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Ambulance integration model in smart city for health services

Rafiqa Dewi[1], Tulus[1], Muhammad Zarlis[2], Erna Budhiarti Nababan[1]
[1]Department of Computer Science, Faculty of Computer Science and Information Technology, Universitas Sumatera Utara, Medan, Indonesia
[2]Department of Information Systems Management, BINUS Graduate Program-Master of Information Systems Management, Jakarta, Indonesia

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ABSTRACT

Smart city is a city built to create efficient, sustainable, fair and livable cities. Increasing the percentage of population survival in standard and emergency times or emergency medical services (EMS) is one of the main pillars of a smart city. This study develops previous research. The weakness of this model is that it needs to consider the dynamic travel time factor. The model only considers the fixed travel time between two locations, which may not represent the actual conditions on the highway. It is less flexible because it only finds one threshold value α for all λi. Researchers succeeded in developing a model to overcome the model weaknesses in (4) by adding new constraints that consider ambulance capacity and overcome the shortcomings of the model (5) by adding tighter limits on the value of α to minimize the difference between the values of λi and αλi. In addition, constraints can also be added to ensure that α is a realistic value and meets business requirements.

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Corresponding Author:

Rafiqa Dewi
Department of Computer Science, Faculty of Computer Science and Information Technology
Universitas Sumatera Utara
Medan, Indonesia
Email: rafiqa.atb@students.usu.ac.id

1. INTRODUCTION

A smart city [1]-[5] or smart city is a city that can know early (smart, preventive elements) the real needs of its citizens. In recent years, one of the most prominent ideas in urban policy circles has been the importance of this using information and communication technologies (ICT), to address major urban and societal challenges. This trend gave birth to the idea of 'smart cities' [6]. A smart city is a city that has used intelligent computing technology to integrate essential components of city infrastructure and services, such as city administration, education, health, public safety, real estate, transportation, and other urban needs, where all users must be carried out intelligently. Interconnected and efficient [7]. Meanwhile, planning for a smart city based on environmentally friendly technology is a collaborative plan that involves various agencies in the planning process, for example, through integration, dissemination of information, and interaction of environmental spaces within the city [8]. Sustainable smart cities typically depend on fulfilling multiple information and communication technology (ICT) visions of pervasive computing, especially the internet of things (IoT), where everyday objects communicate with each other and integrate across heterogeneous and distributed computing environments to provide information and services to urban entities and townspeople [9].

Several studies on smart cities include research [10]. This research develops a "Smart City Index," providing various dimensions of city intelligence. This index is used to rank medium-sized cities in Europe based on their level of intelligence. The goal is to provide a better understanding of how cities integrate innovation and technology to improve sustainability, efficiency, and quality of life in urban environments.

Research by Komninos [11] produces a result that shows that the concept of a smart city involves integrating technology, information, and innovation in various aspects of urban life. Researchers argue that using ICT and information systems can yield significant gains in city management, quality of life, citizen participation, and economic growth. This research provides insights into the potential and implications of the smart city concept in creating more intelligent and innovative urban environments.

Research by Caragliu *et al.* [12] in this study, the researchers used a descriptive approach and secondary data analysis to gather information about the concept of smart cities in Europe. They analyze various aspects, including the development of the smart city concept, smart city initiatives implemented in Europe, and the factors that influence the successful implementation of the smart city concept. Through this analysis, researchers identify some common characteristics of European smart cities, such as using ICT to improve quality of life, mobility, energy efficiency, and citizen participation. They also identified several important factors that influence the successful implementation of the smart city concept, including government support, collaboration between the public and private sectors, and active community participation.

This study [13] analyzes the effectiveness of competition models in promoting the adoption of technology in cities. By examining programs in the United Kingdom, the United States, the European Union, and Canada, the researchers found that these competitions successfully encouraged new thinking about technological solutions and fostered relationships to address urban challenges, benefiting both winners and other participants. However, their impact on institutional and systemic change was more limited, often benefiting winners who could implement projects and national governments testing new funding models. The authors recommend improvements in the implementation of future smart city competitions.

