks and Wise, 2013).

Task allocation is one of the main coordination challenges issues in coordinating among a set ofsets of agents in a multi-agent system (MAS) (Liu and Shell, 2012;Nourjou et al., 2011;Chen and Sun, 2012). Agents fail to reach their ultimate goal without the proper assignment of tasks (Reis and Mamede, 2002). In disaster environments, urban search and rescue (USAR) and the assignment of tasks are dynamic processes occurring under uncertain conditions uncertainty (Hooshangi and Alesheikh, 2017). Generally, task allocation on a large scale is influenced by uncertainties and various factors (Cai et al., 2014). Uncertain conditions circumstances have a major impact on the initial planning and results of rescue operations planning (Hooshangi and Alesheikh, 2018). Despite the findings of various investigations, an optimal task allocation solution has not been established projects, these projects could not find an optimal solution (Olteanu et al., 2012).

In many instancescases, the initial allocation may result in face problems, or new tasks may be added to the work-list; therefore, replanning and reallocation is necessaryrequired. Reallocation is an effective reaction to environmental uncertainties and changes in the environments, and it has an important roles in both reducing the wasted time during an operation and increasing operation profitability (Zhang et al., 2014). Presenting strategies for allocation is one of the approaches to improve flexibility against disorder in natural disaster environments. Reallocation after an instantaneous disruption is very important, especially in large-scale distributed systems on large scales (such ase.g., USAR operations) (Olteanu et al., 2012). Therefore, it is better to plan for the process and plan strategies to deal with future situations from the beginning. Presenting strategies for allocation is one of the approaches to improve flexibility against disorder in natural disaster environments.

Task allocation does not take place in only one stage of USAR operations [9]. In natural disaster conditions, uncertainties should be taken into account while making decisions about the assignment of tasks, just as planners should be prepared to deal with task non-compliance.An effective task allocation approach in USAR operations should include strategies for replanning to manage deal with future situations. In natural disaster conditions, uncertainties should be taken into account while making decisions about the assignment of tasks, just as planners should be prepared to deal with task non-compliance. In other words In natural disaster conditions, , the results of the initial task allocation should be changed through by applying uncertainties to reassign tasks in crisis-driven conditions. Because Since tasks might may not be performed well for various reasons, strategies (e.g., such as minimum location displacement) should be applied to initial responses in order to morepreserve additional save more time in during reallocation or future task allocation. It is not enough to only consider the uncertainty in the initial decision-making process, since the working environment is completely dynamic and there may be problems in assigning tasks. This approach to task allocation optimizes planning performance in order to achieve better performance time providingand provides as well as providing conditions for fault tolerance.

The present article is the final part of a research project in Iran. This research project ~~in~~was carried out over three phases. In the first phase, uncertainty in task allocation among agents was considered and task allocation ~~done~~was performed only by considering the proximity (spatial distance) to the tasks. The developed method was evaluated in a square-shaped random environment ~~no~~without a sensitivity analysis (Hooshangi and Alesheikh, 2017). In the second phase, the feasibility of the developed method was investigated in a simulated environment using real regional data. In this phase, the operational environment of a crisis was simulated and the developed method was examined in a real environment. In the simulated system, ~~the~~damage for a 6.8 ~~Richter~~magnitude earthquake damage was calculated for District 3 of Tehran, and rescue operations were modeled (Hooshangi and Alesheikh, 2018). In the third phase using the concepts of previous articles (Hooshangi and Alesheikh, 2018, 2017), spatial strategies were included in task allocation among agents and simulated with real-environment data. The present paper is the output of the third phase of the research project, which aimed

~~The present study aims~~ to improve task allocation in crisis-ridden conditions for agent-based groups by considering proper strategies to manage ~~deal with the available~~ uncertainties. This paper first~~ly~~ develops an agent-based simulation system for USAR operations, then applies uncertainties in agent~~s'~~ decision-making ~~phase~~ by improving an interval VIKOR method ~~in order~~ to perform task allocation, and ~~also~~ defines strategies for conditions ~~in~~ under which the initial assignment has encountered ~~faced~~ a problem and requires reallocation (i.e., managing availability ~~dealing with available~~ uncertainty ~~in~~ during implementation). The main innovation of the study is ~~that it~~ the establishment of ~~presents~~ an approach to improve conditions during reallocations~~,~~ or future allocations~~,~~ when initial allocations ~~face~~encounter ~~face~~ problems due either to ~~available~~availability ~~available~~ uncertainties~~,~~ or the addition of a new task. In general, strategies are selected in such a ~~way~~manner ~~way~~ that the final cost of the system will not increase abnormally if the initial allocations encounter problems. ~~face a problem.~~

~~The paper is organized in the following way. literature review and background are provided in Section 2. The characteristics of the study area are described in Section 3. Section 4 is dedicated to the description of the research scenario and explains the proposed method in five sub-steps. In section 5, some tests are developed and also the results of the simulations of USAR operation are presented. Finally, in section 6, the conclusions of this research along with future directions are summarized.~~

~~4.~~2. Literature review and background

~~4.1~~2.1 ~~Agent~~ Agent-based USAR simulation

An agent-based model is a class of computational models for simulating the actions and interactions of autonomous agents. ~~Simulation has been used in various sciences including disaster management, emergency supply chains, and tsunami.~~ ~~Table 1 presents some of the a~~Agent-based simulations ~~performed in previous researches.~~have been used in various investigations including crisis ~~management~~ /disaster management (Wang et al., 2012;Hooshangi and Alesheikh, 2018), emergency supply chains (Ben Othman et al., 2017), tsunamis (Erick et al., 2012), and collective behavior (Welch et al., 2014). These simulations can be effective in both planning and policymaking (Fecht et al., 2014). Simulation of the operating system involves a simplified real environment, which is used to model a wide range of agents in complex systems. Various researchers have modeled a ~~part~~portion of the behavior of agents in ~~environment~~simulated environments (Erick et al., 2012;Wang et al., 2012;Matarić et al., 2003) and demonstrated collaboration among agents. However, agent cooperation in catastrophic environments has been less extensively studied, ~~,~~such that uncertainty in collaboration among agents has generally not been considered. In previous ~~researches~~studies, a geospatial information system platform was used when preparing the environment and creating a simulation base map (Welch et al., 2014). Spatial analysis and tools related are used in most research endeavors in USAR operations after an earthquake.

Simulation has been used in various sciences including disaster management, emergency supply chains, and tsunami.

Application area	Obvious point	Objective	Result	Ref.
Disaster management	Developed a dynamic agent-based model (ABM) in USAR operations	propose an approach for dynamic collaboration among agents	Considering uncertainty in collaboration among agents can be a highly advantageous in	[1]
	An agent-based model to simulate the emergency medical response to a mass casualty incident was built	Modeling an emergency medical response	Simulated model builds intuition and understanding in advance of facing actual incidents that are rare in operating experiences.	[16]
Emergency supply chains	An architecture based on zoning for the management of emergency supply chains is proposed.	Resources scheduling	Considering agents' cooperation, the DSS provides a scheduling plan that guarantees an effective response to emergencies.	[17]
Tsunami	By analyzing images of the real-world video, the proposed model provides the ability to examine people and output	Combined evacuation model with a tsunami simulation model	An agent-based model was created to define specific features for each of the agents and observe individuals' behavior in the complex process of a tsunami evacuation.	[18]
Collective behavior	Combining General-Purpose Computing on Graphics Processing Units (GPCPU) and Geospatial information system (GIS) computing in the form of expanding agent simulation	A better understanding of the old-world screwworm risks	A tool was created for decision support for policy makers in order to analyze the spatial distribution of OWS and its effects on livestock.	[19]
Distribution of seeds	Investigating the effect of diffusion factors on different species and different competitive societies with and without destructive factors	Simulation of the distribution of seeds	A GIS prototype was created to simulate the distribution of seeds, which are modified by various factors.	[22]

Agent-based systems have been used as simulation tools in various studies. Agent-based simulation models can be used as an effective approach in planning and policy making [20]. Simulation of the operating system involves a simplified real environment, which is used to model a wide range of agents in complex systems. Simulation models can be used as an effective approach in planning and policy making [20]. In the studies presented in Table 1, researchers modeled a part of the behavior of agents in the simulation environment and collaboration among agents. However, the agent's cooperation in catastrophic environments has been less studied, generally, uncertainty in collaboration among agents has not been taken into account. In previous researches, a Geospatial information system (GIS) platform were was used when preparing the environment and creating a base map. Spatial analysis and tools are used in most research endeavors in USAR operations after an earthquake.

4.462.2 Approaches to applying uncertainties in task allocation

Multi-robot task allocation (MRTA) is a type of general task allocation problem (TAP) in which resources and tasks are distributed in pre-defined areas [10]. Agents should include environmental uncertainties in their performance with respect to regarding planning goals. There are four common approaches to considering uncertainty:, including: probabilistic, fuzzy logic, rough set and interval set (Hooshangi and Alesheikh, 2017). U1)

Probabilistic, this method uses different probability distribution functions and statistical parameters such as the mean and standard deviation for modeling. 2) Fuzzy logic, this theory is based on imprecise and non-numerical information (linguistic ambiguities) concepts. 3) Rough set, which is an approximation of a crisp set by lower and the upper approximation of the original set. It completes fuzzy logic. 4) Interval set, in this method, due to the uncertainty in the value of a parameter, that parameter is specified in an interval regardless of the probabilistic distribution (unlike probabilistic theory) or membership function (unlike fuzzy logic) [12]. Uncertainty in taskss allocation has been investigated in various studies that can be categorized as follows:

Ssensors' noise : In this category, uncertainty in the input information of tasks such as noise in operating sensor, agent's location, and noise in measurement sensor has been considered using auction auction based, Hungarian interval algorithm (Liu and Shell, 2011;Bertuccelli et al., 2009;Matarić et al., 2003), and consensus-based bundle algorithm (CBBA) methods, .

Aan Accidental accidental event induring in execution : In this class, a random event prevents the execution of tasks, so while assigning tasks, the uncertainty of not performing tasks must be taken into account. Hill climbing algorithm CNP (Lee and al-yafi, 2010;Li and Cruz Jr, 2005)and two-level hierarchical algorithm have been used to consider this.,

Tthe Occurrence occurrence of new tasks : In these studies, the environment is dynamic and a new task may be created at any time. Therefore, the assignment of tasks is always done with the possibility of entering a new job. The predominant method used in these studies is Q learning [27].(Xiao et al., 2009;Kayır and Parlaktuna, 2014),

Tthe Number number of groups: In this category, the number of individuals or groups whom tasks are assigned between them is not known. The methods used in these studies are machine learning and probabilistic algorithm based on learning automata (Quiñonez et al., 2011;Dahl et al., 2009), .

Tthe Relationship relationship among the agents : This group of studies has been conducted in assigning tasks that require several groups to work together to perform the tasks. CBBA (Choi et al., 2009;Su et al., 2016)and dynamic weighted task allocation are the methods used in this field., and

Ddecision parameters (Hooshangi and Alesheikh, 2017).:

In this category, which are is suitable for MASs, uncertainties are included in the decision parameters for assigning tasks. Therefore, all the information needed to for tasks allocation is considered uncertain. Various methods such as CNP [12], stochastic scheduling [33], and genetic algorithm [34] have been used.

The mentioned methods have been used in various applications such as multi- UAVunmanned aerial vehiclesUAV (Bertuccelli et al., 2009), supply chains (Dahl et al., 2009), moving plants (Tan and Barton, 2016), and disaster environments (Su et al., 2016). There is no dominant wayapproach way to model uncertainty for all phenomena. The appropriate method is determined based on the characteristics of the phenomenon and the purpose of the study. In crisis environments, there is uncertainty in all decision parameters. In the uncertainty in decision parameters category, which is suitable for MASsmulti-agent systems, uncertainties are inassociated with the decision parameters for assigning tasks. Therefore, all information needed for task allocation is considered uncertain. Various methods such as the contract net protocol (CNP) (Hooshangi and Alesheikh, 2017), stochastic scheduling (Tan and Barton, 2016), and genetic algorithms (He et al., 2014) have been used. We in these contexts. Here, we This studyWe presentspresent an approach that includes uncertaintyuncertainties uncertainty in decision parameters, also and includes strategies in the contract net protocol (CNP). The CNP produces local optimal solutions which that are abundantly used in multi-agent systems (Choi et al., 2009). This method is simple, practical, and popularpopularly used popular in agent-based modeling.

