Original Article

Optimal location of medical emergencies in the road network: a combined model approach of agent-based simulation and a metaheuristic algorithm

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Abstract

Background: The ability of ambulance centers to respond to emergency calls is an important factor in the recovery of patients' health. This study aimed to provide a model for the establishment of emergency relief in the road network in 2020 in East Azerbaijan province.

Methods: This applied-descriptive and experimental research with an explanatory modelling approach used the comments of 70 experts to run a model, which was based on the use of a metaheuristic (genetic) algorithm ,Simulation for the number of ambulances and the composition of the monitoring list simultaneously , objective and subjective data combined ,the agent and environmental variables, were determined and modelled through a meta-hybrid approach during the agent-based simulation and the metaheuristic algorithm.

Results: To travel the initial structure for 40 dangerous points and five stations, the initial time was equal to 7860 Minutes, which reached a number between 2700 and 4000 Minutes after genetic optimization, production of a new list, and the mutation of ambulances from one station to another.

Conclusion: This type of optimization can be used to accelerate activities and reduce costs. Due to the dissimilar traffic of the areas, the ambulance does not arrive at dangerous points at equal times. The travel time of all dangerous points can be reduced by changing the location of points, moving forward or backwards depending on the conditions, customizing the features of ambulances and dangerous points, and combining the list of areas to find the best location for emergencies according to the interaction between agents, environmental constraints, and different behavioral features.

Keywords: Algorithms; Computer Simulation; Emergency Service, Hospital; Workplace.

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Introduction

As an essential part of modern health systems, emergency medical centers (EMCs) are responsible for the pre hospital activity, including medical care and the transfer of patients to hospitals, in the health system. Given the vital role of these centers in the health system, many efforts made in the development of EMCs have led to the design of numerous models and strategies for decision-making at the practical level. Three major groups of models, i.e. definitive single coverage, definitive multiple coverages, and probabilistic/random models, for the localization of fixed ambulances introduce the concept of "emergency route" and focus on the issue of re-localization of emergency ambulances. Despite all the advantages of the three modelling methods and recent attempts to model the localization of emergency equipment, the theory of complexity science suggests that the issue of localization is still traceable due to the interaction of complex real-world factors related to this issue. Moreover, none of the recent modelling results will maximally match the existing facts (1). Many efforts have been made to develop methods for EMS dynamics. One of the main topics studied in this science is "emerging property", means that general behavioral is derived from independent components (2).

The agent-based method was considered as a method that models factors or individuals in a society with the characteristics of interest and takes account of the behaviors of factors in the mutual space of influencing and being influenced (3).

The most suitable arrangement for the initial situation of ambulances (as factors-components) in the emergency medical system was determined using a population-based evolutionary algorithm, called the genetic algorithm (GA) (4). It is a population-based meta-heuristic algorithm that uses biological techniques, such as heredity, mutation, biology, and Darwin's principles of selection, to find an optimal answer. Therefore, GAs can considerably reduce the high computational cost of agent-based modelling (ABM) in calculating an optimal set of emergency equipment locations (5).

According to what is described above, the present study aimed to determine factors affecting the optimal location of road emergencies in East Azerbaijan province and the best location of emergencies based on the interaction between factors, environmental constraints, and different behavioral properties of different factors assumed in the problem. Thus, expert opinion polls were used in presenting the model, and objective and subjective data were combined in the implementation of the model, which is based on the application of a metaheuristic algorithm (genetic type).

Methods

A) Theoretical background

In this research, model-solving methods are proposed based on the theory of complexity, the interaction of agents affecting the localization, substantive and functional differentiation of agents involved in the localization of road ambulances and thus the possibility of different behaviors of factors in the agent-based simulation model environment. Therefore, GAs can greatly reduce the high computational cost of ABM in calculating the optimal set of emergency equipment locations.