The results of this study are a systematic presentation and analysis of various smart city applications that have been carried out. Researchers analyzed the types of applications, the technology used, implementation goals, and the benefits generated from each of the smart city applications studied. This research provides insight into various existing smart city applications, including but not limited to transportation management, energy management, waste management, public security, citizen participation, and economic development. Through this research, the researchers hope to provide a better understanding of recent developments in smart city applications and their potential to improve urban living.

Road traffic management has become a significant problem in contemporary society. Where ambulances are blocked by congested traffic and must wait minutes to hours to clear the road, this can lead to loss of life due to lack of timely treatment. To solve this problem and save many lives, a model is proposed in this project which provides the function that the ambulance can reach the patient by finding the shortest path. The search for the shortest route is carried out using the A* algorithm [14].

An article aimed at implementing the facility location problem in the emergency medical service (EMS) in the Belo Horizonte district, Brazil, where the aim is to improve the two previous ambulance service optimization models from the literature to deal with base location and ambulance allocation/relocation problems. The proposed multi-period model introduces the concept of relocation to local EMS, allowing ambulances to move between bases in different periods to increase system coverage. They also offer a bi-objective approach aimed at minimizing the number of floors and maximizing the scope of requests, which is solved using the constraint method. The results show that the coverage rate increases to 31% for the deterministic approach and 24% for the probabilistic approach. Optimizing ambulance relocation can increase coverage rates by up to 21% for a deterministic process and up to 15% for a probabilistic approach when changing scenarios from static to multi-period [15].

Effective EMS are critical to any scale healthcare system. The research presents the optimization of EMS ambulance allocation and base station locations through a genetic algorithm (GA) with an integrated EMS simulation model. The two tiers of the EMS model realize the different demands on the two vehicle classes; ambulances and quick response cars. Several patient classes were modelled, and survival functions were used to differentiate the level of service required. The goal is to maximize the overall expected probability of survival across patient classes. The implementation of the model is carried out using accurate call data from the London Ambulance Service. Simulation models are proven to mimic real-life performance effectively. Optimization of existing resource plans has resulted in a significant increase in the probability of survival of citizens. Optimizing the selection of one-hour periods within the program without introducing additional resources resulted in a marked increase in the number of cardiac arrests survivors per year. Adding other base stations further increases viability when their location and resources are optimized for the main service period. In addition, removing base stations from the system was found to have minimal impact on the likelihood of survival when selected stations and resources were optimized simultaneously [16]. According to the United Nations expectations, improving residents' quality of life in smart cities and enabling a clean, healthy, and sustainable environment is a crucial area for smart city government ranks. One of the leading smart city infrastructures is smart healthcare, which can be enabled by using modern technologies such as the IoT, especially to access patients when they need help.

The main reference of this study [17] is research that contains a relocation model for ambulance facilities. One of the weaknesses of this model is that it needs to consider dynamic travel time factors. The model only considers the fixed travel time between two locations, which may not represent the actual conditions on the road. Traffic, weather, and road conditions can affect travel time and, therefore, the availability of an ambulance at the right location at the right time. In addition, this model also does not consider other factors, such as the patient's severity, specific medical needs, or the ambulance's ability to handle different situations. Therefore, it is necessary to optimize the existing model to take the current weaknesses.

For health services within the scope of a smart city, it is essential to find an ambulance appropriately and quickly so that incidents can be served as soon as possible to increase the life expectancy index and guarantee reliable health services. The lack of information about the geographical location of ambulances causes hindrances to rapid response services to incidents, thereby reducing the life expectancy index among urban residents. Thus, integrating ambulances with service authorities, residents, and hospitals is one of the elements in the health aspect that needs attention in building a smart city. Based on the description, the authors constructed an ambulance integration model in a smart city.

2. MATERIAL AND METHODS

2.1. Research stages

The following is the research framework for this study:

a. Literature review

This section includes a review of the literature relevant to the research topic. At this stage, the researcher collects and analyzes existing literature on the research topic. The purpose of the literature review is to understand the concepts related to research and to identify deficiencies and knowledge gaps that this research can fill. The results of this literature review will be used as a theoretical basis for formulating the objective function and model constraints.

b. Data collection

This section describes the data collection process that will be carried out in the research. The data collection methods, such as interviews, observation, surveys, or document analysis, may vary. Researchers must design systematic and valid data collection procedures so that the data obtained can answer research questions. In addition, researchers must also consider research ethics in data collection, such as the privacy and security of respondent data.

