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Optimization-based planning to assess the level of disaster in the city

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ABSTRACT

BACKGROUND AND OBJECTIVES: After having struck in a major natural disaster like an earthquake, different organizations run about to decrease losses. The lack of accurate demand information is a common problem that all emergency response organizations have to encounter such a crisis. Evaluation of the City disaster level is a mean to feed this information to the disaster response operations. The objective of this research is eschedule a group of experts to assess relief demand. These evaluation teams need to be scheduled to minimize the evaluation time.
METHODS: This paper aims to formulate the routing and scheduling of the assessment teams so that real demand information for savings and rescue would be available as soon as possible. The simulated annealing algorithm is used to solve the scheduling problem.
FINDINGS: Two cost functions, sum of arrival time and max completion time, were evaluated. The latest is found to perform better in evaluation of the teams performance.
CONCLUSION: The performance of the approach is tested on several randomly generated networks and synthesized demand data. The results show a 13 % improvement in the total completion time of operation in comparison with previous approaches.

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INTRODUCTION

A major natural disaster like earthquake kills people around the world every few years. Each emergency management process includes four steps: (i) mitigation, which is all activity that should be done to decrease disaster impact. (ii) Preparedness defined as activities that make society ready for encountering disaster. (iii) The response is also the activities that save the affected people and prepare their primary requirements. (iv) Finally, recovery is the long term scheduled plan that restores damages and builds up the city (Albris *et al*., 2020; Altay and Green, 2006; Galindo and Batta, 2013). Of course, each of these stages is composed of several operations. Some of these operations are in pre-disaster management and some are in the post (Edrisi and Askari, 2020; Malik and Cruickshank, 2016). One may say the response to disaster is the most critical part of disaster management because it is directly associated with human life and more appropriate performance in this part saves more lives (Konstantinidou *et al*., 2015; Wu and Chen, 2019). The term appropriate here means fast and accurate, so time is a critical issue. In the emergency response phase, four operations are mostly considered in previous researches: Demand prediction, relief assessment, search and rescue operation, and humanitarian logistics. Relief demand is considered as feed to search and rescue and logistic operations and this may affect the accuracy of operations. However, demand prediction gives the decision-maker a good view, but this data may not be accurate. Prediction of demand is extensively considered in previous researches (Tang *et al*., 2017). These predictions are mostly taken based on structural and transportation reliability, the strength of buildings, earthquake intensity, and so on (Edrisi and Askari, 2019). This demand data may not be valid as the earthquake is a stochastic process. Of course, different agencies start to collect data immediately after the disaster; For instance, police, regional responders, peoples, hospitals, and so forth. This multi-source data could be useful, but still because of the chaotic and nervous situation right after the disaster, this data also may not be accurate. Urban Relief Assessment Teams (URAT) include prepared and well-trained people that can evaluate damages, assess demand, and estimate humanitarian relief to calculate city disaster level accurately. The objective of these teams is just assessing and sending correct and real-time information and they never participate in search and rescue operations as time is a sensitive parameter in emergency response. The objective function of these teams is to finish the operation as soon as possible. So pre-routing their vehicles makes this operation more appropriate. This paper presents a formulation to model this problem based on two main problems, Vehicle Routing Problem (VRP) and Parallel Machine Scheduling (PMS) (Bai, 2016; Li and Zhou, 2018; Wex *et al*., 2014). The contribution of this paper is to utilize these approaches to solve the routing and scheduling of the assessment team. To the best of the authors knowledge, this is the first time that the vehicle routing problem is used for solving the routing and scheduling of the assessment team for the city disaster level. The current study have been carried out in Tehran, Iran in 2019. Among the four mentioned operations of the response phase, relief assessment is less considered in previous studies. However, many other operations require relief assessment as a prior operation. Demand prediction, urban search and rescue operation, and logistics are examples of preliminary operations for relief assessment.

