USAR simulation system: presenting spatial strategies in agents' task allocation under uncertainties

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ABSTRACT

Task allocation in uncertainty 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) operation. The proposed method is presented in five phases: ordering existing tasks, finding coordinating agent, holding an auction, applying allocation strategies, and implementation and observation of environmental uncertainties. The methodology was evaluated in Tehran's District 1 for 6.6, 6.9, and 7.2 magnitude earthquakes. The simulation started by calculating the number of injured individuals, which was 28856, 73195 and 111463 people for each earthquake, respectively. The Simulations were performed for each scenario for a variety of rescuers (1000, 1500, 2000 rescuer). In comparison with contract net protocol (CNP), the standard time of rescue operations in the proposed approach includes at least 13% of improvement and the best percentage of recovery was 21%. Interval uncertainty analysis and the comparison of the proposed strategies showed that an increase in uncertainty leads to an increased rescue time for CNP of 67.7 hours, and for strategies one to four an increased rescue time of 63.4, 63.2, 63.7, and 56.5 hours, respectively. Considering strategies in the task allocation process, especially spatial strategies, resulted in the optimization and increased flexibility of the allocation as well as conditions for fault tolerance and agent-based cooperation stability in USAR simulation system.

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

1. Introduction

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

Task allocation is one of the main issues in coordinating among a set of agents in a multi-agent system (MAS) (Liu and Shell, 2012; Nourjou et al., 2011). 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 under uncertainty (Hooshangi and Alesheikh, 2017). Generally, task allocation on a large scale is influenced by uncertainties and various factors (Cai et al., 2014). Uncertain circumstances have a major impact on the

initial planning and results of rescue operations planning (Hooshangi and Alesheikh, 2018). Despite the findings of various projects, these projects could not find an optimal solution (Olteanu et al., 2012).

Reallocation is an effective reaction to uncertainties and changes in the environments, and it has an important role in 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 instantaneous disruption is very important, especially in distributed systems on large scales (such as 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.

Task allocation does not take place in only one stage of USAR operations (Nourjou et al., 2011). An effective task allocation approach in USAR operations should include strategies for planning. 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, the results of the initial task allocation should be changed through applying uncertainties to assign tasks in crisis-driven conditions. Since tasks might not be performed well for various reasons, strategies (e.g., minimum location displacement) should be applied to initial responses in order to save more time in 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 as well as providing conditions for fault tolerance.

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

2. Literature review and background

2.1 Agent based USAR simulation

Simulation has been used in various sciences including disaster management, emergency supply chains and tsunami. Table 1 presents some of agent-based simulations performed in previous researches.

Table 1 Agent-based simulations in different disciplines

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	(Hooshangi and Alesheikh, 2018)
	An agent-based model to simulate the emergency medical response to a mass casualty incident was built	Modeling an emergency medical response	Simulated model build intuition and understanding in advance of facing actual incidents that are rare in operating experiences.	(Wang et al., 2012)
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.	(Ben Othman et al., 2017)
Tsunami	By analyzing images of 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.	(Erick et al., 2012)

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.	(Welch et al., 2014)
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.	(Qiu et al., 2008)

Agent-based systems have been used as simulation tools in various studies. 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 (Fecht et al., 2014). 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, 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 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.

2.2 Approaches 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 (Chen and Sun, 2012). Agents should include environmental uncertainties in their performance regarding planning goals. There are four common approaches to considering uncertainty: 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, 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) (Hooshangi and Alesheikh, 2017). Uncertainty in tasks allocation has been investigated in various studies that can be categorized as follows:

Sensors' 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 based (Matarić et al., 2003), Hungarian interval algorithm (Liu and Shell, 2011) and consensus-based bundle algorithm(CBBA) methods (Bertuccelli et al., 2009).

Accidental event 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) and two-level hierarchical algorithm (Li and Cruz Jr, 2005) have been used to consider this.

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 (Kayır and Parlaktuna, 2014) (Xiao et al., 2009).

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 (Dahl et al., 2009) and probabilistic algorithm based on learning automata (Quiñonez et al., 2011).

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) and dynamic weighted task allocation (Su et al., 2016) are the methods used in this field.

Decision parameters: In this category, which are suitable for MASs, uncertainties are included in the decision parameters for assigning tasks. Therefore, all the information needed to tasks allocation is considered uncertain. Various methods such as CNP (Hooshangi and Alesheikh, 2017), stochastic scheduling (Tan and Barton, 2016) and genetic algorithm (He et al., 2014) have been used.

The mentioned methods have been used in various applications such as multi-UAV (Bertuccelli et al., 2009), supply chain (Dahl et al., 2009), moving plants (Tan and Barton, 2016) and disaster environments (Su et al., 2016). There is no dominant 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. This study presents an approach that also includes strategies in contract net protocol (CNP). The CNP method is simple, practical and popular in agent-based modeling.

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

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 (Hooshangi and Alesheikh, 2017). The interval VIKOR method is described in (Sayadi et al., 2009).

2.3 Reallocation and reassigning methods

Different algorithms have been proposed for scheduling and task reallocation in accordance with the required tasks and available conditions within the environment (Gokilavani et al., 2013). Some reallocation methods are applied to the reassignment of individuals in organizations (Barnum and Gleason, 2010). In such methods, the solution's run time is not important; 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 should be performed dynamically and instantaneously.