The present applied-descriptive research with an explanatory modelling approach used the comments of experts to run a model, Factor and environmental variables were modelled through a meta-hybrid approach and the metaheuristic algorithm during agent-based simulation in the NetLogo software environment. There was a statistical population of 70 Emergency and health network experts and specialists; Professors of Industrial Management and Industrial Engineering. This number is based on the statistics available in East Azerbaijan province in 2018 and is the basis of the statistical population and will be counted. whose comments were used in ABM and defined the relationship between factors and their behaviors in the environment. Using a combination of library and field methods, agent-based simulation was done based on components such as the interaction of agents/actors involved in the optimal location of ambulances in the road network and the behavior of agents. The model was then run using a hybrid approach of agent-based simulation and metaheuristic algorithms. In the agent-based simulation, the behaviors and characteristics of the factors were defined in the problem, and the functions of their behavior were implemented in the

Table 1. A summary of the most important research results concerning localization and decision-making methods

Ref	Proposed model	Grouping model	Results	Disadvantage	Additional variable
Toregas et al. (6)	LSCP	Operational level/static model/definitive single coverage	Coverage of incoming calls	Increasing necessary ambulances and no guarantee of full coverage	
Church & ReVelle (7)	MCLP	Operational level/static model/definitive single coverage	Optimal coverage of incoming calls	No guarantee of full coverage	
Daskin & Stern (8)	HOSC	Operational level/static model/definite multiple coverages	Minimizing used ambulances and guaranteeing full single coverage	Non-optimal use of additional ambulances for all areas	
ReVelle & Hogan (9)	BACOP1 BACOP2	Operational level/static model/definitive multiple coverages	Minimizing used ambulances and trying in twice full coverage	Constant movement radius of ambulances	
Gendreau et al. (10)	DSM	Operational level/static model/definitive multiple coverages	Minimizing used ambulances and guaranteeing full single coverage		Movement radius of ambulances
Batta et al. (11)	AMEXCLP	Operational level/ a static/probabilistic model	Maximizing the expected coverage and eliminating the independence condition of ambulances	Constant travel movement at different time intervals	Ambulance travel time at different times
Goldberg et al., (12)	MEXCLP+	Operational level/ a static/probabilistic model	Maximizing the expected coverage, Dispatch based on the priority list		Dispatch based on the call priority variable
ReVelle & Hogan (13)	PLSCP	Operational level/ a static/probabilistic-random model	Coverage of incoming calls based on likely location	The work ratio is the same for all ambulances.	Call occurrence variable
Marianov & ReVelle (14)	Q-PLSCP & Q-MALP	Operational level/ a static/probabilistic-random model	Calculating the number of required vehicles. The system reliability is used for assurance.		
Beraldi et al. (15)	Robust random location-allocation models	Operational level/ a robust static/random model	Minimizing costs under demand satisfaction constraints		The cost of opening the stations and the cost of submitting the request
Beraldi & Bruni (16)	Robust random location-allocation models (biphasic)	Operational level/ a robust static/random model	Minimization of ambulances and maximization of responses		
Nickel et al. (17)	Robust random location-allocation models of discrete sampling	Operational level/ a robust static/random model	Minimization of fixed costs while guaranteeing a specific coverage level for all scenarios		
McLay & Mayorga (18)	MSLP+	Operational level/ a static model/maximum survival	Maximizing casualties' survival and considering variables coverage time threshold and response		Intervention delays and variables of coverage time threshold and response
Zhang & Li (19)	Parity models	Operational level/ a static model/parity models	Fair access to services with minimizing waiting time range		Fair access to services
McLay & Mayorga (18)	Parity models	Operational level/ a static model/parity models	Fairness in the admission and waiting times for patients		Patient admission and waiting time variables
Su et al. (20)	MELP	Operational level/ a static model/parity models	Minimizing jealousy as non-observance of justice	Minimizing local envies	Jealousy variable
Chanta et al. (21)	MPELP	Operational level/ a static model/parity models	Finding optimal locations for p ambulances to minimize total jealousy		Jealousy variable
Repede & Bernardo (22)	TIMEXCLP	Operational level/ a static model/multi-period relocation	Calculating the maximum coverage differs between periods assuming demand patterns and the number of available vehicles.	Expenses for relocation between periods were not calculated explicitly.	Number of time-varying medical vehicles and time-varying demand patterns
Rajagopalan et al. (23)	DACL	Operational level/ a static model/multi-period relocation	Calculating the maximum coverage by determining the minimum number of required vehicles to ensure the coverage of each demand area with a certain confidence level and considering multiple periods		
Basar et al. (24)	MPBDCM	Operational level/ a static model/multi-period relocation	Maximizing coverage by determining the location and time of ambulance stations on a multi-period planning horizon		
Mason (25)	RtMvGcRM	Operational level/ a dynamic model/dynamic relocation	Maximizing coverage by reloading with real-time multipurpose coverage		
Macal (26)	ADP	Operational level/ a dynamic model/dynamic relocation	Priority-based responses to calls		System visit time from the status and cost of transferring from one status to another

NetLogo software environment. Then, the factors were positioned in the environment to implement their interactions with the environment and other factors.