In USAR operations, ~~the~~ complete individual expertise ~~of the individuals~~ is impossible due to a lack of environmental knowledge; therefore, determining membership function and the probability distribution is a complex and ~~time consuming~~time-consuming step. ~~In this study,~~We used interval analysis ~~has been taken into account in order~~ to ~~overcome~~manage ~~overcome~~ these shortcomings and to consider the intervallic nature of available data within ~~the~~ a rescue operation~~s~~.

~~1) Probabilistic, this method uses different probability distribution functions and statistical parameters such as the mean and standard deviation for modeling. 2) Fuzzy logic, this theory is based on imprecise and non-numerical information (linguistic ambiguities) concepts. 3) Rough set, which is an approximation of a crisp set by lower and the upper approximation of the original set. It completes fuzzy logic. 4) Interval set, i~~In the interval set ~~this~~ method, due to the uncertainty in ~~the~~a parameter's value ~~of a parameter~~, that parameter is specified ~~in~~as an interval regardless of the probabilistic distribution (unlike in probabilistic theory) or membership function (unlike in fuzzy logic) (Hooshangi and Alesheikh, 2017).~~In order to deal with interval data in CNP, different multi criteria decision making (MCDM) methods are proposed.The interval- based VIKOR method was used extensively to coordinate agents for the assignment of tasks with interval data~~ [12]~~. The interval VIKOR method is described in [35].~~

~~4.47~~2.3 Reallocation and reassigning methods

~~Different~~Distinct ~~Different~~ algorithms have been proposed for scheduling and task reallocation in accordance with the ~~required~~ tasks and available conditions within ~~the~~ an environment (Gokilavani et al., 2013). Some reallocation methods (e.g., data envelopment analysis (Barnum and Gleason, 2010)) and exact algorithms (e.g., a branch-and-bound algorithm with column generation) resolve problems on a smaller scale (e.g., 10 jobs and three vehicles). ~~are applied to the reassignment of individuals in organizations~~ [37]~~.~~ In such methods, ~~the solution's run time is not important~~the process is time-consuming and slow for resolving large-scale problems (Cai et al., 2014). Therefore, they are not suitable for the allocation of tasks that should be performed dynamically and instantaneously in large-scale problems.

~~; therefore, they are mostly used in concepts of industries and for the assignment of resources such as the re-engineering of the organization in order to rearrange organization members. They do not assign tasks which~~ that ~~should be performed dynamically and instantaneously.~~

In some research, such as ~~addressing~~the investigation of ~~those addressing~~ gate reassignment problems ~~(GAP)~~, initial assignment tables ~~were~~ have been created using heuristic methods in such a ~~way~~manner ~~way~~ that a succession delay is minimized (Cheng, 1997). The incidence of adverse events may disrupt the original table. ~~are~~Notably, this method is ~~These methods are~~ not ~~responsive~~suitable ~~responsive~~ for a ~~great~~large ~~great~~ number of tasks. Some other task allocation methods are interdependent with the plan's ongoing tasks, such as ~~is the case~~ in construction operations (Olteanu et al., 2012). In ~~such~~those mathematical calculations, when a task fails, all other tasks ~~which~~that were based on ~~the~~its correct implementation ~~of that task should~~must be replanned.

~~In USAR, any rescue process is generally independent of any other rescue processes.~~

~~Creating the initial table and revising it for any disruption or new input is impossible in disaster environments, considering the scale of space and the nature of the assignment, and because the input task rate and uncertainty are not specified at all and the time table needs to be constantly edited. .On the other hand, i In disaster environments, only some parts of the workflow are ready to be implemented and assigned. Maximizing the number of survivors in the possible shortest time is the purpose of rescue operations. Therefore, there exists nothing like the concept of delay, but only the implementation or non-implementation of a specified task. The concept of prioritizing the tasks is the most important in USAR operations and the concept of delay is not acceptable.~~

~~Some task allocation methods are interdependent with the plan's ongoing tasks, as is the case in construction operations ~~[14]~~. In such mathematical calculations, when a task fails, all other tasks which were based on the correct implementation of that task should be replanned. In USAR, any rescue process is generally independent of any other rescue processes.~~

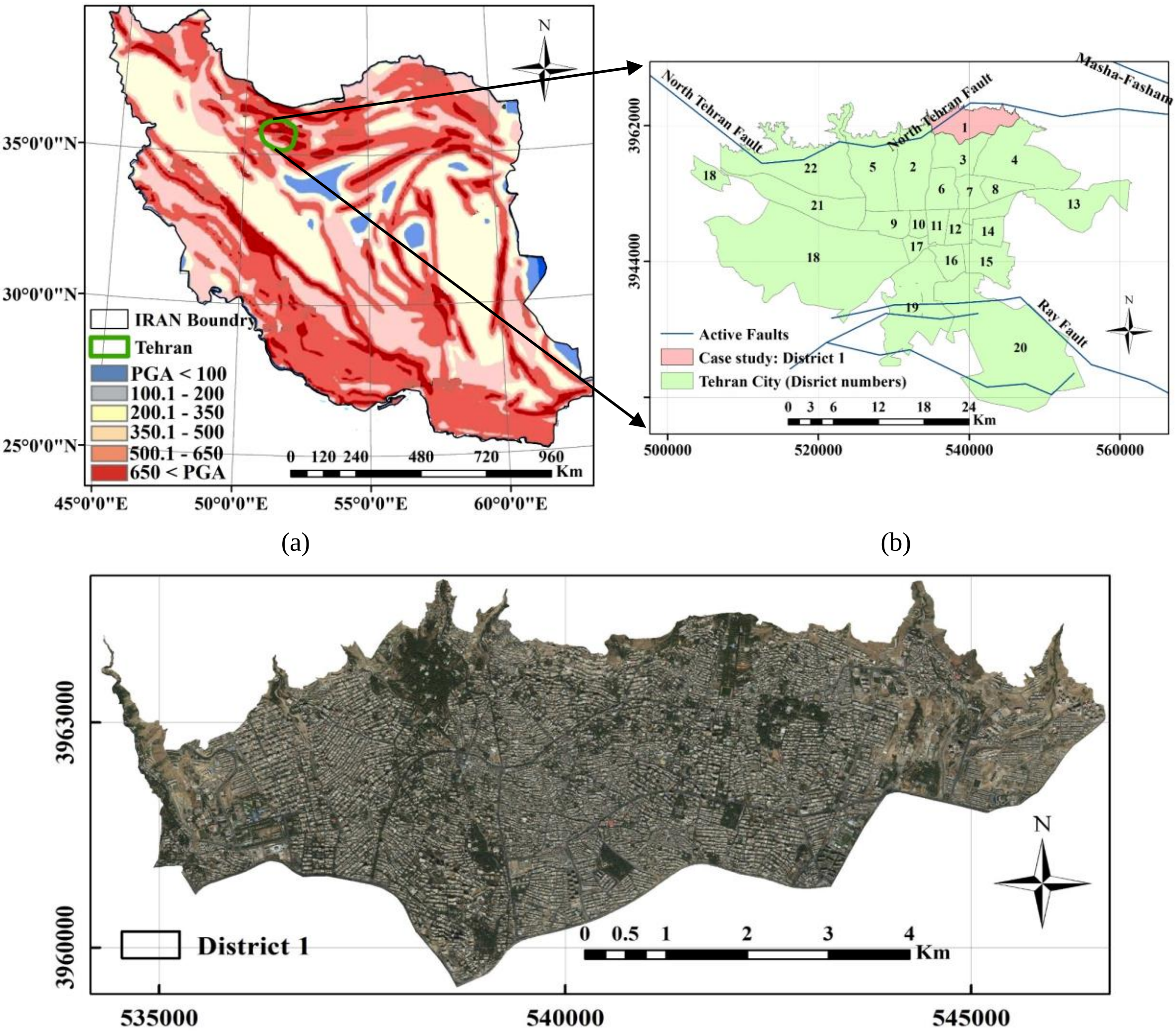
~~Methods such as simulated annealing (SA) and the ant colony optimization algorithm cannot find a global optimization of the problem and provide local solutions instead ~~[13]~~. In contrast, the exact algorithms like the branch-and-bound with column generation (BBCG) algorithm resolve the problems on a smaller scale (e.g., 10 jobs and three vehicles) but it is very time-consuming and slow in resolving large-scale problems ~~[13]~~. Therefore, an ~~An appropriate reallocation method must be applied with respect to ~~regarding ~~the nature and scale of the problem. In USAR, a rescue process generally ~~independent~~occurs independently of any other rescue processes, and only ~~parts~~a portion of the workflow is ready to be implemented and assigned. ~~a~~Moreover, because of the

~~Due to the a ~~large number of rescue groups in USAR operations, as well as the available uncertainties and ~~the~~ dynamic nature of multi-agent systems in disaster environments, the concept of general planning is ~~common~~uncommon ~~not very common ~~and ~~it plan~~appropriate plans ~~the plan ~~should be~~is better that the plan is~~ produced both locally and cross-sectionally. ~~Planning is appropriate for cases in which the number of initial tasks is fixed and the changes are minimal. There are several methods to resolve the problem of assigning tasks, but most of these algorithms cannot be developed for uncertain conditions and restrictions, as is the case for USAR operations. Despite the application of reallocation methods in other studies, this issue has been rarely applied to critical rescue environments (such as USAR in earthquakes). ~~Most available methods to resolve the problem of assigning tasks cannot be developed for uncertain conditions and restrictions such as in critical rescue environments (e.g., USAR after earthquakes).

~~Regarding~~With respect to ~~Regarding ~~USAR operations, task allocation methods ~~should ~~mustinclude different strategies for all conditions and be dynamically generated in a real-time environment. ~~Despite the application of reallocation methods in other studies, this issue has been rarely applied to critical rescue environments (such as USAR in earthquakes). Unlike~~In contrast to ~~Unlike ~~previous studies, we define an approach based on spatial strategies~~ so~~, such that ~~so that ~~the results of the initial task allocation are used ~~in the~~for future ~~for other ~~task allocations~~,~~ and are appropriate in the rescue environment. Time limitations ~~are~~constitute ~~are ~~another issue in the ~~replanning~~reallocation and ~~in~~reassignment of ~~reassigning regarding reallocation in ~~rescue teams. Therefore, the present study aims to expand the CNP method ~~as a~~for rapid ~~method for resolving the ~~problem resolution.

~~6.~~3. Case study and data

The proposed approach can be implemented in ~~different~~various ~~different ~~study areas. ~~In t~~This study~~,~~ used a part of Tehran (District 1 in the capital of Iran)~~,~~ ~~in order ~~to evaluate the feasibility of the proposed method ~~and according to~~on the basis of available data~~, a part of Tehran (District One in the capital of Iran) was selected~~. District ~~One ~~1 is one of 22 central districts of Tehran Province, Iran~~Tehran Province, Iran~~. ~~The d~~District ~~One ~~1 has ~~a~~an area of~~a~~ 210 ~~square km (km^2) area, which~~ and ~~square km (km^2) area, which ~~is located in the northernmost part of the city of Tehran (Figure 1). Its population is 433,500.



(c)

Figure 1 Location of case study: (a) peak ground acceleration map of Iran for a return period of 2475 years and approximate location of Tehran, (b) location of District 1 and active faults in Tehran (c) Map of District One 1 (study area) and active faults, Tehran.

The Recent recent Tehran earthquake (5.2 RichtermagnitudeRichter) on in December 2017 attracted the attention of many urban planning organizations. This metropolis is one of the vulnerable areas to earthquakes. The rapid growth of urbanization and the vulnerability of structures have increased the potential risk of the city [39]. Tehran is a highly seismic area asbecauseas it is surrounded by the Ray, Masha-Fasham, and North Tehran faults (Figure 1(b)). Seismologists have statedreported stated that a severe earthquake expectedmay occur could be expected in Tehran in the future (Hosseini et al., 2009). The North Tehran fault is the city's biggestlargest biggest fault and is aboutapproximately about 35 km long. It and has the potential for a 7.2 magnitude earthquake. For this purpose, the North Tehran fault scenario, with the capacity to cause the most destructive potential earthquake in Tehran, is was selected. in the present study. Various scenarios can be implemented. toIn accordance with According to the suggestions of theseismologist the experts, we simulated the magnitude 6.6, 6.9, and 7.2 magnitude earthquakes. The basic data used in environment simulation arewere block maps, population, distance from the fault, building material, agent' location, '-year of building construction, and building height.

