Intelligent Decision Support for Centralized Coordination during Emergency Response

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ABSTRACT

Automated coordination is regarded as a novel approaches in Emergency Response Systems (ERS), and especially resource allocation has been understudied in former research. The contribution of this paper is the introduction of two variants of a novel resource allocation mechanism that provide decision support to the centralized Emergency Operations Center (EOC). Two quantitative models are computationally validated using real-time, data-driven, Monte-Carlo simulations promoting reliable propositions of distributed resource allocations and schedules. Various requirements are derived through a literature analysis. Comparative analyses attest that the Monte-Carlo approach outperforms a well-defined benchmark.

Keywords

Decision support systems, optimization, coordination

INTRODUCTION

Recent 2010 earthquakes in Haiti and Chile manifested problems in conducting disaster management measures. Improvised and decentralized actions of local rescue teams have been observed (Dmitracova, 2010). Based on this incompetence a strong need for innovation and rethinking of established structures, processes, and governance is being heard (Schimmelpfennig, 2010).

Resource allocation as one important coordination issue is often conducted by several Emergency Operations Centers (EOCs) by means of the following "greedy" policy: given a certain amount of afflicted, a priori prioritized scenes, the most severe incidents are handled by the closest, idle rescue units. Estimated processing times are typically not taken into account for scheduling. This rather naïve - albeit in many cases common and favorable - rule is applied to the remaining less severe incidents thereafter. Similar procedures are used by international search-and-rescue teams in response to major earthquakes (Comfort, 1999). Adopting this heuristic is often suboptimal for the emergency response and results not only from poor communication between EOCs, a lack of clear governance or from inappropriate coordination (Dmitracova, 2010). A centralized supervision of heterogeneous rescue teams that are divers in nationalities, capabilities, and equipment cannot be guaranteed.

Research in the broad field of disaster management has been gaining importance and public attention over the last few decades. The first basic arrangements of information systems used for disaster management dealt primarily with the modeling, classification, and description of information workflows and communication processes – before, whilst, and after catastrophes. Emergency Response Systems (ERS), which emerged from these arrangements, incorporate a dynamically evolving, multi-disciplinary concept, interconnecting information technology and socio-communication networking in an organizational design (Shen and Shaw, 2004). Yet, ERS may also provide enhancements in terms of decision support systems for the immediate organizational coordination of resources (personnel, material), which is considered to be one of the key issues during emergency response and an understudied research issue (Altay and Green III, 2006; Chen et al., 2008;

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Quarantelli, 1988; Tierney, 1985). In our setting, coordination denotes the establishment of organizational schedules of (interdependent) actors. Profound preparation is crucial in order to react effectively and efficiently upon any catastrophe, but, when chaos is at its peak, plans are not assured to prevail and spontaneous ad-hoc actions become necessary. Accordingly, the objective of this paper is to present an expedient, novel approach of organizational decision support in order to minimize harm caused by an emergency. We seek to support centralized decision-makers. The deployment of situation-oriented rules defines a correct code of conduct for the assignment of rescue units to incidents and their schedules. These rules are formally mapped so as to enabling their incorporation into ERS allowing a fully automated, centralized coordination of resources in the range of allocations in response to i.e. natural disasters, catastrophes, and terrorist attacks. Incomplete information in terms of uncertain numbers of events and resources, variable processing times and unknown distances between incidents and rescue units, and an urgent need for quick decision support impede the evolution of the models. The quantitative models are deemed to present a so-called operation schedule by optimizing allocating and scheduling issues in favor of any central EOC. This paper emphasizes on the success of our approach in comparison to processes currently being conducted by established aid organizations. The contributions of this work will be the computational validation of an approach that provides fast and reliable allocations propositions for all responsible authorities in charge. The possibility to co-allocate rescue units and spatial dependencies will be incorporated.

Following this introduction, the paper is structured as follows: in the next section, we identify requirements for our models by an extensive related work analysis. Secondly, proper decision models will be derived which suffice these requirements. We will evaluate by means of simulation runs that our optimizations outperforms the traditional approach of resource coordination and give recommendations on which extension is to be used in particular catastrophic settings. Finally, a discussion and an outlook towards future works conclude the paper.