B) Empirical background

Table 1, summarizes the results of the most important studies conducted in this field to explain the existing research gap in the field of localization methods and dispatch decisions. In this table, the variables of call positions and ambulance stations can be observed in almost all models.

Table 1, shows the historical course of modelling ambulance localization for an optimal and reasonable response, and each model attempts to model an aspect of the realities of the problem. This process evolution, multi-layered and time-varying modelling, and considering more realistic aspects further complicate the problem of localization, which means the emergence of a set of equations with higher variables together with more equation and inequation constraints. These constraints cannot be solved by classical mathematical methods; hence, researchers have inevitably sought approximate solution methods such as dynamic programming and metaheuristic algorithms. However, if the issue of ambulance localization is accepted as a problem in the space of complexity theory, which deals with factors, ambulances, environmental conditions (including roads, central control centers, and station conditions), and incoming calls, it seems that these factors interact together, and their behaviors and characteristics are prone to evolution and change. Thus, the use of ABM becomes inevitable for such a complex system. In this research, therefore, ABM is used as a convenient tool for modelling complex systems to model and analyze the problem. Metaheuristic algorithms (e.g., GA) will be used in the decisions of central control stations and optimal initial distribution to find faster solutions to the relevant equations and to avoid trapping the response in local optimizations.

C) Conceptual model

According to a review of theoretical literature and research background, the analytical framework of the present research can be presented as follows in Figure 1:

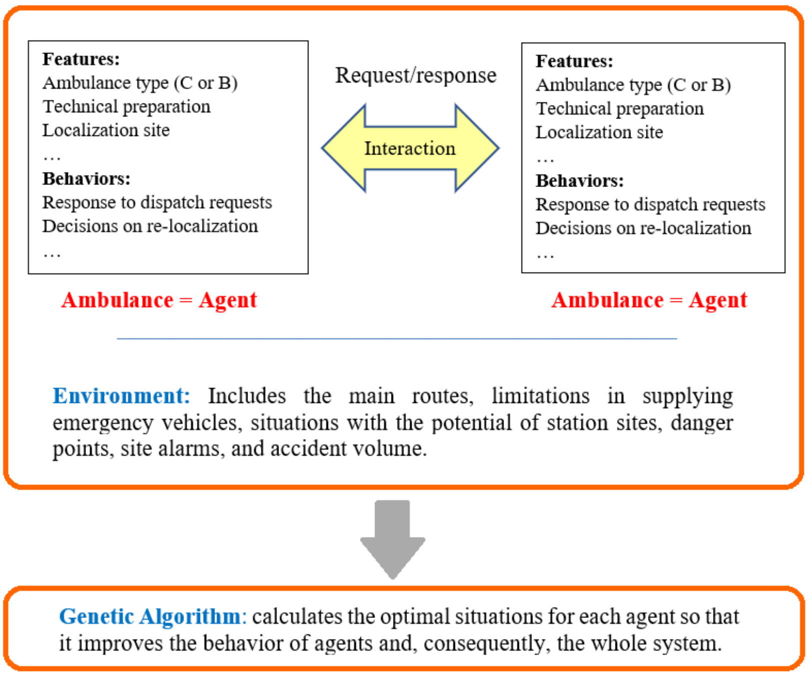

Figure 1. Conceptual model of research

It is necessary to simulate a road conceptually to optimize the location of ambulances on a road in the problem. This road has different traffic or quality in different parts of the route that affect the speed of cars, particularly ambulances. A space is considered with X and Y extensions, with more extensions in the X-direction. In the written code, the extension in the Y direction can be adjusted according to X. Some random points are generated in this extension to indicate danger points on the road. In Figure 2, for example, this road is produced by 100 and 50 extensions in the X and Y directions, respectively, which is changeable. Figure 2, shows an example of a produced road that is randomly divided into different sections by 40 danger points. Each section has a specific distance and a certain traffic coefficient that determines the speed of the car and the required travelling time.