8.4. Materials and Methods

In this section, the simulated scenario and the proposed method are described.

8.14.1 The sScenario of proposed agent-based USAR simulation

The proposed methodology is a general approach to various phenomena. In this study, it is assumed that there is a disaster environment, and detailed information on the characteristics of the environment is not available (in the environment, events are uncertain). We assume the presence of a disaster environment in which events are uncertain. In this scenario, athea crisis is assumed to be an earthquake. The injured individuals are trapped under the rubbles and the number of themsuch individuals them in each building block is uncertain. Rescuing injured people is the main goal. Saving each person is a task that must be performed through the cooperation of rescue agents. After an earthquake, the numbers of injured and deaddeceased dead people can be estimated by using different formulas by determining the magnitude and the location of the earthquake, as well as the urban context data of the buildings (Kang and Kim, 2016). alsoFurthermorealso, Saving each person is a task that must be done. Tthe possible locations of injured individuals can be predicted using buildings damage assessment models. Therefore, the simulation inputs are the injured individualsindividuals' locations and their characteristics, which are available with some uncertainty. uncertainly accessible. The rescue agents are tryingattempting trying to save the injured onesindividuals ones by moving up toward to the task location. Given the results of previous studies (He et al., 2014;Hooshangi and Alesheikh, 2017;Sang, 2013;Chen et al., 2012) and expertsin accordance with expert opinion according to experts on USAR operations, the uncertainties include the number of injuries, the severity of the victims' injuries, duration of the operation, infrastructure priorities, agent energy, route status, task runtime by an agent, and risk level for theeach agent. These are important uncertainties in task allocation. All these parameters are specified intervalas intervals by an interval during the task allocation process. After taskstask identificationdetermining the tasks, an agent is assigned a task and pursues it. Then, iIf an agent fails to complete his an assigned task tobecause of due to any existing disruptions, the task is updated with respect to concerningwith respect to concerning uncertainties and reported to the central agent, resulting in the restartingre-initiation restarting of the task allocation process. In this process, task allocation strategies are applied to minimize the cost of the system.

In this studyscenariostudy, there is a central agent-, as well as and several coordinators, rescuers, and injured agents in the environment. These independent agents are rational and can communicate with each other. hasThe agents have Each of which has the following roles and characteristics:

- **Central agent:** This agent is responsible for sorting the tasks, specifying the coordinators, determining the results, and announcing rescuers, and applying allocation strategies.
- **CoordinatorCoordinating Coordinator agent:** Coordinator The coordinator is a rescue agent who is responsible for sending the characteristic of work details to rescuers, receiving their proposalse (bids), holding auctions, and submitting the results and rescuers'rescuer rescuers' prioritization data to the central agent.
- **Rescue agent:** RescuerThis agent Rescuer identifies and moves to the task location, searches for the injured individuals, and sends the tasks uncertainty to the central agent, and rescues injuriesinjured individualsinjuries from the debris.
- **Injured agent:** This agent exists in the environment and hishas a his critical condition that changes continuously. HeThis agentHe has no activity or communication with other agents.

4.2 USAR simulation

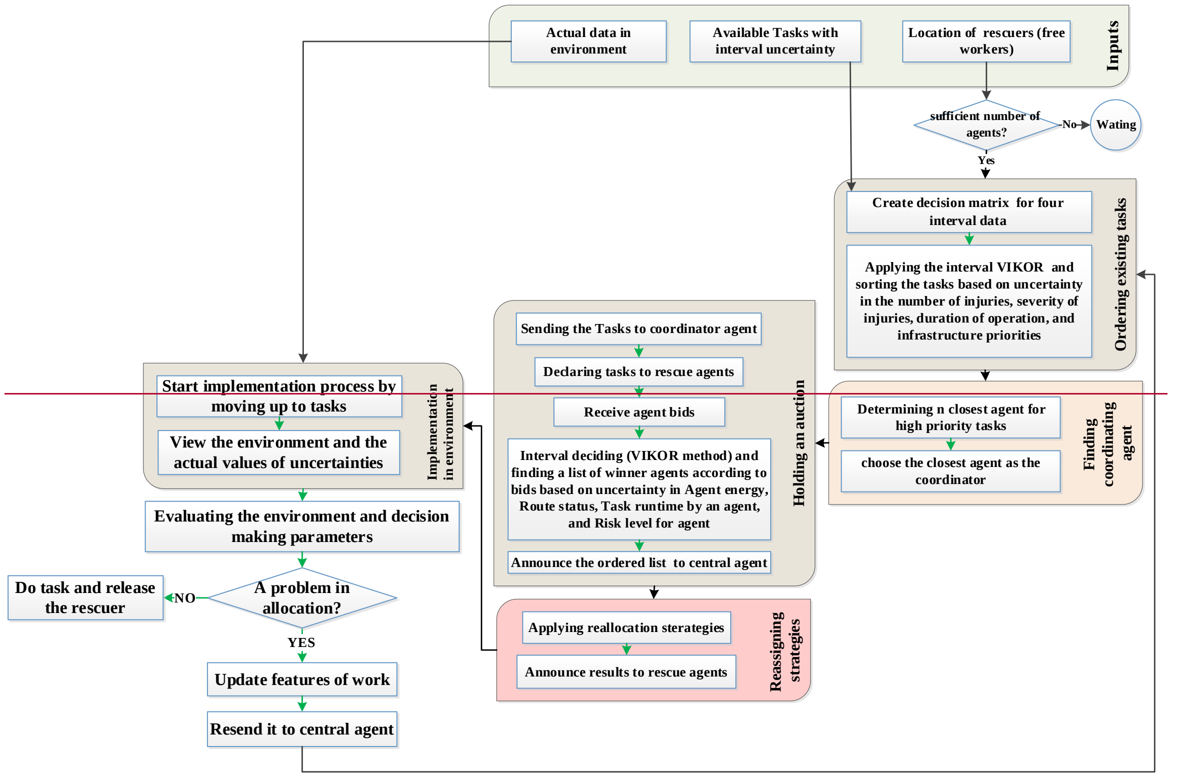
In ~~preparing~~preparation for the USAR operation simulation, there are three main parts: 1) calculating the damage rate of the area and people (simulating an earthquake-damaged environment), 2) defining agents and their characteristics, and 3) implementing the suggested method for task allocation between agents.

To simulate an earthquake-damaged environment, an earthquake risk assessment model was developed based upon the Japan International Cooperative Agency (JICA) model. The JICA model is the output of cooperation between the Center for Earthquake and Environmental Studies of Tehran and the JICA. The results of this project and ~~how to implement it are~~its implementation have been presented ~~in~~previously (Mansouri et al., 2008) and used in various ~~researches~~studies (Hooshangi and Alesheikh, 2018;Vafaeinezhad et al., 2009). This model can calculate the buildings' level of destruction and the number of injured people based on the earthquake intensity, earthquake location, building vulnerability, and the population in ~~them~~these buildings.

In ~~this study~~our scenario~~this study~~, we ~~have~~included ~~have~~ four types of agents: injured individual, rescuer, coordinator, and central agent. The tasks described in the previous section ~~are~~were ~~are~~ implemented for each agent. The initial locations of injured agents were based on building damage and the locations of rescue groups ~~was~~were randomly generated in the environment. The definitions of agents and their characteristics ~~of agents~~ ~~are~~were described in detail in our previous article (Hooshangi and Alesheikh, 2018).

~~8.2~~4.3 The proposed method

The proposed model for task allocation with uncertainties in earthquake USAR operation is ~~given~~ shown in Figure 2.



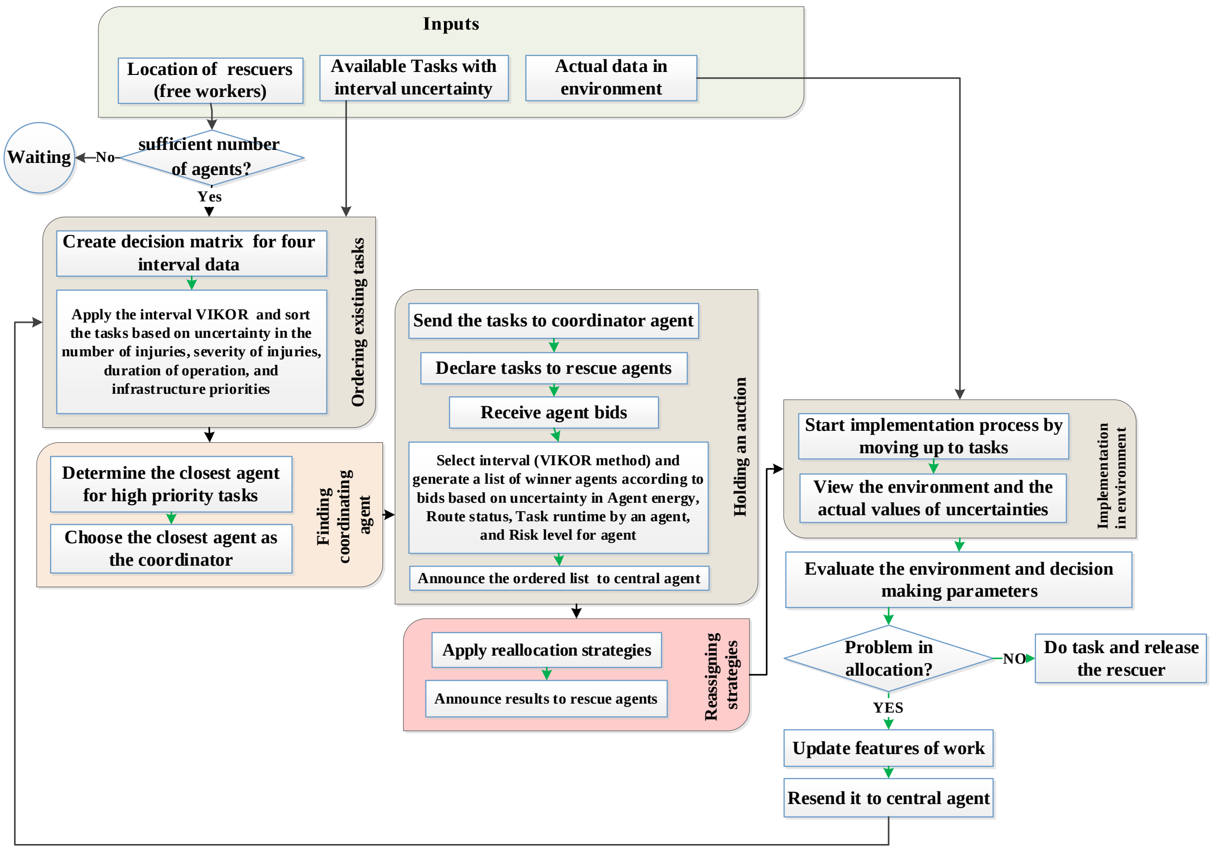


Figure 2 Task allocation flowchart in the proposed approach, separated into five steps within an environmental simulationTask allocation flowchart in the proposed approach by five steps and environmental simulation

The five steps of the proposed approach are the ordering of existing worksworkworks, specifying the coordinators, holding an auction, applying reassigningreassignment reassigning strategies (the innovation of this paper), and implementing and observing environmental uncertainties (performed by thean agent.).by the agent. The proposed method is presented below.as follows:

8.2.14.3.1 Ordering existing tasks

In crisis-ridden areas, there are differentvarying always different degrees of urgency (Chen et al., 2012). Tasks with a higher priority tomust need to be doneperformed done first. Four parameters were are used to prioritize tasks: the (number of victims, the severity of the injuries, the time required for a rescue operation, and infrastructure priorities). The initial tasks with their uncertainties in the environment (four priority parameters) are available to the central agent. The interval VIKOR method is described in [35]. Therefore, for each task feature, an interval such as that expressed in Table 2 1 is specified.