In some research, such as those addressing gate reassignment problems (GAP), initial assignment tables were created using heuristic methods in such a way that a succession delay is minimized (Cheng, 1997). The incidence of adverse events may disrupt the original table. These methods are not responsive for a great number of tasks. 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, 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 (Olteanu et al., 2012). 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. 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 (Cai et al., 2014). Therefore, an appropriate method must be applied regarding the nature and scale of the problem.

Due to the large number of rescue groups in USAR operations, the available uncertainties and the dynamic nature of multi-agent systems in disaster environments, the concept of general planning is not very common and it is better that the plan is produced 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. Regarding USAR operations, task allocation methods should include 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 previous studies, we define an approach based on spatial strategies so that the results of the initial task allocation are used in the future for other task allocations, and are appropriate in the rescue environment. Time limitations are another issue in replanning and reassigning regarding reallocation in rescue teams. Therefore, the present study aims to expand the CNP method as a rapid method for resolving the problem.

3. Case study

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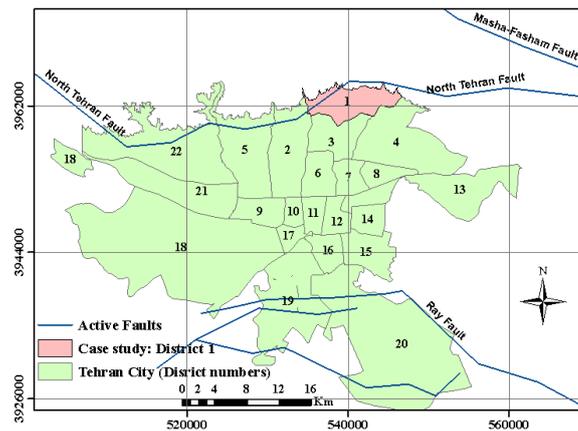
Figure 1 Map of District One (study area) and active faults, Tehran

Recent Tehran earthquake (5.2 Richter) on December 2017 attracted the attention of many urban planning organizations. This metropolis is one of the vulnerable areas to earthquake. The rapid growth of urbanization and the vulnerability of structures have increased the potential risk of the city (Hosseini et al., 2009). Tehran is a highly
185   seismic area as it is surrounded by the Ray, Masha-Fasham and North faults. Seismologists have stated that a severeearthquake could be expected in Tehran in the future (Hosseini et al., 2009). The North fault is the city's biggest fault and is about 35 km long and has 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 selected. Various scenarios can be implemented. According to the suggestion of the experts, we simulated the magnitude 6.6, 6.9 and
190   7.2 earthquakes.

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

4.1   The scenario 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
195   a disaster environment and detailed information on the characteristics of the environment is not available (in the environment, events are uncertain). In this scenario, crisis is assumed to be an earthquake. The injured individuals are trapped under the rubbles and are spread with different values of uncertainty in this environment. Rescuing injured people is the main goal. Saving each person is a task that must be done. The possible location of injured individuals can be predicted using buildings damage assessment models. Therefore, the model inputs are injured individuals
200   location and their characteristics, which are uncertainly accessible. The rescue agents are trying to save the injured ones by moving up to the task location. Given the previous studies (Chen et al., 2012; He et al., 2014; Hooshangi and Alesheikh, 2017; Sang, 2013) and according to experts on USAR operations, the uncertainties include the number of injuries, severity of the victims' injuries, duration of the operation, infrastructure priorities, agent energy, route status, task runtime by an agent and risk level for agent. These are important uncertainties in task allocation. All these
205   parameters are specified by interval during the task allocation process. After determining the tasks, an agent is assigned a task and pursues it. Then, if an agent fails to complete his task due to any existing disruptions, the task is updated with respect to uncertainties and reported to the central agent, resulting in the restarting of the task allocation process. In this process, task allocation strategies are applied to minimize the cost of the system.
In this study, there is a central agent and several coordinator, rescuer and injured agents in the environment. These
210   independent agents are rational and have the ability to communicate with each other. 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.
- **Coordinator agent:** Coordinator is responsible for sending the characteristic of work to rescuers, receiving
215   their propose (bids), holding auctions and submitting the results and rescuers prioritization to the central agent.
- **Rescue agent:** Rescuer identifies and moves to the task location, searches for the injured individuals and sends the tasks uncertainty to the central agent.

- **Injured agent:** This agent exists in the environment and his critical condition changes continuously.