A) Production of ambulance location centers

To localize ambulances, the target area on the road is first specified by determining the points along the X-direction and then by interpolating and determining the Y value. This point was optimized during various developments, and this point was simulated with the nearest blackspot due to optimization. For further optimization, a table for travelling time between the distances of all points is obtained and saved in an array. To calculate the travelling time between points, the required value is extracted only by referring to the relevant array, and there is no need for recalculation.

In Figure 2, blue and red points represent the location of ambulances and danger points, respectively.

For each location of ambulances, some danger points are considered as covered areas that are saved in the location memory. In the first stage, the list of points covered by each ambulance is optimized with the GA based on the reaching time of each ambulance to the location. In this program, most information is based on location points as a class with parameters such as situation, neighboring points, number of monitored points, monitored list, time to reach each point of the monitored list, and total monitoring time of points in the monitored area. In the next steps, factors are incorporated into the program to add agent-based features.

B) Site optimization of location points

The reaching time of the ambulance to the danger points will not be equal due to the dissimilar traffic of the points. Therefore, the travel time of all danger points can be reduced by changing the location points, hence, some points are randomly selected and compared with the nearest location. If the target point reduces the monitoring time for the list of points covered by the old location, the location will mutate from the old to the new location. Figure 2, shows an example of the combination and mutation created in a sample. The red, blue, and yellow dots are the danger points, initial locations, and optimized points, respectively. In this process, the list of monitoring points is also optimized by a GA. The relevant program was tested with a uniform distribution of ambulances in the location centers, and no non-uniformity was created with equal distribution of points. All location points were maintained in their situations and uniformed with the monitored list in terms of number, which confirmed the accuracy of the program. In this optimization problem, there will be few changes in terms of the type and number of ambulances due to the uniformity of location points. Road traffic will be the only factor affecting the problem so location points in the latter monitor 7, 8, 10, 8, and 8 points form from left to right, respectively.

The optimization process of the parameters in the location class can be evaluated by examining the total monitoring time of the points. This time indicates the total time travelled by the ambulances stationed at the location, provided that only one ambulance

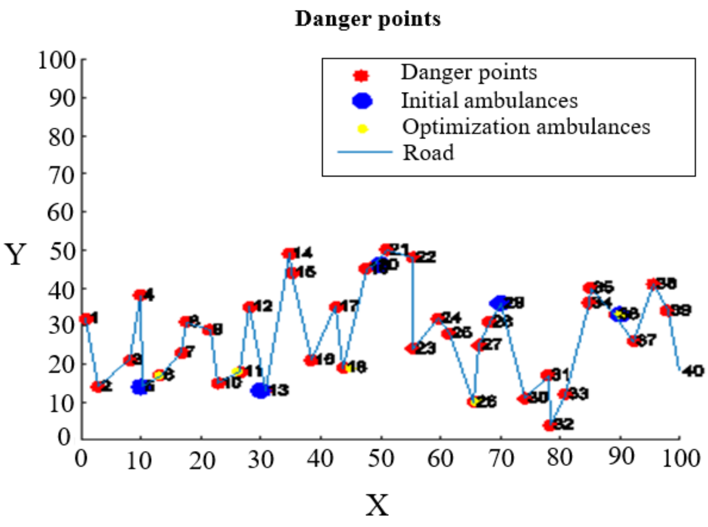

Figure 2. Danger points and initial and new location points of ambulances

exists in each location. Figure 2, shows the temporal evolution resulting from the mentioned optimizations and the reduction of the total monitoring time. Figure 2, represents the total times for six implementations with the same arrangement, which is done by initially producing and saving the initial structure, and then it is read and optimized in different stages. Therefore, the initial structure is the same in all cases of Figure 2, but each optimization is located in one of the local optimal points or the main optimal points. The difference in the times of the optimized cases is caused by being situated in local minima, which requires a long time to exit, but the effect of the performed optimization can be observed by reducing the time.

C) Simulation results of the number of ambulances

In the initial program, the conditions were considered such that only one ambulance was assigned to each location. At this stage, the number of ambulances is considered more than the locations (an agent-based feature) and is distributed randomly. For the required optimization using the random mutation algorithm, the ambulances in the program mutate from one place to another to perform the required optimization along with combining the monitored list.