c. Formulating model objective functions

This section deals with developing models or concepts that will be used in research. The model's objective function is a mathematical or statistical formulation that will be used to model the relationship between the variables involved in the study. This objective function reflects the purpose of the research and can vary depending on the type of research being undertaken, such as quantitative or qualitative research.

d. Formulating model constraints

This section explains the limitations or constraints in the developed model. Model constraints can be in the form of limited data available, assumptions used in the model, or methodology limitations. Formulating model constraints is essential to acknowledge research limitations and maintain the validity of research results.

e. Evaluation

This section covers the process of evaluating the model that has been developed. Evaluation is carried out to test the validity and effectiveness of the model in answering research questions or achieving research objectives. Evaluation can be done through statistical analysis, hypothesis testing, comparison with related literature, or expert validation. The evaluation results will assist in drawing conclusions and providing implications for the research.

2.2. Related research

In this study [18], testing and evaluation of the model's performance were carried out using simulation data and field data. The evaluation results show that the proposed model can increase the efficiency of ambulance routes, reduce travel time, and optimize the use of ambulance resources in a smart city environment. This research contributes to developing a more efficient and responsive ambulance dispatch system in the context of a smart city. Using an optimization approach and considering relevant factors, this study provides a practical guide to improve the efficiency and effectiveness of EMS in a smart city environment.

In this study [19], the researchers developed algorithms and systems capable of automatically integrating real-time data, performing complex analyses, and sending ambulance dispatch instructions. The result is an ambulance dispatch system that is responsive, efficient, and able to optimize the use of ambulance resources in providing EMS. The results of this study indicate that the use of IoT technology and big data analytics in a real-time ambulance dispatch system can increase response time, optimize ambulance routes, and increase the efficiency of resource use in smart cities.

The study [20] aims to develop a real-time system for detecting accidents and automatically dispatching emergency assistance. The system utilizes sensors such as accelerometers and gyroscopes to identify collisions, then sends a notification containing GPS coordinates to the emergency center to deploy an ambulance promptly. Testing results show high accuracy and rapid response times, making the system effective in reducing fatalities from traffic accidents. With the integration of GPS technology and cellular networks, the system is expected to be widely implemented to enhance road safety.

The study [21] discusses the development of algorithms to optimize the fleet staging of air ambulances within EMS systems. The main focus of the research is on the efficient allocation of air ambulance resources to minimize response times and operational costs, considering factors such as geographic location, service demand, and time constraints. The authors propose the use of a Tabu search algorithm to solve this problem, which has been shown to achieve near-optimal solutions with more efficient computational time compared to traditional optimization methods. This study makes a significant contribution to improving the operational efficiency of air ambulance services, which is crucial in emergency situations.

This study [22] discusses a smart traffic management system designed to accelerate the movement of ambulances on the roads. The system utilizes technologies such as the IoT, traffic sensors, and real-time data processing algorithms to dynamically control traffic lights, prioritizing ambulances. By optimizing traffic flow, the system aims to reduce the travel time of ambulances to emergency locations and medical facilities. The authors also review the implementation challenges, such as the necessary infrastructure and technology integration. The study concludes that the smart traffic management system has great potential to improve emergency service efficiency and save more lives.

The study [23] proposes an intelligence-based traffic control system for ambulances using IoT technology. The system integrates traffic sensors and IoT devices to monitor traffic conditions in real-time and dynamically control traffic lights, prioritizing ambulances on their way to emergency locations. With artificial intelligence-based data processing, the system can identify traffic obstacles and select the fastest route for the ambulance, significantly reducing response time. This study demonstrates that the application of IoT technology can improve ambulance dispatch efficiency and accelerate emergency services.

The study [24] proposes a smart ambulance system that combines game-building theory and optimization techniques to enhance emergency response. This system uses optimization algorithms to determine the fastest route for ambulances based on dynamic traffic conditions and prioritized arrival times. Game-building theory is applied to coordinate between various actors in the system, such as the control center, ambulance drivers, and hospitals, ensuring efficient information flow and quick decision-making. The research shows that the application of these techniques can reduce emergency response times and improve medical service efficiency, with the hope of saving more lives in critical situations.