4.2   The proposed method

220   The proposed model for task allocation with uncertainties in earthquake USAR operation is given in Figure 2.
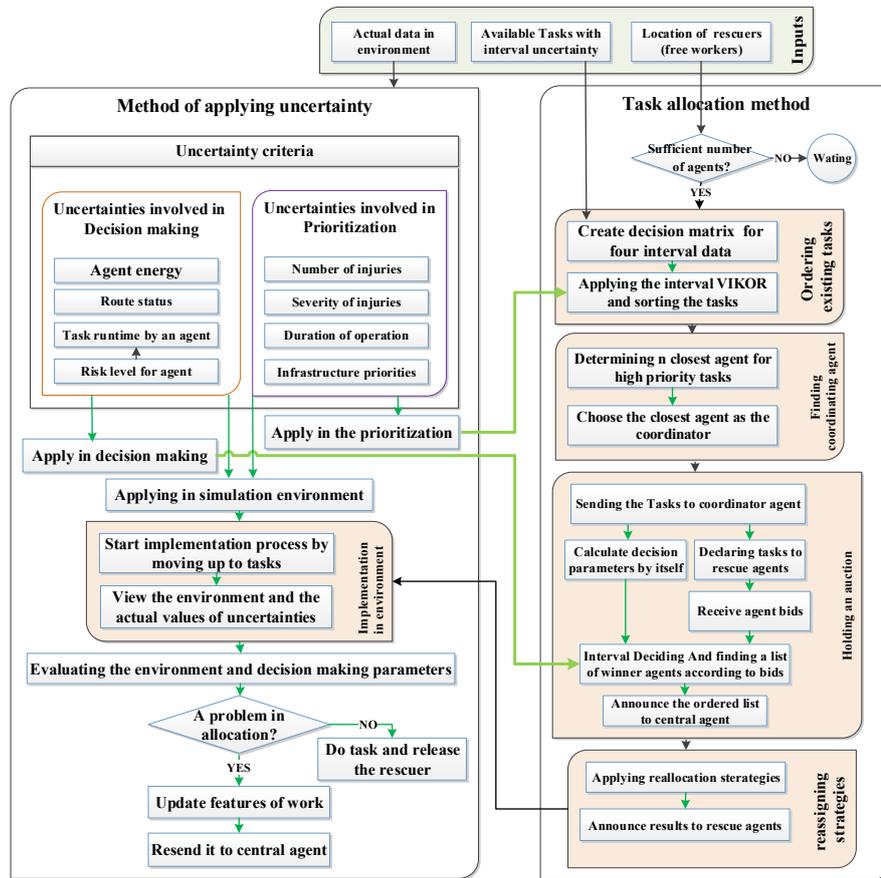
Figure 2 Task allocation flowchart in the proposed approach by five steps and environmental simulation

The five steps of proposed approach are the ordering of existing works, specifying the coordinators, holding an auction, applying reassigning strategies, and implementing and observing environmental uncertainties by the agent. The proposed method is presented as follows:

225   #### 4.2.1   Ordering existing tasks

In crisis-ridden areas there are always different degrees of urgency (Chen et al., 2012). Tasks with a higher priority need to be done first. Four parameters were used to prioritize tasks (number of victims, severity of the injuries, time required for rescue operation, infrastructure priorities).

In real applications, after an earthquake the number and location of the injured persons can be estimate based on
230   the buildings destruction (Kang and Kim, 2016). The infrastructure priorities and the duration of the operation can be determined by the location of the area and the spatial data. The initial tasks with their uncertainties in the environment (four priority parameters) are available to the central agent. Therefore, for each task feature an interval such as that expressed in Table 2 is specified.

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Table 2 Tasks characteristics based on intervals

Task NO.	X Coordinate	Y Coordinate	Infrastructure priorities	Number of injuries	Severity 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	$[I_{ln}, I_{un}]$	$[N_{ln}, N_{un}]$	$[S_{ln}, S_{un}]$	$[D_{ln}, D_{un}]$

Ordering is summarized in the decision matrix and the interval based VIKOR method was applied due to the nature of the data, since the priority level of saving a specific injured individual comes from different factors in the disaster
245 environment. This evaluation is performed by the central agent.

4.2.2 Finding coordinating agent

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

255 ### 4.2.3 Holding an auction

Coordinating agents hold auctions after receiving the task characteristics and the list of agents in the subgroup. CNP, including uncertainty, is used. This method produces local optimal solutions which are abundantly used in multi-agent systems (Choi et al., 2009). In this method, agents bid for tasks and the person who offers the highest value for the task is the winner. During the auction, rescue agents offer an interval for the rout conditions, the time needed to
260 execute the task by the agent, the possible risk level and their energy, instead of a value. For this, the agent calculates numbers for each of the four decision-making criteria, such as a variable X, based on the following equations. These relationships are based on expert opinions. Based on the rate of uncertainty that is considered for the environment (for example, 30%), an interval for this number is estimated. The first number of this interval will be in the range between
265 [X, X + 30%X] and the second number in the range [X - 30%X, X].

Agent energy (Energy Level, Distance, Number of people) = Energy Level - Distance/500 - Number of people*0.3
Task runtime by an agent (Distance, Number of people, Severity) = Distance/150 + number of people*15 + severity*2   (1)
Risk level for agent (Energy Level, Priority) = Priority - Energy Level
Route status (Distance) = Distance

In the real world, each person can introduce intervals according to their experience and their knowledge of the environment. In this research, we used the above equations with respect to the expert opinions to simulate the real environment. The unit of decision-making parameters does not matter in the calculations, because the coordinating
270 agent will calculate the winning interval using the VIKOR method and does not need a unit.

The coordinating agent applies the interval-based VIKOR method to order the agents. The coordinating agent sends the results to the central agent after ordering the agents. The use of a central agent provides the opportunity to make the best decision considering the task priorities as well as the capacity of other agents.