Related Work

Information systems can be used to support operation services across multi-organizational, jurisdictional, and geographical boundaries (Chen et al., 2008). ERS research generally deals with issues throughout all operational stages of an emergency (Altay and Green III, 2006): Crisis Preparedness, Response, and Recovery. While preparation tasks do not only address planning, training, and the establishment of necessary emergency services beforehand, recovery tasks comprise intelligent infrastructure repair and the continued provision of various types of emergency services and resources in order to recover most important infrastructure facilities. Chronographically, the Crisis Response stage is between the two stages Preparedness and Recovery Literature contributions are arranged along the three phases and the tasks supported (see Table 1). Due to space limitation and the focus of our contribution on decision support by mathematical programming during Crisis Response, we unfold only those literature contributions that target especially this research subfield. Based on the analysis, we finally derive requirements for decision support systems that favor the elaboration of optimization models.

Research streams such as those based on organization theory seek to define rules and courses of action for creating stable, resilient, and even high reliability organizations (HRO) beforehand (Weick et al., 1999). (Bharosa and Janssen, 2009) and (Kendra and Wachtendorf, 2003) account for clear role allocations during and in the aftermath of an emergency. Another ERS-stream addresses Data Gathering and Assessment methods which provide for enhanced computational metrics throughout the whole emergency life-cycle, including infrastructure sensitivity analysis and damage assessments (Hiete and Merz 2009; Hsieh 2004; Gonzalez 2009; Jain and McLean, 2003; Chang and Nojima, 2001). The establishment of capabilities in how to incorporate ERS to serve communication channels (Information Distribution) plays a vital part before and during an emergency (Bui and Sankaran, 2006; Owen et al,. 2008; Mendonça et al., 2000), and others). Expedient design principles for creating effective ERS can be seen as necessary condition for the effective deployment of technology-based support services (Chen et al., 2005; Fern et al., 2008; Franke et al., 2010; Jennex, 2007; Kwan and Lee, 2005; Marchese et al., 2008; Perry, 2003; Turoff et al., 2003).

Our analysis of related articles primarily seeks to identify important findings in the Decision Support Systems (DSS) domain, especially in those works where optimization problems are addressed. Various works (Airy et al., 2009; Comes et al., 2010; Reijers et al., 2007) utilize methods from applied statistics, probability theory combined with mathematical programming approaches to establish novel codes of conduct and metrics (Lambert and Patterson, 2002; Tamura et al., 2000) that assist any EOC in those critical minutes of the decision-making process. Auctions and other multi-criteria approaches are suggested. Another research stream follows guidelines from Computational Intelligence research (Leifler, 2008; Van de Walle and Turoff, 2008) to bridge the gap between ERS-Design principles and decision support process architectures. Others make use of empirical investigations (Faraj and Xiao, 2006) of past decision-making conclusions to establish innovative courses of action.

	Decision Support	ERS-Design	Information Distribution	Data Gathering & Assessment	Organization Design
Preparedness	(Grant 2009), (Batta and Mannur 1990), (Leifler 2008), (Tamura et al. 2000)		(Owen et al. 2008), (Santos et al. 2008), (Schurr et al. 2006)	(Hiete and Merz 2009), (Hsieh 2004)	(Gregory and Midgley 2000), (Petrescu-Prahova and Butts 2005), (Weick et al. 1999)
Response	(Airy et al. 2009), (Barbarosoglu et al. 2002), (Comes et al. 2010), (Engelmann and Fiedrich 2007), (Falasca et al. 2009), (Faraj and Xiao 2006), (Fiedrich et al. 2000), (Lambert and Patterson 2002), (Reijers et al. 2007), (Rolland et al. 2010), (van de Walle and Turoff 2008)	(Chen et al. 2005), (Fern et al. 2008), (Franke and Charoy 2010), (Jennex 2007), (Kwan and Lee 2005), (Marchese et al. 2008), (Perry 2003), (Turoff et al. 2003)	(Blecken and Hellingrath 2008), (Bui and Sankaran 2006), (Catarci et al. 2008), (Comfort et al. 2004), (Fritsch and Scherner 2005), (Mendonça et al. 2000), (Schoenharl et al. 2006), (Shen and Shaw 2004)	(Gonzalez 2009), (Jain and McLean 2003)	(Bharosa and Janssen 2009)
Recovery	(Bryson et al. 2002), (Nikolopoulos and Tzanetis 2003)			(Chang and Nojima 2001)	(Kendra and Wachtendorf 2003)