Demand prediction

The challenging point of demand prediction is the uncertain relief demand information in large-scale emergencies (Sarma *et al*., 2020). Time series and autoregressive models are extensively used to model dynamic demand prediction (Aviv, 2003). Because of diversity in relief demand information sources, Time-varying demand is modeled based on the multi-sensor fusion method (Sheu, 2007). Sun *et al*., (2013) proposed a fuzzy rough set approach for emergency demand prediction to overcome inaccuracy and incomplete information and also the chaotic environment of decision making.

Urban search and rescue operation

Minimizing the number of fatalities is the main aim of search and rescue operations (Nadi and Edrisi, 2017). The findings proof that the cooperation between assessment and response teams can improve the total life saving in an emergency response. Fiedrich *et al*., (2000) Modeled a dynamic optimization approach to locating resources respect to minimization of fatalities in this operation. This is almost the case with robot-focused search and rescue operations and decision support systems. Blitch (1996) Demonstrated the critical issue in the application of knowledge-based artificial intelligence and robotics to the urban search and rescue (USAR) operation. Chen and Miller-Hooks (2012) Proposed multistage stochastic programming based on the column generation method to route USAR teams. Their objective was the maximization of the total number of survived people in this operation.

Logistic operations

The disaster relief logistic operation is well considered in previous researches (Rodriguez-Espindola *et al.*, 2018). Luis *et al.*, (2012) Represented a comprehensive review of routing problems that have been solved to deliver goods and services to disaster-affected regions. In logistic operation, different objective functions have been taken introduced and evaluated. They identified several areas where modeling can capture more characteristics of relief distribution. Besides, they have found that Risk-averse behavior in routing has not been studied in depth yet while the characteristics of different disasters and relief organizations will continue to provide more opportunities and challenges for researchers. Barbarosoğlu and Arda (2004) Used the total cost of deliveries respect to satisfying all demands, and Ozdamar *et al.*, (2004) proposed an integrated multi-commodity network and vehicle routing problem to model mixed pick-up and delivery planes. Their findings indicate that the mthod discloses the uncertainty during the progress of the response. Yi and Kumar (2007) Proposed an ant colony optimization to minimize the sum of unsatisfied demand for all commodities and also unsaved people in each node. All the above-mentioned operations are preliminary to the urban relief assessment operation which is the main subject of this study.

Urban relief assessment operation

While emergency response is well studied in other phases, but there are just a few studies that consider optimization in urban relief assessment operations (Zhu *et al.*, 2020). Huang *et al.*, (2013) Introduced an assessment routing problem and proposed a continuous approximation approach to solving it. They compare discrete optimization with their purposed continuous algorithm; however, their approach reduces the need for detailed data. Nevertheless, they use the sum of arrival time as the objective function. In the case of the assessment team, as time is susceptible, this objective function could not be the perfect one. However, the sum of arrival time can consider the service time of each region (Campbell *et al.*, 2008), but the service time of the last region in the list of each vehicle would not be considered. In this paper, a discrete simulated annealing optimization used to find the best route for URAT considering parallel machine scheduling and vehicle routing problems.

MATERIALS AND METHODS

To formulate the proposed model as an optimization problem, following introduces the used notation in this approach.

Notations

K	number of vehicles in the depot
I	number of affected regions
$S_{i,k}$	Service time of region *i* for vehicle *k*
$ST_{i,k}$	The start time of vehicle *k* in region *i*
$FT_{i,k}$	Finish time of vehicle k in region *i*
P_i	The population of region *i*
R_i	Vulnerability ratio of region *i*
D_i	Relief demand of region *i*
$To_{i,k}$	Travel time of vehicle *k* between depot and region *i*
$T_{i,j,k}$	Travel time of vehicle *k* between region *i* and *j*
$A_{i,k}$	Arrival time of vehicle *k* to region *i*
V_i	Speed of vehicle *k*
C_k	Completion time of vehicle *k*
$Cmax_k$	Maximum completion time
A_k	Sum of arrival time for vehicle *k*
$X_{i,j,k}$	Flow variable that is equal to 1 if (*i,j*) is traversed by vehicle *k* and 0 otherwise
$Xo_{j,k}$	Flow variable that is equal to 1 if the link from depot and *j* is traversed by vehicle *k* and 0 otherwise
T	control parameter of the *SA* algorithm