4.2.4   Applying allocation strategies

275   Regarding the disaster environment, only some parts of the workflow are operational and many of the existing tasks are unexpected and uncertain. In this situation, it is not possible to definitively resolve the issue of task allocation. In many cases, the initial allocation may face problems, or new tasks may be added to the work list; therefore, replanning and reallocation are required. In this case, it is better for the initial allocation to be done in such a way that if reallocation is needed, it wastes the least amount of time. This phase is the main innovation of the present study.

280   Based on different strategies in this stage, the central agent begins to assign tasks after obtaining all lists from coordinating agents. In each strategy, a priority is given to specific tasks. In this section, four different strategy-based approaches are described, as follows:

Task allocation with higher priority: In this strategy, task allocation begins with assigning tasks of higher priority once the task order and the priorities of the rescue team have been established in the previous stage (prioritizing and
285   auction). Therefore, the agent with the best performance is selected for high priority tasks and is then excluded from the lists of agents with no tasks. Later, the tasks of lower priority are assigned in the same order. The problem related to this strategy is that some agents may be left with no tasks to do in the last stages of this process.

Assigning tasks to all agents, preferably the agent with the best outcome: This strategy is based on optimally using all rescue teams. In this strategy, all agents are assigned a task. For this purpose, the task is first assigned to an
290   agent who has applied for the minimum number of tasks. Then, the agent and the task are eliminated from the agent and task lists, and the allocation continues with the next agent who has made few requests. Based on this strategy, a task will be assigned to all agents.

Allocation by keeping a strategic spatial agent: Based on this strategy, the strategic agents who play an important and strategic role in the task allocation process are excluded in order to help with the implementation of the tasks if
295   there are problems during the task allocation process. Agents with strategic roles may be defined differently. Agents who participated in the auction of more tasks are the agents with strategic locations. In this situation, this agent is close to many tasks (has a strategic spatial location) and can be used if these tasks are not implemented. Figure 3 shows the difference between the task allocation results for strategy 2 and strategy 3.
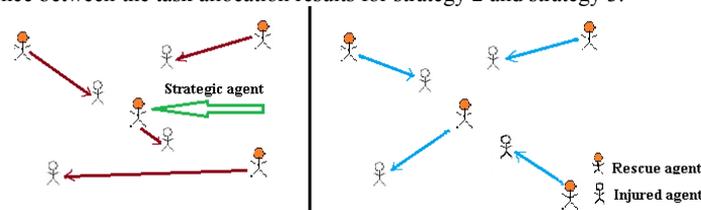
Figure 3 Shows the strategic agent, the red arrow indicating the winning searchers in strategy 2 and the blue arrow shows the final result for strategy 3.

Assigning tasks by creating the best density in the environment: This strategy is based on the optimal density of
300   rescue agents. With this strategy, the assignments of the tasks are made in such a way as to ensure a uniform distribution of the agents in the environment. Generally, no exact information is available about the conditions of the tasks; therefore, this strategy aims to ensure the uniform distribution of rescue teams within the environment if the uncertainty is high. In disaster environments like earthquakes, the incident takes place over a wide area and the damage and injured population have uniform distribution due to the texture of the area. Therefore, the highest number of
305   injured people is not accumulated in any one spot. In addition, applying this strategy prevents the convergence of rescue teams. In order to apply this strategy, the tasks of the highest priority in the task lists should be given to the agents and the environmental density should be the highest. The issue of the optimal density can be solved through innovative algorithms. In our study, the simulated annealing (SA) method was used. Figure 4 shows the difference between task allocation outcomes for strategy 2 and strategy 4.
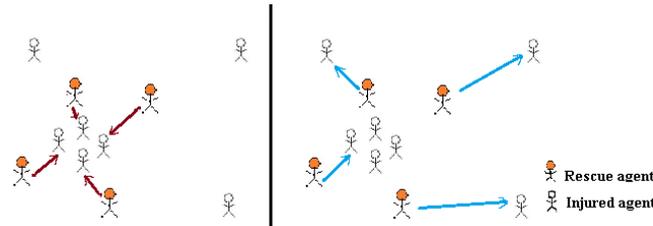
Figure 4 Shows the best density strategy, the red arrow indicating the winning searchers in strategy 2 and the blue arrow shows the final result for strategy 4.

310   **4.2.5   Implementation and observation of real values in environment**

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

If the agent observes a big difference between the auction information and the real environment, he abandons the task. In this case, he updates the uncertainties and sends the work to the central agent. There can be different conditions in which agents will reallocate a task if the environment is different from the expected one. For example, the agent
320   can abandon the task if three out of eight decision-making parameters are out of range by 5%. Otherwise, the rescuer finishes the work by accepting the new conditions.

The central agent assigns new added tasks within the reallocation framework. When a new task is assigned, the task allocation is mixed with new tasks as well as incomplete ones.

4.3   Evaluation Method

325   The purpose behind simulation is to assess the quality and reliability of the allocation strategies. Assessing a task allocation algorithm is 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 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. We model our proposed approach in
330   the form of detail simulation.