Results

The results of four simulations for a similar primary structure with the mutation for the number of ambulances and the combination of the monitoring list are concomitantly shown in Table 2. To produce this table, an initial structure was first created for 40 danger points and five stations. The initial time to travel the non-optimized structure was 7860minutes. After optimization by the GA, the production of a new list, and the mutation of ambulances from one station to another, the obtained results (as in the above graph) decreased to a number between 2700 and 4000. The difference in the obtained times results from being in the local optimization minima; nonetheless, a remarkably small optimized time is observed for this sample. This clearly indicates that optimization is made possible by adding a feature, for example, the number of ambulances for a simple problem, and the travel of all danger centers by ambulances of EMCs decreased to a number between 1500 and 2300. Therefore, the volume of optimization can be greatly expanded owing to the magnitude of conditions and available facilities, and the use of this type of optimization can significantly accelerate activities and reduce costs.

Table 2. Results of four simulations for a similar primary structure with mutation for the number of ambulances and the concurrent combination of the monitoring list

Row	First run		Second run		Third run		Fourth run	
Station No.	No. of points	No. of ambulances	No. of points	No. of ambulances	No. of points	No. of ambulances	No. of points	No. of ambulances
1	9	1	8	1	6	1	9	2
2	5	1	6	1	5	1	7	1
3	14	3	10	2	11	2	10	2
4	8	1	14	2	12	2	8	1
5	8	1	6	1	6	1	7	1
Optimal time (Min)	2311		2109		1570		1764	

In the integration process in the agent-based GA, when a station is unable to answer all incoming calls from its covered danger points, some of these points with high accident probability are covered by more than one station. The definitive multiple coverage model is used in this algorithm (four danger points in the first and second runs, and one danger point in the fourth run are conjointly covered by more than one station).

D) Specialization in ambulances

First, the features of ambulances are introduced into the simulation. These agents include the breakdown level, speed, internal facilities of the ambulance, a doctor's presence in the ambulance, the facilities needed to perform medical services on the move, available facilities for the patient to travel long distances, and other specialized items. Using each of these items helps introduce the features of the set agents as a parameter in the agent-based simulation.

Here, the real and applicable features for the genetic simulation of ambulances, such as preparation time for dispatch and the ambulance speed and range, are added to ambulance specifications. To this end, the ambulances can be classified technically in terms of medical and relief service quality as described below.

Ambulance A: This ambulance is defined as a basic ambulance with a delay of 10-time units for each dispatch and a speed of 1 (per unit of time in the distance). The range of this ambulance is only limited to the area monitored by one station.

Ambulance B: This ambulance is considered a high-speed ambulance with a preparation time of 5 and a speed of twice that of the basic ambulance.

Ambulance C: This ambulance is a long-range ambulance with a speed and time of preparation similar to a basic ambulance, but it covers the main station area together with two neighboring stations.

In fact, the behavior of ambulance C is considered a response to a request for help from a nearby EMC (neighbor agent) when it cannot answer all incoming calls, which is typical in the real world.

E) Mutations in the agent of agent-based simulation for ambulances

In the simulation of a normal GA, the mutation was applied by shifting the location of stations. However, since agent-based ambulances are applied in agent-based simulation by the GA, mutations should also be applied to ambulances to further utilize the feature of ambulances in this context. Accordingly, except for the first-type ambulances, other ambulances mutate randomly between different stations in the same order as the normal mutation algorithm. If the total time decreases with this mutation, it is acceptable, and if the time increases, no change will occur.

Table 3. Agent-based simulation outputs

No.	Land dimension	No. of danger points	No. of stations	Monitoring time in ambulance location optimization	First algorithm running time	Second algorithm running time	Third algorithm running time
1	5000	1000	100	5110900	4505400	4387400	4421500
2	5000	1000	200	2712400	1902900	1939600	2304300
3	5000	1000	500	1109500	1057700	1092100	1109500

Compared to a low-quality ambulance, a high-quality ambulance will be acceptable and undergo a change if it reduces both the time to reach danger points and the monitoring time of all points while being mutated from one station to another.

Table 3, shows the GA-based simulation without using agent bases for 5000 and 1000 danger points and different numbers of stations.

The results in Table 3, indicate a decrease in total call answer time with an increase in the number of stations. However, it should be noted that the obtained numbers indicate a nonlinear relationship between the reduced total time of answers and the number of centers. The application of agent-based conditions is compared by first changing the type of ambulances, and the actual characteristics of the ambulances should be defined to add the agent-based feature according to the three types of ambulances. Therefore, features such as preparation time for dispatch, speed, and range of the ambulance are added to the ambulance specifications, for which three types of ambulances are defined with the above specifications.