Table 2 1 Tasks characteristics based on intervals

Task NOno.	**X Coordinate coordinate**	**Y Coordinate coordinate**	**Infrastructure priorities**	**Number of injuries**	**The SSeverity everity of victim injuries**	**Duration of operation**
1	X_1	Y_1	$[I_{l1}, I_{u1}]$	$[N_{l1}, N_{u1}]$	$[S_{l1}, S_{u1}]$	$[D_{l1}, D_{u1}]$
2	X_2	Y_2	$[I_{l2}, I_{u2}]$	$[N_{l2}, N_{u2}]$	$[S_{l2}, S_{u2}]$	$[D_{l2}, D_{u2}]$
...	...	...	...	...	...	...
i	X_i	Y_i	$[I_{li}, I_{ui}]$	$[N_{li}, N_{ui}]$	$[S_{li}, S_{ui}]$	$[D_{li}, D_{ui}]$
...	...	...	...	...	...	...
n	X_n	Y_n	$[I_{ln}, I_{un}]$	$[N_{ln}, N_{un}]$	$[S_{ln}, S_{un}]$	$[D_{ln}, D_{un}]$

To withmanage deal with interval data in the CNP, differentvarious different multi-criteria decision-making(MCDM) multi-criteria decision making (MCDM) methods are proposed. The interval-based VIKOR method wasis used extensively to coordinate agents forin the assignment of tasks with interval data (Hooshangi and Alesheikh, 2017). The interval-based VIKOR method ishas been previously is described in (Sayadi et al., 2009). Ordering is performed by the central agent.

8.2.24.3.2 Finding the coordinating agent

For each task indefined by in the central agent, the most appropriate agent will be determinedis identified will be determined as the coordinating agent. The coordinating agent is an agent that who is close tolocated near close to that task and is not currently working. ChoosingThe selection ofChoosing a coordinating agent and creating groups to execute any task can be achieved through different methods and is based on various criteria (Chen and Sun, 2012;Su et al., 2018). In this study, in order to simplify the calculations, only the criterion of proximity (spatial distance) has beenis used to determineidentify determine the coordinating agent. Therefore, the nearest agent to the task is selected as the coordinator and is responsible for the auction. Selection of a Choosing the coordinating agent leads to the performance of calculations being performed at a distributed point. By selecting the coordinating agents, the computational overhead of the central agent will beis reduced.

8.2.34.3.3 Holding an auction

Coordinating agents hold auctions after receiving the task characteristics and the list of agents in the subgroup. In the CNP, agents bid for tasks, and the person agent who offers the highest value for the task is the winner. During the auction, rescue agents offer intervalintervals (rather than values) an interval for the route conditions, the time needed required for the agent needed to execute the task by the agent, the agent's possible risk level, and their energy, instead of a value. AccordinglyFor this, the agent calculates numbers for each of the four decision-making criteria, such as a variable X, based on the following eEquations 1. In Equations 1, the distance is measured (in meters, the),distance is measured in meters, the severity of victimsthe victims' injuriesvictims, and task priority isare based on the values declared by the central agent. Based on the rate of uncertainty presumed that is considered for thea given the environment (for example, 30%), an interval for this number is estimated. The first number of this interval will beis in the range between [X, X + 30%X] and the second number is in the range [X –– 30X – 30%X, X].

Agent energy (Energy energy Levellevel, Distancedistance, Number number of people) = Energy Level level –- Distance/500 –- Number of -people rescued*0.3
Task runtime by an agent (Distancedistance, Number number of people, Severityseverity) = Distance/150 + Number of people rescued number of people*15 + severitySeverity*2 (1)
The Risk rRisk level for an agent (Energy energy Levellevel, Prioritypriority) = Priority –- Energy Level
Route status (Distancedistance) = Distance

In the real world, each person can introduce intervals according to their experience and their knowledge of the environment. In this researchstudyresearch, we used the above equations thebased on with respect to the expert opinions to simulate the real environment. The coordinating agent applies the interval-based VIKOR method to order the agents' bids. The coordinating agent sends the results to the central agent after ordering the agents. The use of a central agent in this phase provides the opportunity to make the best decision considering the task priorities capacityand capacities as well as the capacity of other agents.

8.2.44.3.4 Applying allocation strategies

In operations where there is uncertainty, it is not possible to definitively resolve the issue of task allocation. .cannot be definitively resolved. In this phase, the initial allocation should be it is better for the initial allocation to be done in such a waymanner way that if a potential reallocation wasteswould waste is needed, it wastes the leastsmallest least amount of time. Based on different strategies in at this stage, the central agent begins to assign tasks after obtaining all lists from coordinating agents. In each strategy, a priority is givenassigned given to specific tasks. In this section, four different strategy-based approaches are described, as follows:

Task allocation higheraccording to with higher priority (strategy 1): In this strategy, task allocation begins with tasksthe assignment assigning tasks of higher--priority oncetasks, following establishment ofhigher priority once the task order and the priorities of the rescue team have been established in the previous stage (prioritizingprioritization prioritizing and auction). Therefore, the agent with the best performance is selected for high priority tasks and is thensubsequently then excluded from the lists of agents with no tasks. theSubsequentlyLater, the tasks of lower priority are assigned in the same order. The tolimitation of problem related to this strategy is that it may cause some agents may be left with no tasks to do in the last stages of this process.may be left with noto not receive tasks to do in the last stages of this process.

Assigning tasks to all agents, preferably agentto specific agents the agent with outcomeoptimal outcomes the best outcome (strategy 2): This strategy is based on optimally usingthe optimal use of optimally using all rescue teams. In this strategy, all agents are assigned a task. For this purpose, the a task is first assigned to an agent who has applied for the minimum number of tasks. Then, tThe agent and the task are then eliminated from the agent and task lists, and the allocation continues with the next agent who has made few requests. onUsing Based on this strategy, a task will be assigned to all agents.

Task allocation on ~~Allocation by keeping~~ a strategic spatial ~~agent~~basis ~~agent~~ (strategy 3): ~~on~~Using ~~Based~~ on this strategy, ~~the strategic~~ agents who play ~~an~~ important and strategic roles in the task allocation process are excluded ~~in order~~ to ~~help with~~ensure their availability for ~~help with~~ the implementation of ~~the~~ tasks if ~~there are~~ problems are encountered during the task allocation process. Agents with strategic roles may be defined differently. Agents who ~~participated~~participate ~~participated~~ in the ~~auction~~auctions ~~auction~~ of more tasks are ~~the agents~~those ~~the agents~~ with strategic locations. In ~~agent is~~such instances, these agents are ~~this situation, this agent is~~ close to many tasks (~~has~~ have~~a~~ strategic spatial locations) and can be used ~~if~~ when these tasks are not implemented. Figure 3 shows the difference between the task allocation results for ~~strategy~~ strategies 2 and ~~strategy~~ 3. In Figure 3, a ~~the~~ rescue agent located ~~part~~centrally~~in the central part~~ has a strategic position and will try to maintain this position. Although the total movement may increase, if there ~~problem~~are problems ~~is a problem~~ in performing other tasks, this agent can help all other groups.

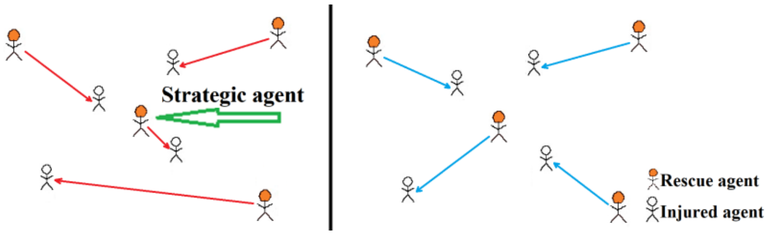


Figure 3 ~~strategic~~Strategic agent~~, the blue arrow shows~~ illustration. Blue arrows show the final ~~result~~results for strategy 2~~,~~ and ~~the~~ red ~~arrow indicating~~arrows show the ~~winning~~successful rescuers in strategy ~~Shows the strategic agent, the blue arrow shows the final result for strategy 2the red arrow indicating the winning searchers in strategy 2, and the red arrow indicating the winning rescuers~~ in strategy 3~~and the blue arrow shows the final result for strategy 3~~.

Assigning tasks by creating the best density in the environment (strategy 4): This strategy is based on the optimal density of rescue agents. ~~With~~ Using this strategy, ~~the~~task ~~the~~ assignments ~~of the tasks~~ are made in ~~such~~ a manner that ensures the ~~way as to ensure a~~ uniform distribution of ~~the~~ agents in the environment. Generally, no exact information is available ~~about~~concerning ~~about~~ the conditions of the tasks; therefore, this strategy aims to ensure ~~the~~ a uniform distribution of rescue teams within the environment if the uncertainty is high. In disaster environments ~~like~~such as ~~like~~ earthquakes, the incident ~~place~~occurs ~~takes place~~ over a wide area~~ and~~, such that ~~and~~ the damage and injured population ~~distribution~~are uniformly distributed ~~have uniform distribution~~ due to the texture of the area. Therefore, the highest number of injured people is not accumulated in any one spot. ~~Besides~~Furthermore~~Besides,~~ ~~In addition,~~ applying this strategy prevents the convergence of rescue teams. To apply this strategy, the tasks of the highest priority in the task lists should be given to the available agents ~~and~~where ~~and~~ the environmental density ~~should be~~is the highest. The ~~issue~~concept ~~issue~~ of ~~the~~ optimal density can be solved through innovative algorithms. In our study, the simulated annealing ~~(SA)~~ method was used to ~~find~~determine ~~find~~ uniform density. The implementation stages of simulated annealing ~~SA~~ have been described ~~in~~previously ~~are described in~~ (Sabar et al., 2009). Figure 4 shows the difference between task allocation outcomes for strategy 2 and strategy 4.

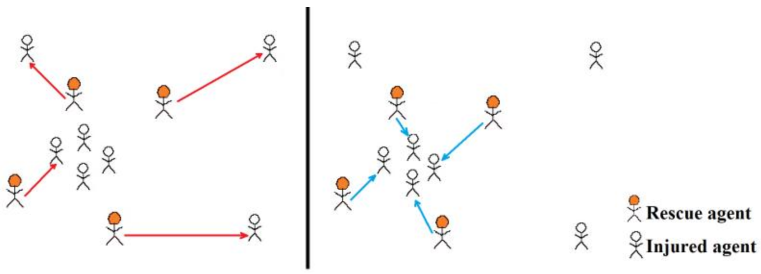


Figure 4 tBest density strategy, the blue arrow indicating the winning illustration. Blue arrows indicate the successful rescuers in strategy 2 and the red arrow showsarrows indicate the final resultresults for strategy 4.Shows the best density strategy, the blue arrow indicating the winning rescuers in strategy 2 and the red arrow shows the final result for strategy 4.

8.2.54.3.5 Implementation and observation of real values in the environment

TheDuring the The implementation phase, of the tasks is are implemented by the agents in a dynamic environment where there are always uncertainties during the task execution of the tasks. The rescuer observes the difference between his predicted values and the actual environment after working.the work beginshe starts working. In this research, to model the real environmentstudy, a random number in the [X –– 30%X, X + 30%X] interval is was chosen. to model the real environment. In the real world, the difference between the predicted environment (through building vulnerability estimation models) and the real environment will determine the agent's performance of the agent.

If the agent observes a biglarge big difference between the auction information and the real environment, he the agent abandons the that task. In this caseinstancecase, the agent he updates the task's values and uncertainties and sendsreturns sends the work to the central agent. The new uncertainty interval will be 80% smaller than the original interval. There differentare various can be different conditions in under which agents will reallocate a task if the environment differentdiffers is different from the expected onescenarioone. For example, the agent can abandon the task if three out of eight decision-making parameters are out of range by 5%. Otherwise, the rescueragent rescuer finishes the rescue work by accepting the new conditions.

The central agent assigns newly added tasks within the reallocation framework. When a new task is assigned, the task allocation is mixed mixedcombined with that of both new tasks as well asand incomplete onestasks. mixed with new tasks as well as incomplete ones.