In this study, the modeled environment was a disaster environment hit by an earthquake. We simulated three scenarios for the earthquake in Tehran's District 1 with magnitudes 6.6, 6.9 and 7.2. We also estimate the number of dead and injured individuals who were distributed in in the center of the relevant building blocks and rescued by 1000, 1500 and 2000 rescue agents. Also, in uncertain analysis of suggested method, the lower and upper bounds of uncertain
335   values are calculated. The proposed method was compared with simulated annealing (SA) and CNP. The intended task allocation is efficient if profitability parameters are maximized. According to a number of recent studies (Hooshangi and Alesheikh, 2017; Liu and Shell, 2012; Sang, 2013), 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.

340   **5. Results**

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 include calculating the damage rate of the area, specifying the
345   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
350   (CEST) and the Japan International Cooperative Agency (JICA).The results of this project is presented in (Mansouri et al., 2008a), And has been used in various researches (Hooshangi and Alesheikh, 2018; Vafaeinezhad et al., 2009).

According to expert opinions, three probable earthquakes were simulated with magnitudes of 6.6, 6.9 and 7.2. Figure 5 shows the vulnerability of buildings in these scenarios in the ArcGIS environment.

355
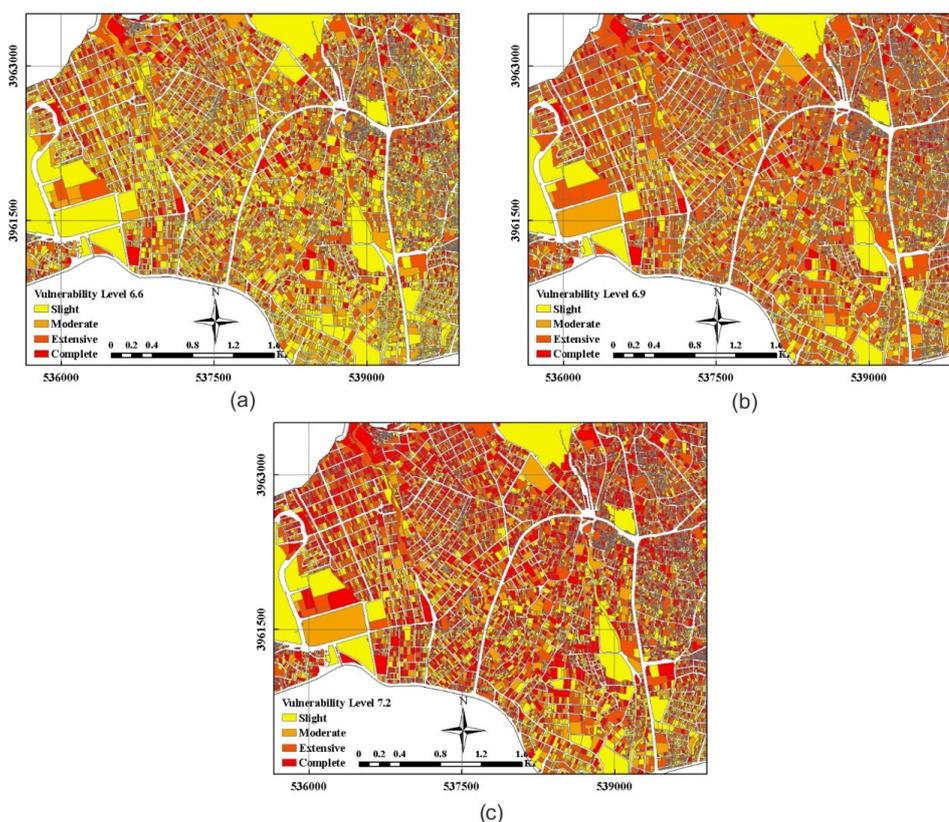
Figure 5 Vulnerability maps in District 1, an earthquake with magnitude: a) 6.6 on the Richter scale, b) 6.9 on the Richter scale, c) 7.2 on the Richter scale

Based on buildings destruction, the number of injured and dead people can be calculated. Equation 1 is the output of the JICA model for calculating the human vulnerability in earthquakes (Mansouri et al., 2008b):

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

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.

360

Table 3 Results from implementing a 6.6 Richter scale earthquake

Severity level	Number of affected populations		
	6.6 Richter	6.9 Richter	7.2 Richter
Uninjured	374295	270455	182340
Injured	28856	73195	111463
Deceased	30349	89850	139697

The computational scale of the JICA model is urban blocks. Therefore, the number of dead and injured in each urban block was calculated. The location of the injured individuals was considered in the center of the block.

365 The simulation of the environment and the proposed method were performed in AnyLogic software. This software has the ability to enter GIS data. The distribution of rescue agents is random. In order to simplify the environment and reduce the volume of calculations, each agent was considered as a group in the real world. Figure 6 shows the simulated environment.
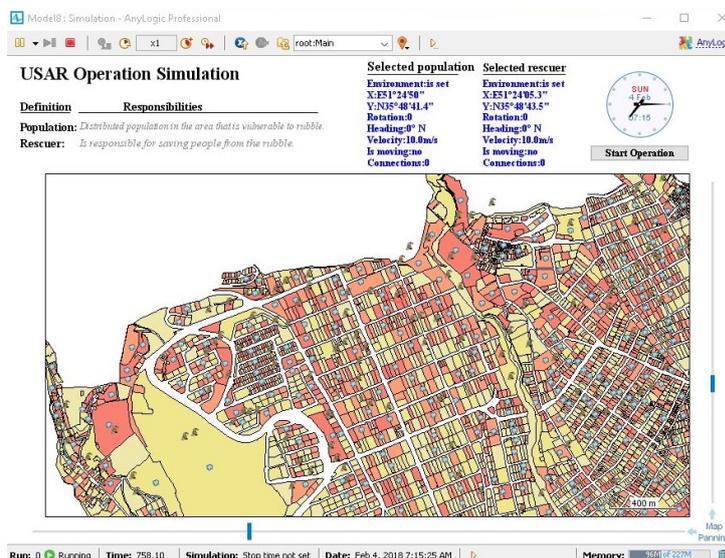
Figure 6 An overview of USAR simulator by using AnyLogic software (https://www.anylogic.com/)