Table 1. Research incorporating ERS listed by operational stage and task type

Artifacts presenting quantitative models that favor resource allocations during emergency response have been evolved particularly since 2000. Models for preparation purposes such as infrastructure and location planning, i.e. (Batta and Mannur, 1990), persist even longer. In more detail, works in the critical response stage approach the decision-making process by assisting several decentralized agents (Airy et al., 2009; Barbarosoglu et al., 2002; Falasca et al., 2009; Fiedrich et al., 2000). These works argue that distributed allocations (assignment & schedules) remain independent from failures of a single EOC, communication bottlenecks evolve more seldom, and loss minimization is achieved more easily.

Only one work (Rolland et al., 2010) clearly suggests applying math programming models in a centralized manner, especially for the assignment of distributed rescue units and incidents. However, the work neglects the fact that (international) rescue units are diverse in their characteristics, possess different capabilities and, at times, it is necessary to co-allocate them. Accounting for the aforementioned standards in ERS research, we derive and stick to distinct requirements that have not been addressed jointly in previous works.

(R1) ***Fast and Spontaneous Planning:*** Recent catastrophic events demonstrated a critical need for timely reactions in resource allocations: the first 72 hours after any catastrophe, the so-called critical deadline, are essential for loss of life minimization (Engelmann and Fiedrich, 2007; Reijers et al., 2007). Other constraints, such as workload requirements and resource availability, make timely and ad-hoc task assignments and scheduling even more difficult (Rolland et al., 2010). Decision support therefore calls for fast and spontaneous planning. Yet creating “cost-effective” decisions (loss minimization as objective) throughout the assignments needs to be pursued, as stated in (Barbarosoglu et al., 2002).

(R2) ***Centralized Allocation and Scheduling:*** The lack of centralized coordination in past emergency response scenarios led to deficiencies in terms of control over decentralized actions. Adopting the argument of (Rolland et al., 2010), we argue in favor of a centralized model to ensure congruent activities according to the central EOC and non-interference among detached decision-makers. By installing a single EOC, we claim that applying computer assisted decision support tends to be consistent, penetrative and thus more effective. This also accounts for a major disadvantage caused by a high degree of decentralization, as stated by (Airy et al. 2009): the lacking control over homogeneous coordination by multi-autonomous actors that have limited information about other units’ status and positions. We exclude the possibility of facing a communication or transportation bottleneck at the EOC even though infrastructure capabilities may have been struck.

(R3) ***Dispatch of Distributed Rescue Units:*** Spatially detached aid organizations collide during any large-scale emergency and do not completely communicate with each other but rather with the EOC. Distances between incidents, between incidents and rescue teams, and other important factors such as travel and individual processing times need to be respected in any task assignment method (Fiedrich et al.m 2000). Cultural and organizational differences pose another difficulty in coordination, thus we need to introduce the concept that rescue units differ in their capabilities.

(R4) ***Co-allocation of Rescue Units:*** Occasionally – if not always – several capabilities are required at the same scene, which leads to a need for co-allocation of resources. For example, in a basic earthquake scenario, it is likely to happen that firemen ensure the stability of a building, and search and rescue the injured, while paramedics give first aid.

The Models

Before introducing the formulation of optimization models Table 2 gives an overview about which model is apt to fulfill our predefined requirements.

	Fast Planning (R1)	Centralized Allocation and Scheduling (R2)	Dispatch of Distributed Rescue Units (R3)	Co-allocation of Rescue Units (R4)
ASSIGNMENT MODEL (P1)	✓	✓	✓	–
DISTRIBUTED COLLABORATION MODEL (P2)	✓	✓	✓	✓