8.34.4 Evaluation Method method

AssessingAssessment of Assessing a task allocation algorithm is usually donetypically performed usually done in the first phase through modeling and simulation due to the dynamic and heterogeneous nature of different environments (Olteanu et al., 2012). Simulating Simulation is a suitable approach for the implementation and validation of a proposed method (Nourjou et al., 2011). In a real testing situation, the situations and conditions of the implementation scenario are very difficult to reproduce. In thisthe present studyIn this study, we simulated three scenarios for the earthquakes in Tehran's District 1 with magnitudes of 6.6, 6.9, and 7.2. We also estimated the numbers of deaddeceased dead and injured individuals who were are distributed in in the centers of the relevant building blocks and need to be rescued by 1000, 1500, and or 2000 rescue agents. Also, iIn the uncertainuncertainty uncertain analysis of the suggested method, the lower and upper bounds of uncertain values arewere also are calculated. The proposed method was compared with the traditional CNP. The intended task allocation iswas considered is efficient if profitability parameters are were maximized. toIn accordance with According to a number of several recent studies (Liu and Shell, 2012;Sang, 2013;Hooshangi and Alesheikh, 2017), three criteria were used to evaluate the performance of the proposed method~~. These criteria are~~: the number of deceased victims, ~~the~~ number of incorrect allocations, and ~~the~~ rescue time. Results ~~were achieved with 1000 randomized runs.~~

Some of the major problems in ~~replanning~~reallocation and in the task allocation environment include scalability, reliability, performance, and ~~the~~ dynamic resource reallocation ~~of resources~~ (Gokilavani et al., 2013). In this study, the results of ~~the~~ two analyses (scalability of the proposed method and interval uncertainty analysis) ~~were~~ are presented.

The first analysis focused on the evaluation of the proposed approach ~~on~~ at different scales and for different criteria. Comparison and assessment were carried out ~~on~~ at different scales ~~in order~~ to ~~recognize~~measure ~~recognize~~ the effectiveness of the proposed approaches in USAR operations. Nine scenarios were applied in this study and compared with traditional the CNP.

The second analysis focused on interval uncertainty analysis and ~~studying~~studied ~~studying~~ the rescue operation ~~time~~duration ~~time~~ in the 6.9 ~~Richter~~magnitude ~~Richter~~ earthquake ~~for~~ at different levels of uncertainty. In this analysis, time changes ~~of~~ in rescue operations ~~on~~were investigated according to ~~based on~~ different levels of uncertainties ~~are investigated~~. The duration of ~~the~~ a rescue operation in the ~~simulated~~simulation ~~simulated~~ model ~~depends~~ depended on two main components: ~~1-P~~prioritization of tasks and, outputs ~~2- Outputs~~ of each operation ~~at~~ in each phase (Hooshangi and Alesheikh, 2018). Equation ~~1~~ ~~3~~2 defines the final model for calculating the operation ~~time~~duration ~~time~~ based on these two components.

$$T(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8) = \sum_{n=1}^{n+1} \alpha_n (x_1, x_2, x_3, x_4) + \sum_{w=t}^{n+t} \beta_w (x_5, x_6, x_7, x_8) \qquad (~~1~~~~3~~2)$$

~~The v~~Variables x1 to x8 ~~are~~constitute ~~are~~ the number of injuries, ~~the~~ 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. α_n is the function of task~~s'~~ prioritization and β_w is the function of bidding.

~~Interval~~To our knowledge, interval ~~Interval~~ uncertainty analysis has rarely been employed~~investigated in previous researches~~. The method used in this research ~~is~~ was adapted from ~~research~~previous literature ~~research~~ (Lan and Peng, 2016). In ~~research~~our analysis~~this research~~, Chebyshev points are used. Equation ~~2~~ ~~4~~3 ~~is~~depicts a ~~is~~ Chebyshev formula ~~to generate~~for generating m collocation points ~~on~~ in the interval [0, 1] (Lan and Peng, 2016):

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

(~~2~~~~4~~3)

Equation ~~2~~ 3 ~~is~~ was used to create different numbers for the decision-making parameters. The output of the model ~~is~~ was then calculated for various numbers ~~in~~within ~~in~~ the intervals. This technique ~~creates~~created ~~creates~~ different values for the output of the model.

~~9.~~5. Results

~~Different~~Multiple ~~Different~~ scenarios and experiments were designed ~~in order~~ to evaluate the proposed methods and strategies. The results are presented in this section.

~~5.1 Simulation~~

~~Simulation of the agent-based USAR operation includes calculating the damage rate of the area, specifying the initial location of agents, specifying the agents' characteristics, and, finally, implementing the suggested~~

method for task allocation. It is necessary to know the seismic resistance and vulnerability of existing buildings. The most obvious use of earthquake-risk assessments with different scenarios is to help in planning, preparedness, and providing response instructions to the public. An earthquake risk assessment model has been developed based upon the JICA model. The JICA model is the output of cooperation between the Center for Earthquake and Environmental Studies of Tehran (CEST) and the Japan International Cooperative Agency (JICA). The results of this project is are presented in [43], And and has have been used in various researches [1, 44]. In accordance with According to expert opinions, three probable earthquakes were simulated with magnitudes of 6.6, 6.9, and 7.2. Figure 5 shows the vulnerabilityvulnerabilities vulnerability of buildings in these scenarios in the ArcGIS environment.

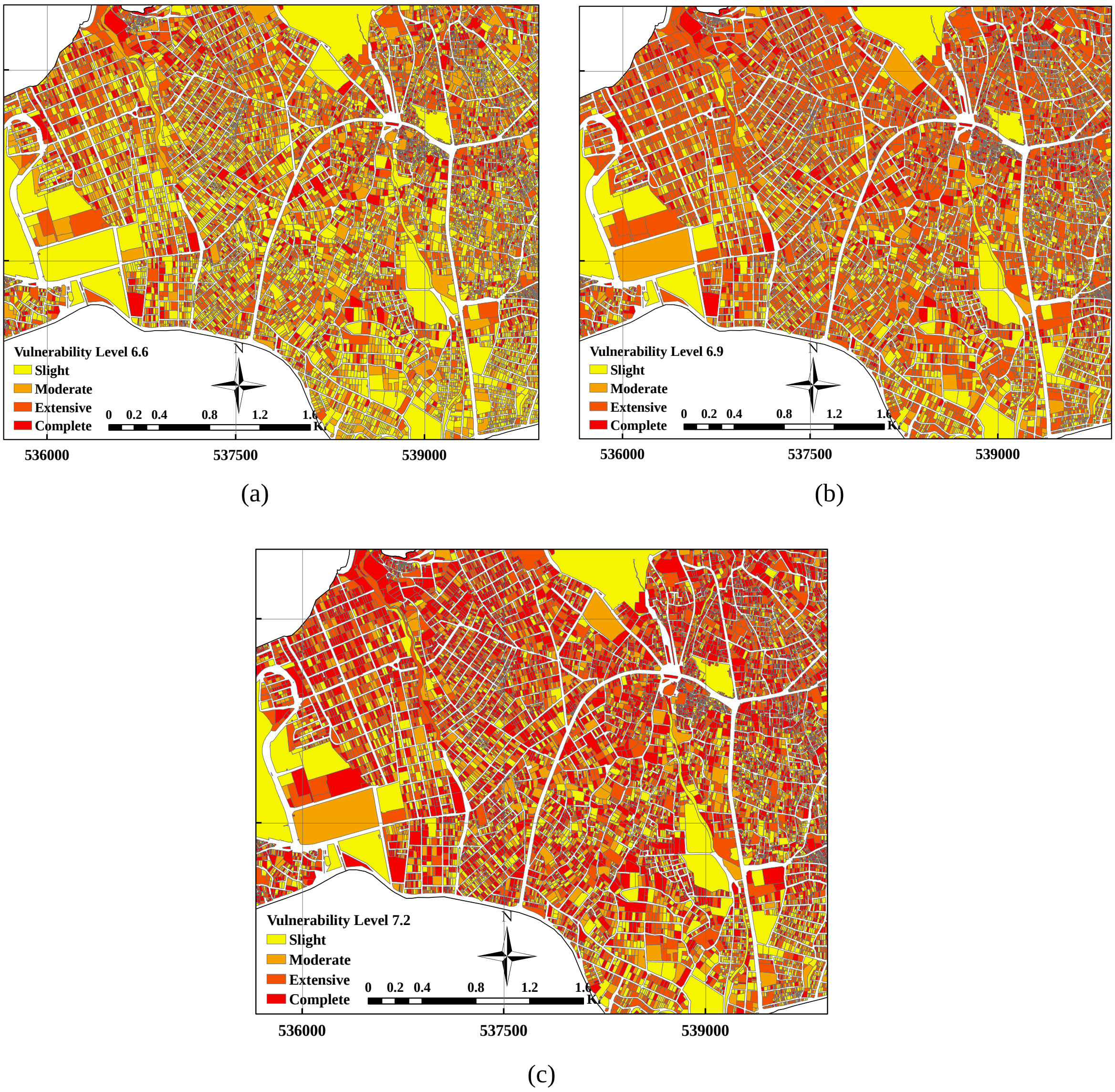


Figure 5 Vulnerability maps infor District 1, an earthquakebased on earthquakes with magnitude:magnitudes of a) 6.6 on the Richter scale, b) 6.9 on the Richter scale,, and c) 7.2 on the Richter scale.Vulnerability maps in District 1, an earthquake with magnitude: a) 6.6 on the Richter scale, b) 6.9 on the Richter scale, c) 7.2 on the Richter scale

Based on ~~buildings~~the level of building destruction, the ~~number~~numbers of injured and ~~dead~~deceased people can be calculated ~~by~~using the JICA model. The numbers of injured and ~~dead~~deceased people in scenarios with 6.6, 6.9, and 7.2 magnitude earthquakes are ~~demonstrated~~listed in Table 2.

~~Based on buildings destruction, the number of injured and dead people can be calculated. Equation 1~~ 2 ~~is the output of the JICA model for calculating the human vulnerability in earthquakes~~ [47]~~:~~

$$\begin{bmatrix} Uninjured \\ Injured \\ Dead \end{bmatrix} = \left(\frac{Population}{Buildings}\right) \begin{bmatrix} -0.073 & 1.040 & 0.650 \\ 0.071 & 0.047 & 0.062 \\ 1.001 & -0.087 & 0.289 \end{bmatrix} \begin{bmatrix} Slight \\ Moderate \\ Extensive + Complete \end{bmatrix} \quad (12)$$

~~JICA model calculations were performed in ArcGIS software. The number of injured and dead people in scenarios 6.6, 6.9, and 7.2 earthquakes are demonstrated in Table 3.~~

Table ~~3~~ 2 Results ~~from implementing a 6.6 Richter scale~~of earthquake simulations ~~Results from implementing a 6.6 Richter scale earthquake~~

Severity level	**~~Number~~Numbers of affected ~~populations~~individuals~~Number of affected populations~~**		
	6.6 Richter	**6.9 Richter**	**7.2 Richter**
Uninjured	374,295	270,455	182,340
Injured	28,856	73,195	111,463
Deceased	30,349	89,850	139,697

The computational scale of the JICA model ~~is~~uses ~~is~~ urban blocks. Therefore, the numbers of ~~dead~~deceased ~~dead~~ and injured individuals in each urban block ~~was~~ were calculated. The ~~location~~locations ~~location~~ of ~~the~~ injured individuals ~~considered~~were presumed to be ~~was considered~~ in the centers of the ~~block~~respective blocks~~block~~.

The environmental simulation ~~of the environment~~ and ~~the~~ proposed method were ~~performed~~implemented ~~performed~~ in AnyLogic software. This software ~~has the ability to enter GIS~~can process geospatial information system data. ~~has the ability to enter GIS data.~~ To simplify the environment and reduce the calculation volume ~~of calculations~~, each agent was ~~considered~~regarded ~~considered~~ as a group in the real world. Figure 6 shows the simulated environment.