370

There are many injuries in the environment. The central agent first sorts the tasks according to their priority and after determining the coordinating agent, sends the task properties to coordinating agent. The coordinator holds a tender. Rescue agents are bidding in accordance with their environmental and working conditions. Rescuers are in a ready state at the start of the operation. Each winning rescue agent moves to the task's location. After reaching the task

375 position, he starts rescuing the injured agents. During the execution of the work the agents may find a significant difference between the real-world information and the expressed information in the tender. In this situation, the agent may stop performing the task and report the existing dispute to the central agent.

Results were achieved with 500 randomized runs. In this section, the results of the two analyses were presented. The first analysis focused on the evaluation of the proposed approach on different scales and for different criteria. The

380 second analysis focused on interval uncertainty analysis and studying the rescue operation time in 6.9 Richter earthquake for different levels of uncertainty.

5.2 Scalability of the proposed method

Some of the major problems in replanning and in the task allocation environment include scalability, reliability, performance and the dynamic reallocation of resources (Gokilavani et al., 2013). Comparison and assessment were

385 carried out on different scales in order to recognize the effectiveness of the proposed approaches in USAR operations. Nine scenarios were applied in this study and compared with traditional CNP. Simulated annealing (SA) was also applied to assign the tasks. This method is described by Sabar et al. (2009).

Table 4 shows the time of the USAR operations in different scenarios and scales. In creating this table, an uncertainty of 30% was considered. For this purpose, the range of tasks characteristics was made in the intervals [X,

390 X + 30%X] and [X-30%X, X]. Also, at each stage that agent participates in the auction, for his decision-making parameters, agent converts its number randomly into an interval. The average range of agent tasks and decision-making was used for the implementation of CNP and SA instead of interval values. The results indicated that more than six hours were required to resolve the issue on the scale of 1000 agents and 28856 tasks in SA method. The computer used in all samples was a Core i7 with a central processor and 6 GB ram. SA fails to indicate proper

395 applicability due to the high rate of input tasks in USAR operations.

400

Table 4 comparison of the suggested method with CNP (based on 30% uncertainty)

Agents	1000			1500			2000		
Simulated earthquake	6.6R	6.9R	7.2R	6.6R	6.9R	7.2R	6.6R	6.9R	7.2R
Tasks	28856	73195	111463	28856	73195	111463	28856	73195	111463
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

405

The operational time decreases when the number of agents in rescue operations increase but the number of tasks remains fixed. The reduction rate ranges between 54% and 60% when the number of agents is doubled. The time of a USAR operation increases when the number of tasks increases for a certain number of agents. Therefore, the time of the rescue operation is related to the number of rescue agents and the number of available tasks in a scenario. There
410 is an inverse relationship between the time of the USAR operation and the number of search agents, and a direct relationship between the time of the operation and the number of tasks.

The inclusion of uncertainty in any allocation strategy could provide better results, as compared to the CNP method. The smallest improvement in the results with uncertainty using the proposed strategies was 2.9 hours for a scenario with 2000 agents and 28856 tasks (6.6 Richter earthquake). The maximum improvement was 60.6 hours for
415 1000 agents and 111463 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 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
420 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
425 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
430 are shown in Figure 7. In these figures, for each of the four priority parameters and decision parameters of the agents, a 30% uncertainty level was considered.
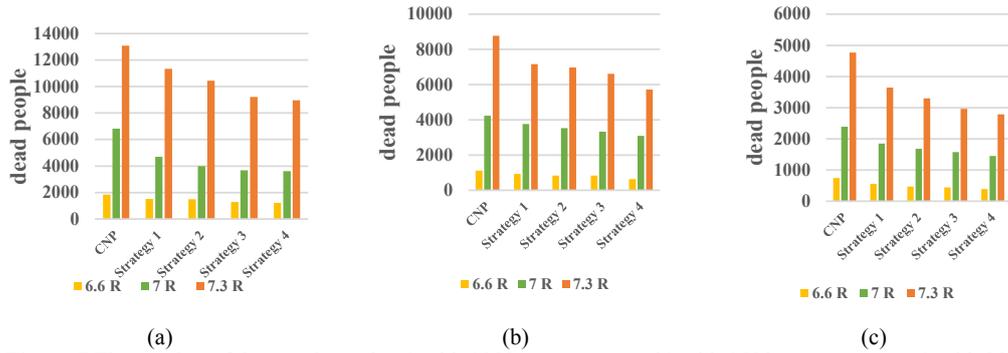
Figure 7 The number of deceased people: a) with 1000 rescue agents, b) with 1500 rescue agents, c) with 2000 rescue agents.