Table 2. Mapping of requirements to proposed Optimization Models

The primary goal of emergency response measures, as we discussed in previous sections, can mathematically be modeled by means of the following optimization problem that seeks to minimize societal harm. In our settings, a centralized EOC seeks to find the best assignment rescue units and tries to allocate them efficiently to incidents. We suppose that all necessary – even though uncertain – information is given a priori. The first model to be introduced will be referred to as the ASSIGNMENT MODEL (P1):

$$\min_{X_{ikt}} \sum_i w_i \left(\sum_{k,t} X_{ikt} \cdot C(i,k,t) \right) \quad (1)$$

$$\text{s. t.} \quad C(i,k,t) = \sum_{j \neq i} X_{jk(t-1)} \cdot \left(C(j,k,t-1) + s_{ji} + p_{ki} \right), \; i \in I, k \in K, t \in T^{>1} \quad (2)$$

$$C(i,k,1) = X_{ik1} \cdot (\overline{s}_{ki} + p_{ki}), \; i \in I, k \in K \quad (3)$$

$$\sum_{k,t} X_{ikt} = 1, \; i \in I \quad (4)$$

$$\sum_i X_{ikt} \leq 1, \; k \in K, t \in T \quad (5)$$

$$X_{ikt} = 1 \Rightarrow \text{cat(i)} \in \text{capab(k)}, \; i \in I, k \in K, t \in T \quad (6)$$

$$\text{cat} : I \Rightarrow \{A_1, \ldots, A_n\}, \; \text{capab} : K \Rightarrow \mathcal{P}(\{A_1, \ldots, A_n\}) \quad (7)$$

$$X_{ikt} \in \{0,1\}, i \in I, k \in K, t \in T = \{1, \ldots, |I|\} \quad (8)$$

$$w_i, s_{ji}, p_{ki}, \overline{s}_{ki} \in \mathcal{R} \quad (9)$$

The objective function (1) minimizes the total weighted completion times above all incidents. Total weighted completion times are to be interpreted as damage that incurs over time until incidents have been operated completely. Complete operation of an incident is equivalent to the state when all (trapped, injured) persons are rescued, and infrastructure capabilities are stabilized. w_i is a so-called factor of destruction of incident i that represents the severity of an incident. This factor needs to be determined by sensors or on-site agents that report its value. We assume in our models that it is known. Consequently, the lower the factor of destruction, the less severe is the incident. X_{ikt} is the binary decision variable that accounts for the assignment of incident i at position t in the queue of rescue unit k. Let X_{ikt} be an optimal solution for incident $i=1,2,\ldots,|I|$, rescue unit $k=1,2,\ldots,|K|$, in queue slot $t=1,\ldots,|I|$. $C(i,k,t)$ represents incident i's completion time when processed by rescue unit k at position t. By definition, any completion time is the time needed until an incident has vanished and can be formulated, according to constraints (2) and (3), as a recursive function. This recursion depends on schedules and prior assignments of the rescue unit. Mathematically, it consists of the sum of completion times of previously processed incidents, the travel time s_{ji} a rescue unit necessitates for moving from the last processed incident (central station respectively, as condition (3) states) to the actual incident, and the individual processing time the rescue unit requires to finish the incident. Constraint (3) emanates from the premise that there is one incident that is handled first by any rescue unit – no previous completion times exist and the travel time $\bar{s}_{ki}$ considers the distance between a rescue unit's station and the incident itself. p_{ki} is thence a matrix containing all possible combinations of rescue units and incidents. These depend trivially on the incident and the individually assigned rescue unit. Constraint (4) ensures that every incident has to be processed by any rescue unit at any position in the respective queue. Constraint (5) requires a maximum number of one processed incident for any rescue unit at a single position in the queue. No simultaneousness of parallel processing one incident is allowed in the model. We figure in (7) that an incident embodies a special type of destruction A_n, such as casualties or fire damage and on the other hand, a rescue unit is only able to operate pre-defined, specific types of incidents, $P(\{A_1,\ldots,A_n\})$. Explicitly, it is possible that rescue units possess more than a single capability. Furthermore, if any distinct rescue unit is assigned to a specific incident, the unit fulfills the incident's capability requirements, as one can see in (6). Condition (8) defines the binary decision variables X_{ikt}, lets incident i belong to array I of incidents, and the number of slots in a queue is prohibited to exceed the total number of incidents that wait for being processed. Throughout, we assume that a rescue unit is not able to abort processing an incident before it is finished. Further declarations include that units can operate only one incident at a time. Albeit the possibility exists that an arbitrarily high number of incidents can be handled sequentially by rescue forces each.