Problem configuration

This study consideres a hypothetical city that is divided into n affected area. These regions are assumed to be clustered into the *I* regions based on the vulnerability ratio in the demand prediction phase. Vulnerability ratio is a measure to define the level of vulnerability of a zone to damages in natural disasters.

This nominal vulnerability ratio is not exact and the main aim of urban assessment teams is to evaluate the right vulnerability ratio, but this nominal ratio can be used as the initial feed of URAT. Each region *i* has an entire population P_i that is randomly generated to model this problem. Vulnerability ratio R_i of region i is a random variable between 0 and 1. Relief demand of each region is $D_i = R_i \times P_i$ (Edrissi *et al*., 2013). For each vehicle k in region i there is a service time $S_{i,k}$ that is generated proportionately to D_i, This means in region i service time is different for each vehicle, because in reality, different teams have different functionality, efficiency, and performance. V_k is a randomly generated variable for each vehicle *k*, so travel time can be calculated respect to distances. Also, in Fig. 1, each region has a start, service, and finish time that starts and finish time can be calculated with Eq. 1 and Eq. 2.

$$ST_{j,k} = FT_{i,k} + T_{ij,k} \quad (1)$$

$$FT_{i,k} = ST_{i,k} + S_{i,k} \quad (2)$$

Based on the above configuration, this vehicle routing problem is modeled as parallel machine scheduling. PMS and VRP are mathematically adequate. In PMS, each machine has to process a set of works. Here works are the regions. Each work has process time that is proportionate to service time and each work has a setup time that can be considered as travel time in this problem.

Problem formulation

As vehicles in this problem do not need to carry any equipment, URAT is an incapacitated vehicle routing problem. It is mentioned that their mission is just to evaluate the vulnerability ratio and they do not have to perform any Logistic or search and rescue operations. This problem also does not need any time windows constraint. Because this operation starts right after the disaster and all regions should be visited as soon as possible. In this paper, the objective function of this problem shown in eq.4 is considered to the minimum, maximum completion time of vehicles. The completion time C_k of each vehicle is the finish time of the last region in the list of vehicle k. The maximum completion time is calculated with Eq. 3, and the problem tries to minimize that in Eq. 4.

$$\text{Cmax}_k = \max \sum_{k \in K} C_k \quad (3)$$

This problem is formulated as follows:

$$\min \sum_{k \in K} \text{Cmax}_k \quad (4)$$

Subject to:

$$\sum_{j \in I} \sum_{k \in K} X_{i,j,k} = 1 \qquad (\forall i) \quad (5)$$

$$\sum_{j \in I} \sum_{k \in K} X_{0,j,k} \le K \quad (6)$$

$$\sum_{j \in I} X_{i,j,k} - \sum_{j \in I} X_{j,i,k} = 0 \quad (\forall i) \quad (7)$$

$$\sum_{j \in I} X_{0,j,k} = 1 \quad (\forall k) \quad (8)$$

$$FT_{i,k} + T_{i,j,k} \le FT_{i,k} + M(1 - X_{i,j,k}) \quad (\forall\, i, j) \quad (9)$$