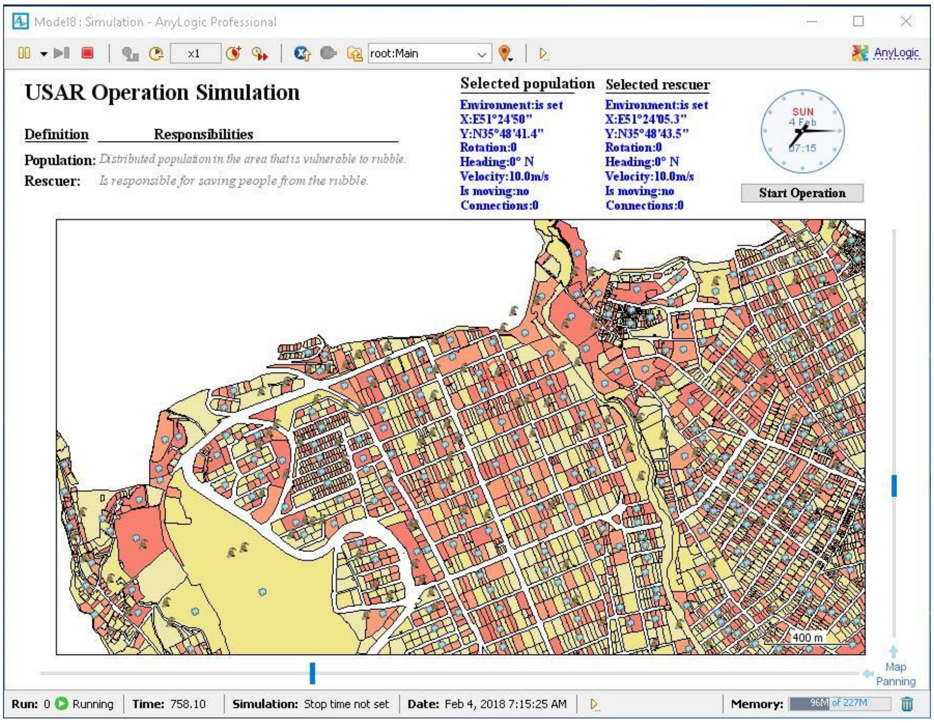


Figure 6 ~~An o~~Overview of the USAR simulator.

There are many injuries in the environment. The central agent first sorts the tasks according to their ~~priority and after determining~~priorities. After the coordinating agent~~,~~ has been determined, the central agent ~~priority and after determining the coordinating agent,~~ sends the task properties to the coordinating agent. The coordinator holds an auction. Rescue agents ~~are~~ bid~~ding~~ in accordance with their environmental and working conditions. Rescuers are in a ready state at the start of the operation. Each ~~winning~~successful ~~winning~~ rescue agent moves to the task's location. After reaching the task position, ~~starts~~the rescue agent begins ~~he starts~~ rescuing the injured agents. During the execution of ~~the~~their assigned ~~the~~ work, the agents may find ~~difference~~considerable differences ~~a significant difference~~ between the real-world information and the ~~expressed~~ information expressed in the auction. In ~~situation~~such instances~~this situation~~, the ~~agent~~agents ~~agent~~ may stop performing ~~task~~their tasks~~the task~~ and report the ~~dispute~~discrepancies ~~existing dispute~~ to the central agent.

Table ~~4~~ 3 shows the ~~time~~durations ~~time~~ of ~~the~~ USAR operations ~~in~~as estimated using ~~in~~ scalability analysis ~~of~~ with the proposed method. In creating this table, an uncertainty of 30% was considered. For this purpose, the range of task~~s~~ characteristics ~~in~~used ~~was made in~~ the intervals [X, X + 30%X] and [X–30%X, X]. ~~Also~~At ~~, at~~ each stage, ~~that~~ a given agent ~~participates~~participated ~~participates~~ in the auction~~,~~. ~~for~~ For that agent's ~~his~~ decision-making parameters, the ~~number~~numbers were ~~agent converts its number~~ randomly converted into an interval. The average range of agent tasks and decision-making was used for ~~the~~ implementation of the CNP~~.~~, rather than ~~instead of~~ interval values.

Table ~~4~~ 3 ~~comparison~~Comparison of operation duration in hours between the ~~suggested~~proposed method ~~with~~and the CNP (based on 30% uncertainty)~~comparison of the suggested method with CNP (based on 30% uncertainty)~~

No. of agents~~Agents~~	**1000**			**1500**			**2000**		
Simulated earthquake magnitude ~~Simulated earthquake~~	**6.6 R**	**6.9 R**	**7.2 R**	**6.6 R**	**6.9 R**	**7.2 R**	**6.6 R**	**6.9 R**	**7.2 R**

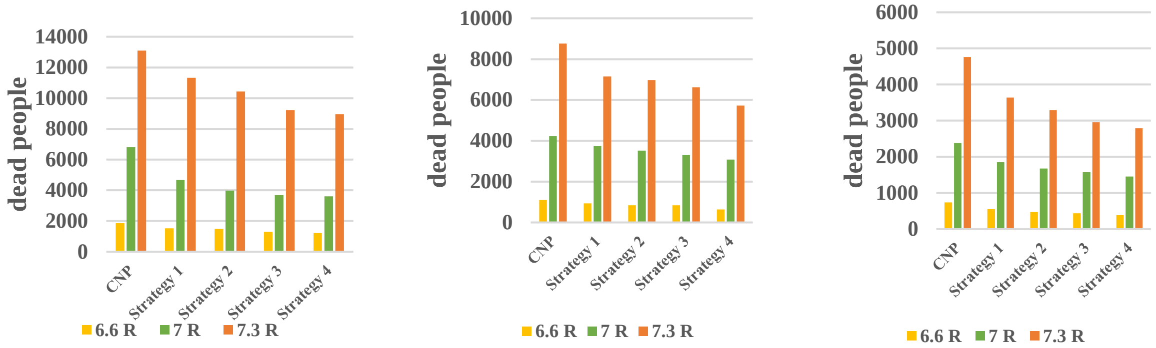
No. of tasksTasks	28,856	73,195	111,463	28,856	73,195	111,463	28,856	73,195	111,463
CNP	53.16	169.03	282.76	32.83	94.24	174.19	22.6	68.95	127.47
Strategy 1	45.37	142.47	241.81	25.22	74.91	135.75	19.643	59.36	108.56
Strategy 2	44.87	137.30	234.92	26.02	76.41	138.52	19.097	58.21	105.58
Strategy 3	43.75	133.76	230.12	25.75	74.33	132.75	18.332	56.33	101.77
Strategy 4	41.63	130.41	222.18	23.89	71.14	127.87	17.013	53.91	97.73

The operational time decreasesdecreased decreases when the number of agents in rescue operations increased with increase but the number of tasks remainsremaining remains fixed. The reduction rate betweenranged from ranges between 54% and to 60% when the number of agents is was doubled. The timeduration time of a USAR operation increasesincreased increases when the number of tasks increasesincreased increases for a certain given number of agents. Therefore, the timeduration time of the rescue operation is was related to the number of rescue agents and the number of available tasks in a scenario. There iswas is an inverse relationship between the timeduration time of the USAR operation and the number of rescuerrescue rescuer agents, and a direct relationship between the timeduration time of the operation and the number of tasks.

The inclusion of uncertainty in any allocation strategy provideprovided could provide better results, as compared to with the CNP method. Using the proposed strategies, the The smallest improvement in the results with uncertainty using the proposed strategies was 2.9 h (13%) hours for a scenario with 2000 agents and 28,856 tasks (6.6 Richtermagnitude Richter earthquake). The maximum improvement was 60.6 h (21%) hours for 1000 agents and 111,463 tasks. The worst improvement was found for 2000 agents with 28856 tasks (13%), the best for 1000 agents, and 111463 tasks (21%).

Among the task allocation strategies, Strategy in this study, strategy 1 presentedproduced the worst response. OnAt each scale offor the discussed scenarios, Strategystrategy 1 presented the highest time for resulted in USAR operations with the longest durations, compared towith other strategies. StrategyStrategies 1 and Strategy 2 indicatedprovided similar results onat different scales, although strategy 2 achieved better results were obtained for Strategy 2.. Strategy 4, involvingwhich involved spatial information in task allocation, indicatedproduced better results onat all scales and presents an improvementincluding improvements of 21%, 24%, and 23% on the scale ofwith 1000 agents for a 6.6 magnitude earthquake measuring 6.6 on Richter Scale, 1500 agents for a 6.9 Richtermagnitude earthquake, and 2000 agents for a 7.2 Richtermagnitude earthquake, respectively, as compared towith the CNP. The average improvement for Strategystrategy 4 was 26.6 hoursh in rescue operations. The use of Strategiesstrategies 3 and 4 is more evidentsuitable in a larger environment in which the distribution ofwith high numbers of both injured people and rescue agents is high, since, because controlling the agent distribution with respect to the expansion of the environment and the uncertaintyuncertain environmental conditions in the environment can be effective in future task allocations of the tasks.. In a real-world crisis-ridden environment, the wholeoverall environment is damaged and the injured people are well- distributed. This is why controllingTherefore, the spatial distribution of the agents playsis an important roleparameter to control in USAR operations.Among the task allocation strategies, Strategy 1 presented the worst response. On each scale of the discussed scenarios, Strategy 1 presented the highest time for USAR operations compared to other strategies. Strategy 1 and Strategy 2 indicated similar results on different scales, although better results were obtained for Strategy 2. Strategy 4, involving spatial information in task allocation, indicated better results on all scales and presents an improvement of 21%, 24%, and 23% on the scale of 1000 agents for earthquake measuring 6.6 on Richter Scale, 1500 agents for 6.9 Richter and 2000 agents for 7.2 Richter, respectively, as compared to CNP. The average improvement for Strategy 4 was 26.6 hours in rescue operations. The use of Strategies 3 and 4 is more evident in a larger environment in which the distribution of injured people and rescue agents is high, since controlling the agent distribution with respect to the expansion of the environment and the uncertainty conditions in the environment can be effective in future allocations of the tasks. In a real-world crisis-ridden environment, the whole environment is damaged and the injured people are well-distributed. This is why controlling the spatial distribution of the agents plays an important role in USAR operations.

The simulation results in terms of deceased people for 1000, 1500, and 2000 agents with different numbers of tasks are shown in Figure 7. In these figures, for each of the four priority parameters and decision parameters theassociated with of the agents, a 30% uncertainty level was considered.



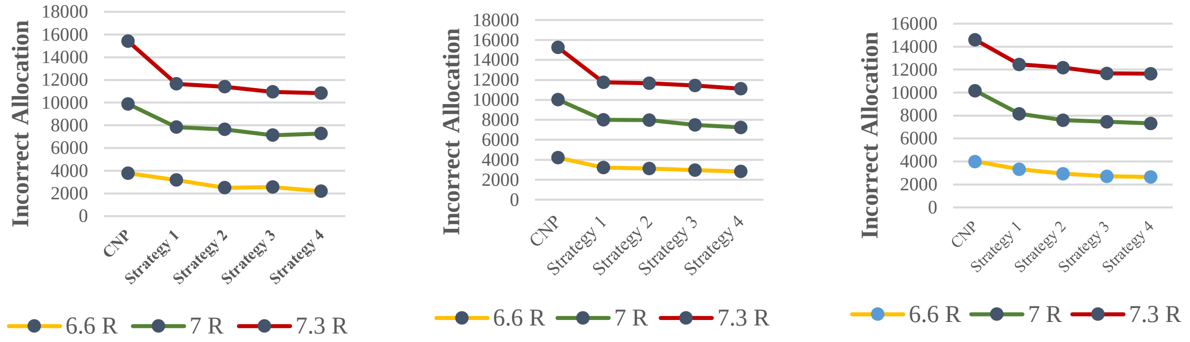
(a) (b) (c)

Figure 7 The numberNumbers of deceased people: a) with a) 1000 rescue agents, b) with 1500 rescue agents,, and c) with 2000 rescue agents.The number of deceased people: a) with 1000 rescue agents, b) with 1500 rescue agents, c) with 2000 rescue agents.

Figure 7 illustrates the numbernumbers of deceased people in the rescue process with different numbers of agents and tasks. Based on Figure 7, an increase in theincreased number of tasks leadsled to an increase in theincreased number of deceased people, while increasing thebut an increased number of rescue agents results in decreasing theled to a decreased number of deceased people. Regarding the numbernumbers of deceased people onat all three scales, the CNP method presentedproduced the worst response. TheAn average number of 7253 people were deceased people in the CNP model on a scale of with 1000 agents is 7253. Conversely, 5853 people. The number of were deceased people in the model employing Strategystrategy 1 on a scale of with 1000 agents equals 5853 people. On the whole, with respect to . Overall, when all strategies, Strategy were considered, strategies 4 and Strategy 1 presentedresulted in the best and worst responseresponses, respectively. As illustrated in Figure 7, the numbernumbers of deceased people iswere approximately equivalent in Strategystrategies 1 and Strategy 2.

Figure 7 illustrates the number of deceased people in the rescue process with different numbers of agents and tasks. Based on Figure 7, an increase in the number of tasks leads to an increase in the number of deceased people, while increasing the number of rescue agents results in decreasing the number of deceased people. Regarding the number of deceased people on all three scales, the CNP method presented the worst response. The average number of the deceased people in the CNP model on a scale of 1000 agents is 7253 people. The number of deceased people in the model employing Strategy 1 on a scale of 1000 agents equals 5853 people. On the whole, with respect to all strategies, Strategy 4 and Strategy 1 presented the best and worst response, respectively. As illustrated in Figure 7, the number of deceased people is approximately equivalent in Strategy 1 and Strategy 2.