Oftentimes, it is beneficial for societal utility to send more than one rescue unit to a scene rather than letting one rescue unit conduct the whole work, even if a single rescue unit fulfilled all capabilities required. The main idea to enhance the Assignment Model towards a disaster setting which requires more than one capability at a scene is to introduce parallel processing of incidents. Parallel processing in our context embodies the possibility that an incident can be operated by more than one rescue unit. The model in the follow-up will be referred to as the DISTRIBUTED COLLABORATION MODEL (P2):

$$\min_{X_{ikt}} \sum_i w_i \left(\max_{k,t}\{X_{ikt} \cdot C(i,k,t)\} \right) \tag{10}$$

$$\text{s. t.} \quad C(i,k,t) = \sum_{j \neq i} X_{jk(t-1)} \cdot (C(j,k,t-1) + s_{ji} + p_{ki}), \; i \in I, k \in K, t \in T^{>1} \tag{11}$$

$$C(i,k,1) = X_{ik1} \cdot (\overline{s}_{ki} + p_{ki}), \; i \in I, k \in K \tag{12}$$

$$\sum_i X_{ikt} \leq 1, \; k \in K, t \in T \tag{13}$$

$$\text{cat(i)} \subseteq \bigcup_{k | X_{ikt}=1} \text{capab(k)}, \; i \in I \tag{14}$$

$$\text{cat} : I \Rightarrow \mathcal{P}(\{A_1, \ldots, A_n\}), \; \text{capab} : K \Rightarrow \mathcal{P}(\{A_1, \ldots, A_n\}) \tag{15}$$

$$X_{ikt} \in \{0,1\}, \; i \in I, k \in K, t \in T = \{1, \ldots, |I|\} \tag{16}$$

$$w_i, s_{ji}, p_{ki}, \overline{s}_{ki} \in \mathcal{R} \tag{17}$$

The differences to the ASSIGNMENT MODEL become evident in the objective function (10) and in constraint (14). The objective is the minimization of the sum of all weighted completion times. Yet, if we suppose e.g. two rescue units in operations at a scene, then the individual incident's completion time is the maximum of the respective two modular completion times. This can be argued as follows: an incident is not finished until all forces have completed their work. The parallel property can be fulfilled by side constraint (14) which denotes that an incident might require more than one capability from rescue units which is also matching our pre-defined co-allocation requirement. Condition (15) still permits that a rescue unit is able to possess more than one capability, and thus might be apt to deliver service to a multilateral incident. The optimization is to figure out an advantageous, in our case optimal assignment – either to split the work among rescue units or to assign the very same to a single force.

In order to exemplify the optimization of the DISTRIBUTED COLLABORATION MODEL, consider the following concrete setting: in the direct aftermath of an (imaginary) earthquake only a single building was struck. It seems to be not only close to collapse, there are also few people in medical need, and moreover, there is a relative insignificant fire burning. The contribution of the model proposed is to figure out, whether it is beneficial to send only a troop of firemen that are capable of handling all issues at the scene, or to address different rescue units, such as paramedics for the injured, firemen, as well as heavy equipment for the stabilization of the building and the extinction of the blaze. Taking individual travel times, processing times, and prior assignments of rescue units into account will thence permit any possible combination. That is, as long as the combination suffices all capability requirements.

Experiment and Evaluation

Essentially, our objective is directed towards finding schedules that efficiently allocate rescue units to incidents by including all requirements and assumptions made within the models. The formulation of these optimization problems is, however, exponential in the size of their input, excluding the use of fast polynomial-time algorithms. Accordingly, it is even unlikely to find a polynomial time algorithm that can identify an optimal schedule. Thus, we seek to find an efficient algorithm which resolves this problem. Based on our discretized models, repeated Monte Carlo experiments were used to randomly generate best solutions. Object-oriented implementations were written in the numerical computing environment MATLAB.

In the simulation runs, we consider more incidents than available rescue units at a time. Trivially, total harm could be minimized a priori by increasing the number of rescue units towards infinity – due to assumed budget constraints this solution is not viable in our case. Table 3 depicts a brief overview of presumptions made in our simulations. We subsequently point out explanations to comprehend the parametric assignments.