$$FT_{i,k} \ge \left(To_{i,k} Xo_{j,k}\right) \quad (\forall i, k) \quad (10)$$

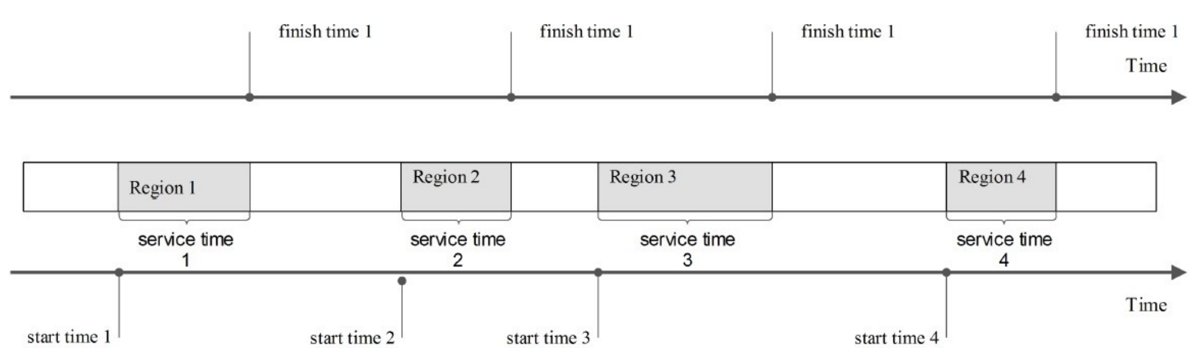

Fig. 1: Time Horizon of each vehicle

$$X_{i,j} \in \{0,1\} \quad (\forall i, j) \tag{11}$$

$$FT_{i,k} \geq 0 \quad , \; T_{i,j,k} \geq 0 \quad (\forall i) \tag{12}$$

Eq. 5 ensures that all nodes are visited. Eq. 6 indicates that k vehicle is used for this operation. Eq. 7 makes sure that each node is visited once. Eq. 8 makes sure that the number of vehicles dispatched is limited to the maximum number of available vehicles. Finally, sub tours are eliminated by the well-known big M method in Eqs. 9 to 11, and Eq. 12 ensures the non-negativity of the finish and travel time, respectively. Fig. 2 shows the procedure of solving this model using simulated annealing. Simulated Annealing (SA) Metaheuristic is used to optimize the objective function of this problem. SA is a stochastic memoryless algorithm. This means that it does not gather any information during the search. This algorithm aims to delay the convergence and escape from local optima (Gonzalez-R *et al*., 2020).

This algorithm is an iterative process. At each iteration, a randomly generated neighbor changes with operators. This new neighbor is acceptable if the cost function *f(x')* of this solution is higher than the previous. Otherwise, this solution is accepted with special probability. This probability depends on the cost difference of these two solutions and the current temperature or control parameter. This temperature is reducing slowly in the next iteration. So the acceptance chance of such a solution decreases. Generally, this probability follows the Boltzmann distribution, which is shown in Eq.13.

$$P(\Delta f, T) = e^{-\frac{f(x') - f(s)}{T}} \tag{13}$$

The novelties of this research are :

1. Formulating routing an scheduling of assessment teams for disaster level in a city.
2. the performance factor of vehicles is added to the formulation to make this problem close to the real situation.
3. max completion time is used instead of the sum of arrival time as a cost function because the performance factor of vehicles can reflect on this objective more accurately.
4. SA algorithm is utilized to solve this optimization problem in an iterative approach.