To examine the effect of the base agent, a set of 70 ambulances is simulated for 50 stations and 1,000 danger points in a space of 5,000 dimensions. In these simulations, the number of parameters mentioned is constant, but the ambulances are of different types, including different features in range, speed, and preparation time.

The results of Table 4, for simulation with dimensions of 5000 and 1000 danger points and 70 ambulances (including 50, 10, and 10 types A, B, C ambulances, respectively) show an increase in the monitoring time of all points. The ambulances are situated in the local minima due to their arrangement in different situations, indicating the difference in obtained times. It is noteworthy that the decreased total response time to calls is directly related to the increased numbers of both stations and ambulances, which were constant in the simulation.

F) Danger points

Since ambulances and danger points are the factors affecting this problem, in addition to adding the features of ambulances and danger points can be added concurrently because all danger points are not equally dangerous in the real world. Table 5, shows a schematic of a synthesis process in the optimized agent-based GA. There are two adjacent stations on the list, each with an equal number of danger points, but the ambulance is better in one station than the normal ambulance in the other. As

Table 4. Agent-based simulation output

No.	Land dimension	No. of danger points	No. of stations	No. of type A ambulances	No. of type B ambulances	No. of type C ambulances	Time
1	5000	1000	50	70	0	0	6909800
2	5000	1000	50	50	20	0	7133500
3	5000	1000	50	50	10	10	7799200
4	5000	1000	50	50	10	10	7771200

Table 5. Running the GA based on the agents of danger points

1	Better ambulance	Danger point No.	1	2	3	4	5	6			
		Accident probability level									
2	Ordinary ambulance	Danger point No.	7	8	9	10	11	12			
		Accident probability level									
3	Better ambulance	Danger point No.	1	2	3	4	5	6	9	10	11
		Accident probability level									
4	Ordinary ambulance	Danger point No.	7	8	12						
		Accident probability level									

mentioned earlier, the product of traveling time multiplied by the probability of an accident at that point is a factor affecting the creation of synthesis and mutation. Therefore, the effective time is further reduced by a faster ambulance when it travels to danger points with more accident probability relative to a normal GA. Therefore, the points with more accident probability will join the list of adjacent stations with better ambulances. This change occurs less frequently in danger points with lower accident probability due to the little effect in reducing effective time. The points with high accident probability with elderly patients and less probability with young patients are listed in Table 5.

As shown in Table 5, the list of high accident probability danger points with an inefficient ambulance is partly relocated to that of adjacent stations with efficient ambulances. Moreover, the study of the total monitoring time and the normalized monitoring time in adding the agents of danger points indicates that the set focuses on the points with the highest accident probability instead of considering all points similarly. The results also revealed that reaching danger points with high accident probability is a priority, and it seems that these points are paid more attention by the system. According to the results, these results will significantly help managers to reduce costs and improve performance.

Discussion

This study was designed on two issues the need to discuss road emergency localization subjects and localization models and methods for this type of facility. According to the present study, it can be concluded that, instead of considering all points the same, managers should focus on points with more accident probability and prioritize ambulance arrival in danger points with high accident probability, which will significantly reduce costs and improve performance. This strategy will also reduce the total call response time by increasing the number of stations, resulting in better access of applicants to medical services of ambulances. Achieving a trustable method to reduce road accidents and their effects necessitates national efforts and impetus and coordination between relevant organizations in the context of a plan such as a road accident management program (27). Given the exponential rise of the problem dimensions and complexities, the inefficiency of classical problem-solving methods, and the efficiency of metahiorestatic algorithms in solving complex problems, the present study focused on developing a metaheuristic GA to solve the mentioned problem.

The agent as one of the concepts of complexity theory is a modelling method. In this application, agents model people in a society with the features of interest, and then agents are introduced into the system to examine their impact on the behaviors of agents or macro-level behavior of the society (3).

The optimal arrangement of vehicles according to their features and behaviors (as agents) as well as peripheral conditions (the environment of agents) explicates an optimization problem. Due to the high complexity of the model, the use of classical solution methods, such as linear and nonlinear programming, to solve this problem faces two main problems: "high computational cost" and "tangling the solver algorithm in local extremes". Therefore, meta-heuristic algorithms as an approximate solution method are used to overcome these two problems. In fact, meta-heuristic algorithms are a type of approximate optimization algorithms that offer solutions for exiting local optimal points and can be used in a wide range of problems (4).