PARAMETER	VALUE, RANGE, DISTRIBUTION	RATIONALE
Rescue Units	*{10, 20, 50}*	Realistic numbers of rescue units; number of incidents according to 2010 Chile earthquake reports
Incidents	*{20, 50, 100, 200}*	
Processing times p_{ki}	Normally distributed: $\mu = 20$, $\sigma = 10$	Occurrence of catastrophes close to overcrowded areas (low travel times); WLOG: significant endurance of (mean) processing times to (mean) travel times
Travel times s_{ji}, $\bar{s}_{ki}$	Normally distributed: $\mu = 1$, $\sigma = 0.3$	
Factor of destruction w_i	Random Integer: *{1,…,5}*	Distinct risk levels introduced by the U.S. Department of Homeland Security
Capabilities $P(\{A_1, \ldots, A_n\})$	n = 5	Distinction between response types: fire fighting, police enforcement, medical aid, military needs, (other) special forces
Instances	*10*	Rather low numbers of instances guarantee fast planning properties in practice
Iterations	*250000*	No significant improvements in the objective functions beyond 250000 iterations

Table 3. Settings in Monte Carlo simulation runs

Data used for conducting our simulation runs was partly extracted from public situation reports and from information of an associate in the UN Chile coordination headquarters which was founded in the upright aftermath of the 2010 earthquake. The central difficulties in generating artificial data and receiving a clear picture about aid organizations in the aftereffect of any catastrophe are their autonomous actions and assignment of aid workers without any compulsory monitoring.

Cross-combinations of predefined numbers of incidents and rescue units were used to test our optimizations in comparison to the heuristic used. The parameters "processing times" and "travel times" follow a normal distribution both. We consider short travels as for most scenes arise in overcrowded areas, such as cities where rescue forces are close. The vector of factors of destruction is to indicate levels of destructive severity and expresses five different stages for each incident based on the differentiation of risk levels introduced by the U.S. Department of Homeland Security: low (1), guarded (2), elevated (3), high (4), and severe (5) harm.

The heuristic we used as benchmark in our simulation runs represents a naïve approach of tradition-alike coordination during emergency response: given incidents and rescue units, the most severe incident is assigned to the rescue unit which can start processing at the earliest possible. Less severe incidents are assigned to units by the same method and in accordance to each unit's incident queue. That is, all processing times of incidents in a queue, howbeit not of the regarded incident, are accounted for in the heuristic. This benchmarking model is referred to as the traditional heuristic. The implemented optimizations were to access best solutions randomly by alternating random incidents in priority queues within the rescue units. We will now take a systematic look at the results depicted by box plots in Figure 1.

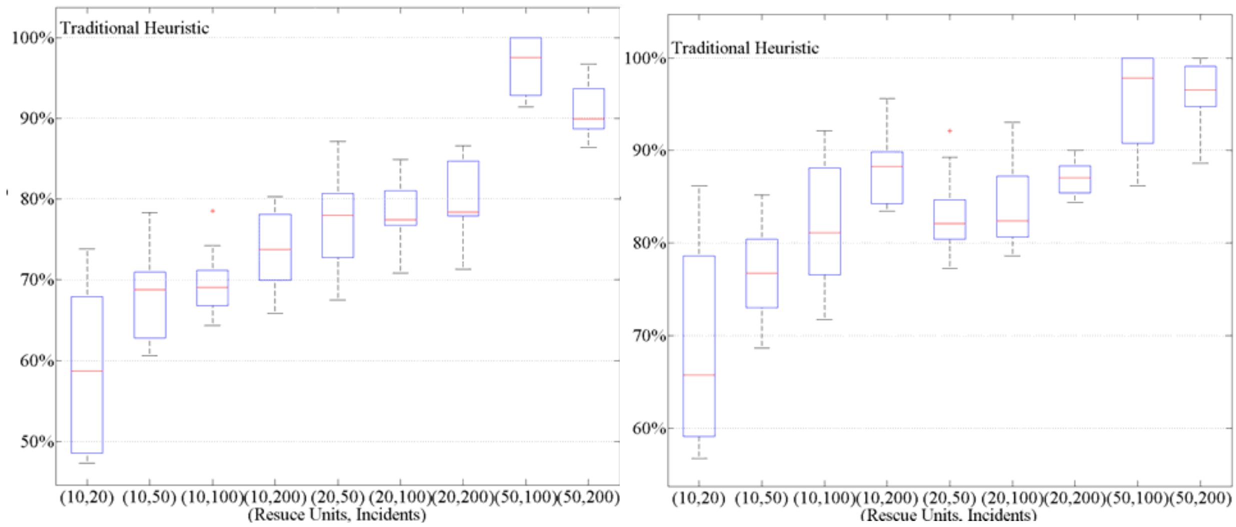

Figure 1. Ratio of simulation results of the ASSIGNMENT MODEL vs. Traditional Heuristic (left) and of the DISTRIBUTED COLLABORATION MODEL vs. Traditional Heuristic (right)