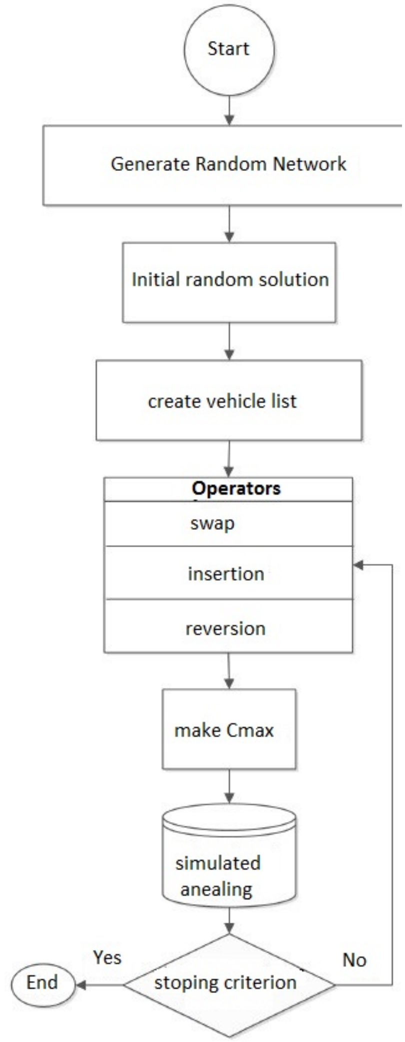

Fig. 2: PMS procedure of vehicle routing URAT

RESULTS AND DISCUSSION

This model is solved in 6 randomly generated networks. The total number of nodes ranges from 5 to 40. The number of vehicles is ranged from 2 to 5 vehicles proportionally. Despite economic problems, in disaster management, depot location should be allocated outside of affected regions. One depot is randomly allocated for each network in this model. The demand of each node is ranged from 10 to 100. The service time of nodes is generated for each vehicle. As mentioned in the previous section, the service time is proportionate to population. it is

Table 1: Properties of randomly generated network

Network	No. of nodes	No. of vehicles
1	5	2
2	10	3
3	15	3
4	20	4
5	30	5
6	40	5

assumed that for one population unit, from 0.1 to 0.5-time unit (for example, minute) is assumed for each vehicle to assess vulnerability. This 0.1 to 0.5 random variable is called Performance Factor (PF). The speed of each vehicle is randomly generated as an integer number between range [10-20] kilometer per hour. This speed is used to calculate travel times in the network. Table 1 indicates the properties of the network.

This problem is solved for each network twice, once concerning maximum completion time as the objective function and once with arrival time. Several iterations for both of these objective functions in each network is constant. Table 2 shows the results for each network. Table 2 compares the results with previous researches indicating that using Cmax instead of the sum of arrival time causes the urban relief assessment team's process to complete sooner. This improvement is averagely 13 percent. The reason for the improvement is that in the sum of arrival time, the performance factor of vehicles does not make sense. While Because of the stochastic situation of emergency response, the performance factor of each vehicle is not constant. That is maybe vehicle k arrives in region i sooner than vehicle k', but because of the low-performance factor of vehicle k, the vehicle k' can finish assessing this region sooner. Assuming that the PF of each vehicle is constant, still, the processing time of the last region in the list of each vehicle is not considered. This fact is shown in the solution column of Table 2. The purposed model in this paper is programmed using Matlab R2012a on a Core i7 and 2 gigahertz Asus with 4 GB RAM.

Fig. 3 depicts the procedure of optimization. It shows that for a specific number of iteration, the best cost of scheduling becomes unchanged for a while and this is the stopping criteria of optimization. Fig 3 is a means to validate the result from the optimization process. It shows that the model is converted to an optimum solution and the algorithm had enough time to explore the search space!

In case of a route closure, the cost of that link is high and consequently, the algorithm finds an alternative solution with the lowest cost. This model can be utilized to be used in a megacity like Tehran. Tehran has 22 municipalities which can be interpreted as 22 nodes. Since this model can quickly converge for networks as big as with 40 nodes. It can easily be adapted for a case study in Tehran. The limitation of this model is that it requires vulnerability ratio of each municipality region. This vulnerably ratio should be evaluated before a disaster.