In this research, agent-based modelling was proposed relying on the complexity theory, interaction of agents affecting localization, and substantive, functional, and behavioral differentiation of various agents involved in the localization of road ambulances that is more compatible with real conditions. However, functional, substantive, and behavioral conditions have been assumed to be the same in previous studies concerning the optimal localization of road ambulances and emergency centers. The travelling movement in different intervals was assumed to be constant in a study by Batta et al. (11). Church & ReVelle (7) referred to an insufficient coverage guarantee. The work ratio was considered the same for all ambulances and the movement radius of ambulances was assumed constant by ReVelle & Hogan (13). Toro-DiAz et al., claimed that they managed dispatch decisions using fixed priority lists. The priority list method allows the policy of the nearest vehicle to both minimize response time and maximize coverage (28). In addition to the nearest vehicle agent, the integration of localization and dispatch decisions can provide better solutions by considering other performance metrics, such as justice.

The following studies are in line with the present study. Shariat-Mohaymany et al. (29) and Bandara et al. (30) presented evidence that dispatching the nearest idle vehicle was not always the best solution adopted in the case of lower priority calls. Although the strategy of dispatching the nearest idle vehicle minimizes the response time to reach the call, this method does not take into account the point that vehicles may be unavailable during the call, which affects the system's capacity to respond to future calls. Rajagopalan et al. showed that the policy of the nearest idle ambulance results in a delayed response fraction that is 2.7 times higher than that probably obtained by the offline policy (23). They then concluded that other dispatch policies should be predicted to improve the system's efficiency. McLay & Mayorga (18) and Bandara et al. (30) used a decision-based approach to achieve optimal dispatch policies seeking to maximize coverage and patient survival.

Agents such as the ability of ambulance medical staff, the technical status of ambulances, etc., as well as the specific conditions of each agent and their interaction, cannot be methodically incorporated into these models. The dominance of such conditions arises from the complex nature of the problem environment and can consequently be explained under the complexity theory. Complexity science examines the rules that exist in all narrative systems and somehow believes that complex behaviors in systems arise from the very simple rules of interrelated components that act collectively.

Furthermore, the use of metaheuristic GA has been a good innovation in finding the optimal points. Since the problem dimensions and its complexities increase exponentially and require spending time in modeling conditions and agent-based simulation, the application of classical problem-solving methods will not be an appropriate method due to the complexities and probably falling into local optima. Therefore, this can explain another aspect of the innovation in the present study.

Due to the non-uniform traffic of the points, the ambulance arrival time to danger points will not be equal within the location range of the ambulances Changing the localization points depending on the conditions, therefore, moving forward or backwards, therefore, with moving forward or backward, mutating the ambulance from one station to another, and synthesizing the monitored list to produce a new list of the results can significantly reduce the total travel time by ambulances stationed at the site of localization. The optimization results revealed that the addition of a facility, such as the number of ambulances, reduced travelling the whole danger centers by the ambulances of EMCs. Therefore, the extent of optimization is very expandable owing to the range of conditions and available facilities, and the use of this type of optimization can significantly help accelerate activities and reduce costs. The results also show a reduction in total call response time with an increasing the number of stations.

Conclusion

In East Azerbaijan province, the localization of emergency stations has not been investigated dynamically, hence, there will be no relocation between stations (if necessary) by changing the level of demand, which sometimes will increase operating costs and response time to demands. On the other hand, a multitude and dynamic different agents affect the localization of road emergency centers and may exhibit different behaviors in a dynamic environment. Therefore, an optimal localization model for emergency facilities should pay special attention to complex conditions and the interaction of different factors involved in the localization of emergency centers.

Recommendations

According to the present study, it is recommended that this model be considered for the development of air ambulances (helicopters) in situations where requests are more than the available capacity and specializing in the characteristics of ambulances and danger points, travel time in all risk points can be reduced.

Author's contribution

Bijan Elmi and Naghi Shoja developed the study concept and design. Abbas Toloie Ashlaghi acquired the data. Soleiman Iranzadeh and Bijan Elmi analyzed and interpreted the data, and wrote the first draft of the manuscript. All authors contributed to the intellectual content, manuscript editing and read and approved the final manuscript.

Informed consent

Questionnaires were filled with the participants' satisfaction and written consent was obtained from the participants in this study.

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Conflict of interest

The authors declare that they have no conflict of interests.

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