Figure 1 (left-hand side) demonstrates that the Monte-Carlo approach delivers better results than the traditional heuristic. Apparently, all problem instances of the first model show a better performance of the Monte-Carlo simulation within acceptable ranges of deviation. At best, harm of a scene could be limited to less than a half of the heuristic. Neglecting the last two instances (50,100) and (50,200), Monte-Carlo simulations delivered damage reductions of at least 20% on average compared to the greedy heuristic which may result in huge savings within the absolute harm values. In particular, our method is even more favorable in scenarios when incidents possess a finite "deadlines" (time-windows) as for completion times can be scaled down due to optimal assignments and schedules. This implies, for example, that injured, buried persons in a collapsed building have a finite "time to live" to be rescued. This is not reflected by the evaluation, as we wanted to obtain a lower bound on the improvement of our coordination mechanisms. In addition, the factor "time to live" is not suitable in all catastrophe scenarios.

The right-hand side of the figure depicts benefits gained by optimizing coordination during a scenario by applying the DISTRIBUTED COLLABORATION MODEL with a Monte-Carlo simulation. The predefined traditional heuristic was also extended by the parallel processing capability. The structure of the results is similar to those of the ASSIGNMENT MODEL. Significant enhancements are apparent especially in small-world environments. Again, we outperform the benchmark by at best more than 40%.

In both scenarios, runtimes of the Monte-Carlo simulations did not exceed 20 minutes in the most complex scenarios (50, 200) based on 250,000 iterations and were even in a four minute range in the simplest settings (10, 20). All solutions of the implemented traditional heuristic were calculated within seconds.

As the solution space, and thus the complexity, increases, results of the Monte-Carlo approach tend in both models towards those of the traditional heuristic. Increasing the number of iterations and covering a wider spectrum of the solution space might resolve this problem in future research on this topic. This "decline" does not resemble evidence of impairment of our approaches. The traditional heuristic is not applicable in non-computer-assisted practice: no (humane) EOC would ever be able to apply this approach for large-scale coordination. Our contribution rather depicts a useful automation in decision support for generating a more than acceptable final outcome. In a nutshell, the traditional heuristic embodies an exorbitant sound benchmark in situations where chaos is dominant due to an unmanageable number of instances and rescue units. Thus, our models provide for upgrades. In cases where optimization seems to not outperform in complex scenarios, one could think of the usage of the sound heuristic instead. This might be advisable for more intricate scenarios wherein runtime analyses revealed a clear increase when finding an optimal schedule.

Results of either model were subjected to the Shapiro-Wilk test which is favorably used to test normality especially of small samples (n<50). We used a significance level 95% to attest the null hypothesis of normality and detected a normal distribution in all optimization instances of the ASSIGNMENT MODEL. In detail, the null hypothesis could not be rejected at the 0.95 significance level. In the next step we sought to approve that our optimizations were within a level of significance of 95% better than the traditional heuristic, based on the simulated results and the normality condition. The results of the significance tests expressed that the simulations of both models do outperform the traditional heuristic within the confidence intervals. We conclude to universally outperform the heuristic by the usage of our models.

Summary and Outlook

ERS as special arrangements of information systems are useful for several application areas within the whole life cycle before, whilst, and after an emergency has happened. Organizational decision support using ERS-technology was stated to be significantly understudied. Our work presented new methods in how to coordinate emergency response and to provide expedient novel approaches for resource allocations. We introduced two different methods on how to allocate resources efficiently during emergency response. The two different models in this work aim at minimizing the total weighted completion times of a high number of emergencies. Concluding, the main contributions of this paper were, firstly, to allocate rescue units to incidents during emergency response efficiently, secondly, to generate acceptable and feasible runtimes due to the model design, and thirdly, to incorporate additional features such as spatial differences and co-allocation of rescue units.

Future work will include a more granular view on specific types of disasters, the consideration of temporal dependencies of rescue actions as well as the incorporation of more influencing factors and requirements given by the nature of a (mass) casualty event. In addition, incidents, once occurred, do have temporal constraints (time-windows) for being operated.

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