Figure 8 illustrates the simulation results for the incorrect allocation of the 1000, 1500, and 2000 agents with number ofseveral different tasks.



(a) (b) (c)

Figure 8 The numberNumbers of incorrect allocations: a) with a) 1000 rescue agents, b) with 1500 rescue agents,, and c) with 2000 rescue agents.The number of incorrect allocations: a) with 1000 rescue agents, b) with 1500 rescue agents, c) with 2000 rescue agents.

The overall trend in iseach chart was the figures is approximately samesimilar the same if all arecharts were figures are considered simultaneously. TheAny The incorrect allocation is not relatedwas unrelated is not related to the number of rescue agents, because since there are were no changes when in increasing the number of agents was increased. The number of incorrect allocations changeschanged changes with the number of tasks, increasessuch that it increased and increases with the an increasing the number of tasks. This increase is observedevident observed in all of the above figures. The incorrectpanels in Figure 8. Incorrectof the above figures. The incorrect allocations usually placeoccurredtake place with at a nearly an almost fixed rate.

Based on the figuresresults, the traditional CNP model presentsproduced the worst response. The total incorrect allocations in the CNP on the scale ofmodel with 1000 agents for 28856and 28,856 tasks, 1500 agents for 73195and 73,195 tasks, and 2000 agents for 111463and 111,463 tasks arewere 3780, 1002710,027, and 1460414,604 tasks, respectively. The numbernumbers of incorrect allocations assigned by Strategystrategy 1 iswere 3174, 8014, and 1245512,455 tasks, respectively. FurtherFurthermore, the evaluation criterion does showcriteria showed the advantages of including uncertainty in task allocation. Therefore, the proposed approaches for all three evaluation parameters indicated aresulted in better performance when, compared towith the traditional CNP method of CNP. The results indicatedindicate that the reallocation of tasks through the proposed approaches and strategies offersoffered a better response, which is better observed usingbased on the scale development sinceof the event, because their differencedifferences from the CNP increases with model increased at a larger scale development.

Based on the figures, the traditional CNP model presents the worst response. The total incorrect allocations in CNP on the scale of 1000 agents for 28856 tasks, 1500 agents for 73195 tasks, and 2000 agents for 111463 tasks are 3780, 10027, and 14604 tasks, respectively. The number of incorrect allocations assigned by Strategy 1 is 3174, 8014, and 12455 tasks, respectively. Further, the evaluation criterion does show the advantages of including uncertainty in task allocation. Therefore, the proposed approaches for all three evaluation parameters indicated a better performance when compared to the traditional method of CNP. The results indicated that reallocation of tasks through the proposed approaches and strategies offers a better response, which is better observed using scale development since their difference from CNP increases with scale development.

The results of interval uncertainty analysis were achieved with 1000 randomized runs of each scenario (Figure 9).

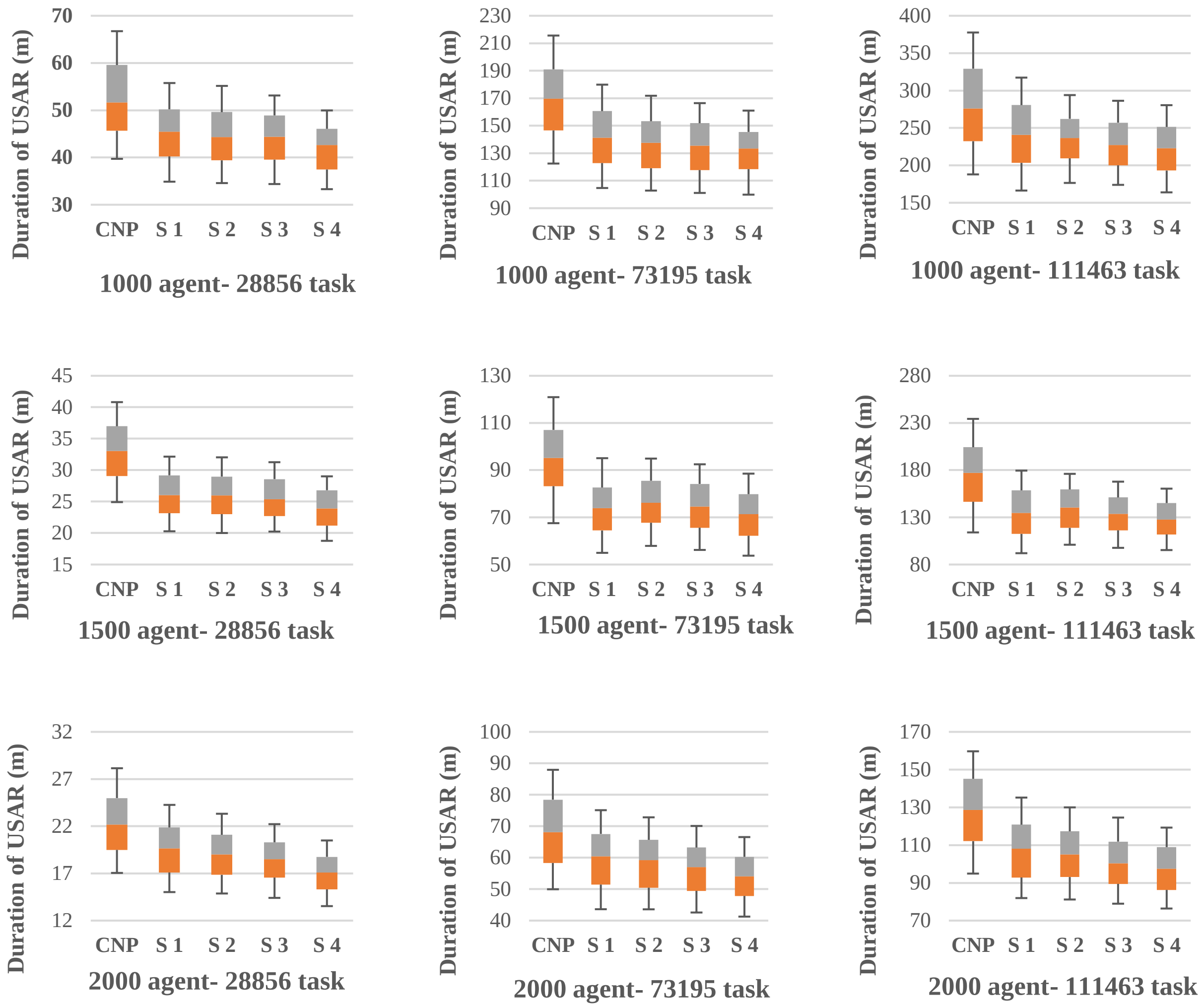


Figure 9 Uncertainty analysis of the proposed method in for USAR operations, for 9 nine simulated scenarios

As shown in Figure 9, there is a direct relationrelationship relation between interval length and operational time. accordingAccording to FormulaEquation 2Because according to Formula 13, assigning fewer tasks leads to less operating time, and as well as causes less uncertainty in the simulated environment.

As mentioned in section 4.3.3, the rescuers use [X, X + 30%X] and [X- – -30%X, X] to determine the intervals. Another analysis was performed for different values ofother than instead of 30% in the estimatingestimationsestimating. The results are shown in Figure 10. An average theevent of the scale studies (1500 agents and 73,195 tasks) was used and a set of different levels of uncertainty (uncertainty between 5% and 55% at five-unit intervals) were randomly generated, investigated, and evaluated. This realistic test aimsaimed to provide an assessment ofassess This realistic test aims to provide an assessment of the proposed scenarios for each uncertainty value.

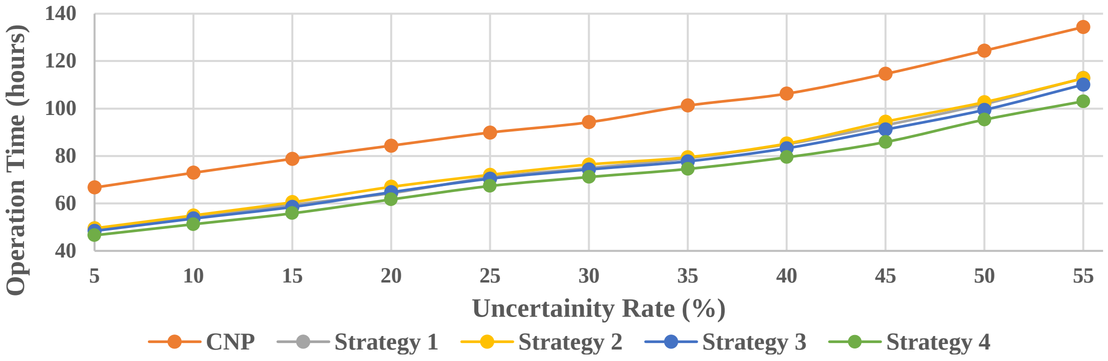


Figure ~~Figure~~ **10** Uncertainty analysis ~~for~~when ~~for~~ different values were used in determining intervals

Figure 10 indicates a relationship between ~~in~~increased ~~an increase~~ in uncertainty (from 5% to 55%) and an increased~~ in the~~ rescue time. The ~~different~~increases differed among ~~increase is different for different~~ strategies. The increase ~~is~~ was 67.7 ~~hours~~ h for the CNP (from 66.8 ~~hours~~h to 134.4 ~~hours)~~ ~~hours) while it is~~h), whereas increases of 63.4, 63.2, 61.7, and 56.5 ~~hours~~h were obtained for ~~Strategies~~strategies 1~~, 2, 3, and~~–4, ~~while it is 63.4, 63.2, 61.7, and 56.5 hours for the Strategies 1, 2, 3, and 4,~~ respectively. Based on the evaluation results, the proposed methods are more efficient and present better responses in the presence of ~~different~~various ~~different~~ uncertainties. Therefore, ~~in~~increased ~~an increase of~~ in uncertainty leads to a delay in USAR operations and ~~to~~possible ~~even to~~ task elimination. ~~result~~Accordingly,~~As a result,~~ delaying rescue operations or removing tasks from the rescue list will increase USAR time.

~~10.~~6. Conclusion

Providing a suitable method for assigning tasks ~~in~~under ~~in~~ uncertain conditions ~~an~~is ~~plays an~~ important~~ role in role in~~, according to the results of simulated ~~the~~ USAR operations~~ simulation result~~. This study presented a task allocation approach that aimed to better assign ~~the~~ initial tasks~~ in order~~ ~~have~~, thus ensuring ~~to have~~ better conditions for potential reallocations of ~~the the~~ tasks~~,~~ and ~~to~~ wasting~~e~~ the ~~shortest~~least ~~shortest~~ time possible for ~~the~~ rescue teams if problems were encountered during the initial allocations ~~face a problem~~ or a new task emerges. Some of the characteristics and advantages of the study include the~~d~~ focus~~ing~~ on the necessity of task reallocation in disaster environments, ~~providing~~the provision of ~~providing~~ an innovative approach ~~with~~for managing ~~to deal with~~ uncertainties that cause non-performance of ~~the~~ tasks in the CNP method (the most widely used task allocation method in ~~MASs~~multi-agent systems~~MASs~~), and ~~defining~~the definition of ~~defining~~ spatial strategies for better task~~s~~ reallocation. The proposed approach can be used in combination with a wide range of algorithms for assigning tasks in accordance with the structure of the system.