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 to 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 illustrate the simulation results for incorrect allocation of the 1000, 1500 and 2000 agents with a number of different tasks.
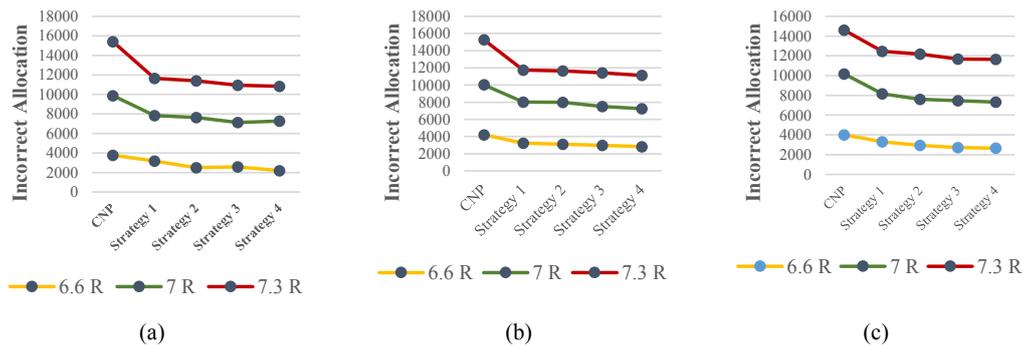
Figure 8 The number of incorrect allocations: a) with 1000 search agents, b) with 1500 search agents, c) with 2000 search agents.

The overall trend in the figures is approximately the same if all figures are considered simultaneously. The incorrect allocation is not related to the number of search agents, since there are no changes in increasing the number of agents. The number of incorrect allocations changes with the number of tasks, and increases with the number of tasks. This increase is observed in all of the above figures. The incorrect allocations usually take place with an almost fixed rate.

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 by means of scale development since their difference from CNP increases with scale development.

5.3 Interval uncertainty analysis

460   In this section time changes of rescue operations based on different levels of uncertainties are investigated. The duration of the rescue operation in the simulated model depends on two main components: 1- Prioritization of tasks and, 2- Outputs of each operation at each phase. Equation 1 defines the final model for calculating the operation time based on these two components.

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

465   The variables x1 to x8 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. α_n is function of tasks prioritization and β_w is function of bidding.

Interval uncertainty analysis has rarely been investigated in previous researches. The method used in this research is adapted from research (Lan and Peng, 2016). In this research, Chebyshev points are used. Equation 2 is Chebyshev formula to generate m collocation points on interval [0, 1] (Lan and Peng, 2016):

470
$$number_i = \begin{Bmatrix} 0.5 \times \left[1 - \cos\left(\frac{\pi(i-1)}{m-1}\right)\right] & for\ j = 1, if\ m = 1 \\ 0.5 & for\ j = 1, if\ m = 1 \end{Bmatrix} \qquad (2)$$

Equation 2 is used to create different numbers for the decision-making parameters. The output of the model is then calculated for numbers in the intervals. This technique creates different values for the output of the model. Results were achieved with 500 randomized runs of each scenario (Figure 9).

1000 agent- 28856 task

1000 agent- 73195 task

1000 agent- 111463 task

1500 agent- 28856 task

1500 agent- 73195 task

1500 agent- 111463 task
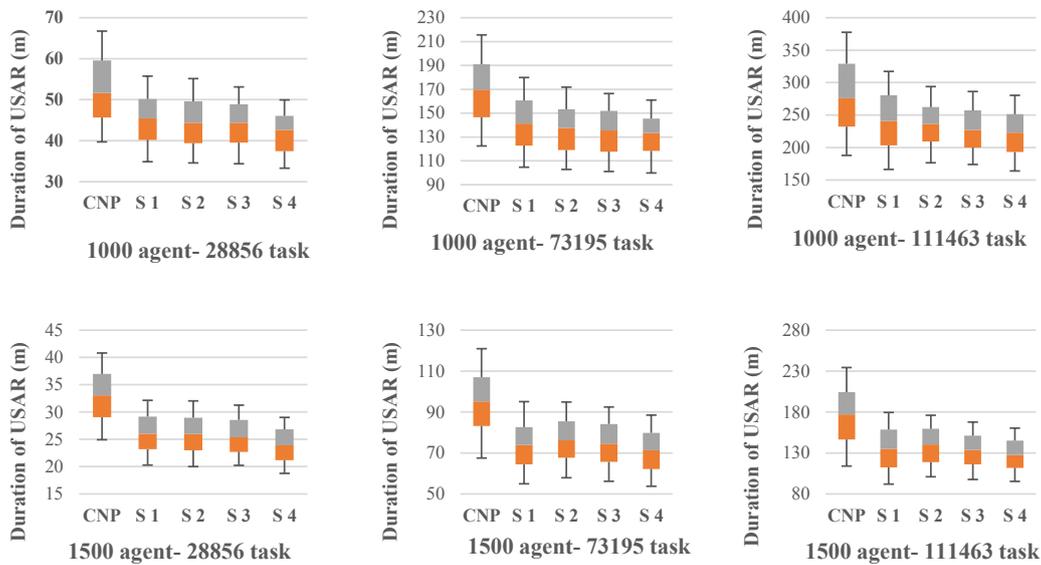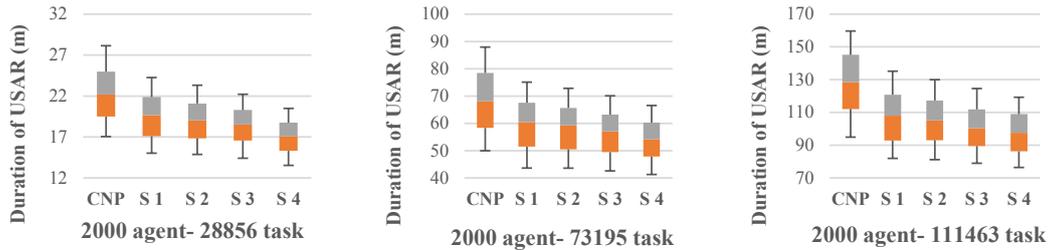
Figure 9 Uncertainty analysis of the proposed method in USAR operations, for 9 simulated scenarios