Table 2: results of model and comparison between Cmax and Arrival time

Net.	Objective function	completion time (minutes)	Improvement (percent)	Solution (Rout)
1	Cmax	99	8	1-5/2-3-4
1	A	107	-	1-3/2-5-4
2	Cmax	129	23	5-6/7-4-1-10-8/9-3-2
2	A	159	-	5-6-2/7-4-1-10-8/9-3
3	Cmax	93	22	6-10-12-2/14-11-9-4-8/13-15-1-5-7-3
3	A	114	-	6-10-12-2/14-11-9-4-7/13-15-1-5-8-3
4	Cmax	177	6	3-6-18-14-8/13-1-7-17-16/15-19-12-10-2/11-20-5-4-9
4	A	188	-	3-6-18-14-8/13-1-7-17-2/15-19-12-10/11-20-5-4-9-16
5	Cmax	114	22	25-3-22-7-4-19-14-21/1-28-23-16-24-6/9-6-18-29-20-10/27-17-26-15-11/8-5-12-13-30
5	A	140	-	25-3-22-7-4-19-14/1-28-23-16-24-21/9-6-18-29-20-10/27-17-26-15-11/8-5-12-13-30-24
6	Cmax	202	8	37-13-1-3-7-29-11-38/2-32-33-18-15-35-31-12/22-25-9-6-26-10/34-21-23-36-5-27-8-40-19/20-24-16-39-17-14-28-4-30
6	A	219	-	37-13-1-3-7-29-11-38/2-32-33-18-15-35-31-12/22-25-9-6-26-10-19/34-21-23-36-5-27-8-40/20-24-16-39-17-14-28-4-30

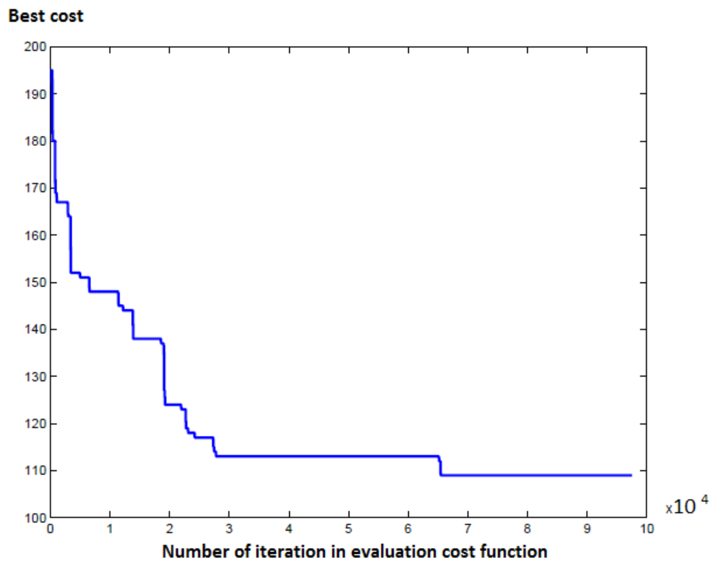

Fig. 3: Number of iteration for the sum of arrival time

CONCLUSION

One crucial part of emergency response operation is accurate relief demand information; this data mostly gathered by people how are not an expert. While sending urban relief assessment teams can give correct and accurate information. As this operation is time-sensitive, a vehicle routing and parallel machine scheduling approach are proposed in this paper. Performance factor (PF) is defined for each vehicle to model this problem more realistic. This performance factor depends on different features, for example, the experience, characteristics, and age of this team's member. In this case, the previously used objective function, sum of arrival time, is not appropriate. So a maximum completion time is used instead and this led to a 13 % improvement of total URAT process on average. For future research, solving this problem with continuous approximation reduces the need for detailed data so it can improve the results. Integrating these teams with the search and rescue team also can lead to better performance in emergency response. Evaluation of PF is an important part that needs more studies. Finally, the application to a practical use case for which the data are known would add to the present study the benefits that this modeling could bring in practice.

AUTHOR CONTRIBUTIONS

A. Nadi commenced the process by conceptualizing and formulating the research idea and also interpreting the results. M. Askari reviewed the literature and prepared the manuscript. A. Edrisi reviewed and edited the final manuscript.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

ABBREVIATIONS

URAR	Urban Relief Assessment Teams
VRP	Vehicle Routing Problem
PMS	Parallel Machine Scheduling
USAR	Urban Search And Rescue
SA	Simulated Annealing
PF	Performance Factor

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