The results obtained from~~ the simulation of~~ simulations with the proposed approach ~~indicated~~revealed ~~indicated~~ that the ~~time~~duration ~~time~~ of rescue operations ~~in~~ when the proposed strategies were implemented was always ~~less~~shorter ~~less~~ than the time required ~~in~~ using the CNP method. The worst improvement was ~~found~~identified ~~found~~ for 2000 agents with 28,856 tasks (13%) and~~,~~ the best for 1000 agents~~, and~~ with 111,463 tasks (21%).~~ In addition~~ ~~Besides~~Furthermore~~Besides~~, the results ~~for~~ at different scales showed that the application of ~~applying~~ uncertainty in ~~the~~ task allocation could improve the ~~time~~duration ~~time~~ of ~~the~~ USAR operations. There is a relationship between ~~an~~ increased in uncertainty and ~~an~~ increased ~~in the~~ rescue operation ~~Further~~duration~~time~~. ~~The increase is 67.7 hours for CNP while it is 63.4, 63.2, 61.7, and 56.5 hours for the Strategies 1, 2, 3, and 4, respectively.~~ Furthermore~~Further~~, the results ~~indicated~~revealed ~~indicated~~ a significant decrease in the numbers of deceased people and wrong allocations due to uncertainties, which ~~and~~demonstrated ~~demonstrates the significance of uncertainty and~~ the importance of ~~its~~uncertainty ~~its~~ inclusion in task allocation. The implemented method can be used for cooperation differentamong between different agents. In an earthquake-stricken environment, rescuers can use assistant agents (devices such as mobile phones and tablets) to implement this methodology.

handHowever,On the other hand, regarding comparisoncomparisons the comparison of the proposed strategies, it is insufficient to consider only uncertainty is not enough in initial decision-making concerning task allocation sincebecause since the working environment is quite dynamic and the assigned tasks may forencounter face problems for various reasonsproblemsreasons. An effective assigningassignment assigning approach should consider both uncertainties in decision-making and strategies for replanningreallocation in order to waste the least time during system disruptions. This optimizes planning to achieve better implementation time and forallows provides conditions for fault tolerance. The strategies for applying uncertainty induring in the implementation process of task allocation improve the efficiency, performance, and stability of agent-based cooperation. Task allocation strategies lead to flexibility in decision-making and decrease the system's overall costs. Furthermore, spatial task allocation strategies can propose a specific arrangement of the rescue team within the an environment in order to prevent time waste when faced with wasting in the event of waste when faced with environmental uncertainties or task reallocation.

Additional research It is recommended that further research could be undertaken to provide new strategies and combine the proposed task allocation strategies of the present study with the a coalition--forming coalition forming method to select thean appropriate the coordinating agent in the our proposed approach. futureFuture In future studies couldshould could also consider the other groups, and, other uncertainties differentwithin a range of in different dynamic simulations.

11.7. Acknowledgments

This research was conducted by the Basic Research Project of the Korea Institute of Geoscience and Mineral Resources (KIGAM) funded by the Ministry of Science and ICT.

References

Barnum, D. T., and Gleason, J. M.: DEA efficiency analysis involving multiple production processes, Applied Economics Letters, 17, 627-632, 2010.

Ben Othman, S., Zgaya, H., Dotoli, M., and Hammadi, S.: An agent-based Decision Support System for resources' scheduling in Emergency Supply Chains, Control Engineering Practice, 59, 27-43, http://dx.doi.org/10.1016/j.conengprac.2016.11.014, 2017.

Bertuccelli, L. F., Choi, H.-L., Cho, P., and How, J. P.: Real-time multi-UAV task assignment in dynamic and uncertain environments, presentado al AIAA Guidance, Navigation, and Control Conference, Chicago, Illinois, 2009,

Cai, B., Huang, S., Liu, D., and Dissanayake, G.: Rescheduling policies for large-scale task allocation of autonomous straddle carriers under uncertainty at automated container terminals, Robotics and Autonomous Systems, 62, 506-514, 2014.

Chen, A. Y., Peña-Mora, F., Plans, A. P., Mehta, S. J., and Aziz, Z.: Supporting Urban Search and Rescue with digital assessments of structures and requests of response resources, Advanced Engineering Informatics, 26, 833-845, 2012.

Chen, J., and Sun, D.: Coalition-based approach to task allocation of multiple robots with resource constraints, IEEE Transactions on Automation Science and Engineering, 9, 516-528, 2012.

Cheng, Y.: A knowledge-based airport gate assignment system integrated with mathematical programming, Computers & Industrial Engineering, 32, 837-852, 1997.

Choi, H.-L., Brunet, L., and How, J. P.: Consensus-based decentralized auctions for robust task allocation, Robotics, IEEE Transactions on, 25, 912-926, 2009.

Crooks, A. T., and Wise, S.: GIS and agent-based models for humanitarian assistance, Computers, Environment and Urban Systems, 41, 100-111, http://dx.doi.org/10.1016/j.compenvurbsys.2013.05.003, 2013.

Dahl, T. S., Matarić, M., and Sukhatme, G. S.: Multi-robot task allocation through vacancy chain scheduling, Robotics and Autonomous Systems, 57, 674-687, 2009.

Erick, M., Anawat, S., Fumihiko, I., and Shunichi, K.: Agent-based Simulation of the 2011 Great East Japan Earthquake/Tsunami Evacuation: An Integrated Model of Tsunami Inundation and Evacuation, Journal of Natural Disaster Science, 34, 41-57, 2012.

Fecht, D., Beale, L., and Briggs, D.: A GIS-based urban simulation model for environmental health analysis, Environmental Modelling & Software, 58, 1-11, http://dx.doi.org/10.1016/j.envsoft.2014.03.013, 2014.

Gokilavani, M., Selvi, S., and Udhayakumar, C.: A survey on resource allocation and task scheduling algorithms in cloud environment, ISO 9001: 2008 Certified International Journal of Engineering and Innovative Technology (IJEIT), 3, 2013.

Grinberger, A. Y., and Felsenstein, D.: Dynamic agent based simulation of welfare effects of urban disasters, Computers, Environment and Urban Systems, 59, 129-141, http://dx.doi.org/10.1016/j.compenvurbsys.2016.06.005, 2016.

Hawe, G. I., Coates, G., Wilson, D. T., and Crouch, R. S.: Agent-based simulation of emergency response to plan the allocation of resources for a hypothetical two-site major incident, Engineering Applications of Artificial Intelligence, 46, 336-345, http://dx.doi.org/10.1016/j.engappai.2015.06.023, 2015.

He, Y. H., Pan, M. C., Xu, W., and Zou, Y. B.: Research of Allocation for Uncertain Task Based on Genetic Algorithm, Advanced Materials Research, 2014, 324-329,

Hooshangi, N., and Alesheikh, A. A.: Agent-based task allocation under uncertainties in disaster environments: An approach to interval uncertainty, International Journal of Disaster Risk Reduction, 24, 160-171, https://doi.org/10.1016/j.ijdrr.2017.06.010, 2017.

Hooshangi, N., and Alesheikh, A. A.: Developing an Agent-Based Simulation System for Post-Earthquake Operations in Uncertainty Conditions: A Proposed Method for Collaboration among Agents, ISPRS International Journal of Geo-Information, 7, 27, 2018.

Hosseini, K. A., Hosseini, M., Jafari, M. K., and Hosseinioon, S.: Recognition of vulnerable urban fabrics in earthquake zones: a case study of the Tehran metropolitan area, Journal of Seismology and earthquake Engineering, 10, 175, 2009.

Kang, H.-s., and Kim, Y.-t.: The physical vulnerability of different types of building structure to debris flow events, Natural Hazards, 80, 1475-1493, 2016.

Kayır, H. H. E., and Parlaktuna, O.: Strategy-planned Q-learning approach for multi-robot task allocation, Informatics in Control, Automation and Robotics (ICINCO), 2014 11th International Conference on, 2014, 410-416,

Lan, J., and 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, edited by: Atamturktur, S., Schoenherr, T., Moaveni, B., and Papadimitriou, C., Springer International Publishing, Cham, 73-81, 2016.

Lee, H., and al-yafi, K.: Centralized versus Market-based Task Allocation in the Presence of Uncertainty, EKC2009 Symposium Information, EU-Korea, 2010.

Li, D., and Cruz Jr, J. B.: A robust hierarchical approach to multi-stage task allocation under uncertainty, Decision and Control, 2005 and 2005 European Control Conference. CDC-ECC'05. 44th IEEE Conference on, 2005, 3375-3380,

Liu, L., and Shell, D. A.: Assessing optimal assignment under uncertainty: An interval-based algorithm, The International Journal of Robotics Research, 30, 936-953, 2011.

Liu, L., and Shell, D. A.: Tackling task allocation uncertainty via a combinatorial method, Safety, Security, and Rescue Robotics (SSRR), 2012 IEEE International Symposium on, 2012, 1-6,

Mansouri, B., A Hosseini, K., and Nourjou, R.: SEISMIC HUMAN LOSS ESTIMATION IN TEHRAN USING GIS, 2008.

Matarić, M. J., Sukhatme, G. S., and Østergaard, E. H.: Multi-robot task allocation in uncertain environments, Autonomous Robots, 14, 255-263, 2003.

Mustapha, K., McHeick, H., and Mellouli, S.: Modeling and Simulation Agent-based of Natural Disaster Complex Systems, Procedia Computer Science, 21, 148-155, http://dx.doi.org/10.1016/j.procs.2013.09.021, 2013.

Nourjou, R., Hatayama, M., and Tatano, H.: Introduction to spatially distributed intelligent assistant agents for coordination of human-agent teams' actions, Safety, Security, and Rescue Robotics (SSRR), 2011 IEEE International Symposium on, 2011, 251-258,

Olteanu, A., Pop, F., Dobre, C., and Cristea, V.: A dynamic rescheduling algorithm for resource management in large scale dependable distributed systems, Computers & Mathematics with Applications, 63, 1409-1423, 2012.

Quiñonez, Y., Maravall, D., and de Lope, J.: Stochastic learning automata for self-coordination in heterogeneous multi-tasks selection in multi-robot systems, Mexican International Conference on Artificial Intelligence, 2011, 443-453,

Reis, J., and Mamede, N.: Multi-Agent Dynamic Scheduling and Re-Scheduling with Global Temporal Constraints, Enterprise Information Systems III, 3, 117, 2002.

Sabar, M., Montreuil, B., and Frayret, J.-M.: An Agent-based Algorithm for Personnel Scheduling and Rescheduling in Assembly Centers, IFAC Proceedings Volumes, 42, 1977-1982, 2009.

Sang, T. X.: Multi-criteria decision making and task allocation in multi-agent based rescue simulation, Japan Graduate School of Science and Engineering, Saga University, Japan, 2013.

Sayadi, M. K., Heydari, M., and Shahanaghi, K.: Extension of VIKOR method for decision making problem with interval numbers, Applied Mathematical Modelling, 33, 2257-2262, 2009.

Su, X., Zhang, M., and Bai, Q.: Coordination for dynamic weighted task allocation in disaster environments with time, space and communication constraints, Journal of Parallel and Distributed Computing, 97, 47-56, 2016.

Su, X., Wang, Y., Jia, X., Guo, L., and Ding, Z.: Two Innovative Coalition Formation Models for Dynamic Task Allocation in Disaster Rescues, Journal of Systems Science and Systems Engineering, 27, 215-230, 10.1007/s11518-018-5365-9, 2018.

Tan, S. H., and Barton, P. I.: Optimal dynamic allocation of mobile plants to monetize associated or stranded natural gas, part II: Dealing with uncertainty, Energy, 96, 461-467, 2016.

Uno, K., and Kashiyama, K.: Development of Simulation System for the Disaster Evacuation Based on Multi-Agent Model Using GIS, Tsinghua Science & Technology, 13, Supplement 1, 348-353, http://dx.doi.org/10.1016/S1007-0214(08)70173-1, 2008.

Vafaeinezhad, A., Alesheikh, A., Hamrah, M., Nourjou, R., and 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, 66-78 pp., 2009.

Wang, Y., Luangkesorn, K. L., and Shuman, L.: Modeling emergency medical response to a mass casualty incident using agent based simulation, Socio-Economic Planning Sciences, 46, 281-290, http://dx.doi.org/10.1016/j.seps.2012.07.002, 2012.

Welch, M. C., Kwan, P. W., and Sajeev, A. S. M.: Applying GIS and high performance agent-based simulation for managing an Old World Screwworm fly invasion of Australia, Acta Tropica, 138, Supplement, S82-S93, http://dx.doi.org/10.1016/j.actatropica.2014.03.021, 2014.

Xiao, Z., Ma, S., and Zhang, S.: Learning Task Allocation for Multiple Flows in Multi-Agent Systems, Communication Software and Networks, 2009. ICCSN'09. International Conference on, 2009, 153-157,

Zhang, J., Qin, W., Wu, L., and Zhai, W.: Fuzzy neural network-based rescheduling decision mechanism for semiconductor manufacturing, Computers in Industry, 65, 1115-1125, 2014.