As shown in Figure 9, there is a direct relation between interval length and operational time. Because according to Formula 1, assigning fewer tasks leads to less operating time, and as well as causes less uncertainty in the simulated environment.

As mentioned in section 4.2.3, the rescuers use [X, X + 30%X] and [X-30%X, X] to determine the intervals. Another analysis was performed for different values instead of 30% in the estimating. The results are shown in Figure 10. An average mode of the scale studies (1500 agents and 73195 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 evaluate. This realistic test aims to provide an assessment of the proposed scenarios for each uncertainty value.
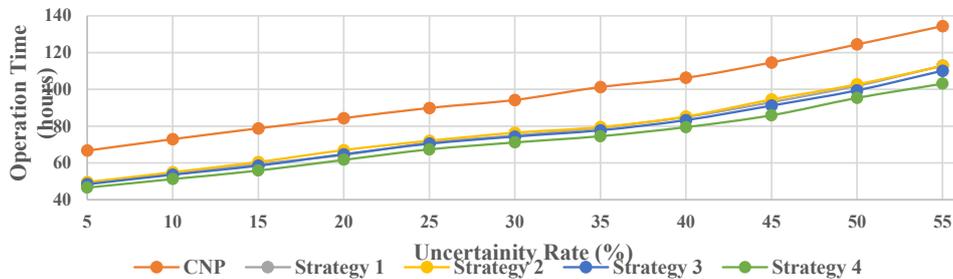
Figure 10 Uncertainty analysis for different values in determining intervals

Figure 10 indicates a relationship between an increase in uncertainty and an increase in the rescue time. The increase is different for different strategies. 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. Based on the evaluation results, the proposed methods are more efficient and present better responses in the presence of different uncertainties. Therefore, an increase of uncertainty leads to a delay in USAR operations and even to task elimination. As a result, delaying rescue operations or removing tasks from the rescue list will increase USAR time.

6. Conclusion

In task allocation within disaster environments, uncertainties should be both considered for decision-making in task allocation and preparation to deal with task non-performance due to uncertainties. This study presented a spatial simulation for USAR operations and also some strategies to apply uncertainties in task allocation to adjust for dynamic changes. In other words, it aimed to better assign the initial tasks in order to have better conditions for potential reallocations of the tasks, and to waste the shortest time possible for the rescue teams if the initial allocations face a problem or a new task emerges. This innovation regarded the improvement of tasks assignment among agent-based groups for the management of USAR operations. Some of the characteristics and advantages of the study included focusing on the necessity of task reallocation in disaster environments, providing an innovative approach to deal with uncertainties which cause non-performance of the tasks in the CNP method (the most widely used task allocation method in MASs), and defining spatial strategies for better tasks 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 the proposed approach indicated that the time of rescue operations in the proposed scenarios was always less than the time required in the CNP method. The worst improvement was found

505   for 2000 agents with 28856 tasks (13%), the best for 1000 agents and 111463 tasks (21%). In addition, the results for different scales showed that applying uncertainty in the task allocation could improve the time of the USAR operations. There is a relationship between an increase in uncertainty and an increase in the rescue operation 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. Further, the results indicated a significant decrease in the number of deceased people and wrong allocations due to uncertainties, which demonstrates the significance of uncertainty and the importance of its inclusion in task allocation.

510   On the other hand, regarding the comparison of the proposed strategies, uncertainty is not enough in initial decision-making concerning task allocation since the working environment is quite dynamic and the assigned tasks may face problems for various reasons. An effective assigning approach should consider both uncertainties in decision-making and strategies for replanning in order to waste the least time during system disruptions. This optimizes planning to achieve better implementation time and provides conditions for fault tolerance. The strategies

515   for applying uncertainty in the implementation process of task allocation improve the effectiveness, efficiency, productivity, 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 propose a specific arrangement of the rescue team within the environment in order to prevent time waste when faced with environmental uncertainties or task reallocation.

520   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 coalition forming method to select the coordinating agent in the proposed approach. In future studies could also consider the other groups, other uncertainties in different dynamic simulations.

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530   Sciences.

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