The study [25] proposes a smart ambulance system based on the IoT and cloud, integrating fingerprint sensors with medical sensors for real-time monitoring of patient vital signs. This system aims to enhance the quality of emergency services by monitoring the patient's condition during transport to the hospital, while also ensuring accurate patient identification through fingerprint technology. Data collected from the medical sensors and fingerprint will be sent to a cloud platform for further analysis by medical teams, enabling faster responses and more precise handling. The research shows that the use of IoT and cloud technology in ambulances can improve patient safety and medical service efficiency.

2.3. Previous research

The main reference of this study is research [5] that contains a relocation model for ambulance facilities by representing the graph G= $(V \cup W, E)$ with $V = \{v_1, v_2, \dots, v_n\}$ and $W = \{v_{n+1}, \dots, v_{n+m}\}$ are the two sets of nodes representing the location of the ambulance facility request and the area of the potential location and $E = \{(v_i, v_j): v_i, v_j \in V \cup W, i < j\}$ is the set of edges. The request location points a node represents equals λi, with each edge associated with a parameter representing the t_{ij}. travel time. $v_i \in V$ and $v_j \in W$, given as (1):

$$\gamma_{ij} = \begin{cases} 1, t_{ij} \leq r_1 \\ 0, other \end{cases} \quad (1)$$

and

$$\delta_{ij} = \begin{cases} 1, t_{ij} \leq r_2 \\ 0, other \end{cases} \tag{2}$$

If the number of ambulance facilities is available and is equal to p(p≤m), then the maximum number of ambulance facilities in the "waiting period" is p_j in $v_j \in W$ set as the penalty coefficient related to relocated ambulance facilities i=1,…,p from the location current request at time t to the destination request location $v_j \in W$. From the following assumptions, it is known that the coefficient M_{jl}^t constantly changes in every period t. As a result, α is the proportion of the number of demand levels that ambulances allocated by r_i units must meet.

In this study, the following variables were used: y_{jl} is a binary variable with a value of 1 if and only if ambulance l is allocated to $v_j \in W$ and x_i^k is a binary variable with a value of 1 if and only if v_i is a location that is met at least k times, so the relocation problem at time t is:

$$\max \sum_{i=1}^{n} \lambda_i x_i^2 - \sum_{j=1}^{m} \sum_{l=1}^{p} M_{jl}^t y_{jl} \tag{3}$$

Constraint,

$$\sum_{j=1}^{m} \sum_{l=1}^{p} \delta_{ij} y_{jl} \geq 1, \forall v_i \in V \tag{4}$$

$$\sum_{i=1}^{n} \lambda_i x_i^l \geq \alpha \sum_{i=1}^{n} \lambda_i \tag{5}$$

$$\sum_{j=1}^{m} \sum_{l=1}^{p} \gamma_{ij} y_{jl} \geq x_i^l + x_i^2, \forall v_i \in V \tag{6}$$

$$x_i^2 \leq x_i^l, \forall v_i \in V \tag{7}$$

$$\sum_{j=1}^{m} y_{jl} = 1, l = 1, \dots, p \tag{8}$$

$$\sum_{l=1}^{p} y_{jl} \leq p_j, \forall v_j \in W \tag{9}$$

$$x_i^l = 0 \text{ or } 1, \forall v_i \in V \tag{10}$$

$$x_i^2 = 0 \text{ or } 1, \forall v_i \in V \tag{11}$$

$$y_{jl} = 0 \text{ or } 1, \forall v_j \in W \text{ and } l = 1, \dots, p \tag{12}$$

In this relocation model, constraints (4) and (5) indicate that r2 units can meet the demand level needs. Constraints (5) and (6) denote the requirement relative to the demand for ambulance services that can be met. Constraint (5) explains that the proportion α at all demand levels can be satisfied when constraint (5) determines that the number of ambulances allocated by unit r_1 must be at least one if $x_i^1 = 1$ or at least two if $x_i^2 = x_i^1 = 1$. Constraint (6) ensures that a point location request cannot be satisfied twice if it was not fulfilled at least once before. Boundary (7) specifies that each available ambulance facility must be allocated to a possible demand area location. Finally, constraint (8) denotes an upper bound on the number of ambulance facilities in the 'waiting period' status at a given demand location.

2.4. Data collection

The data used in this research was obtained from Medankota.bps.go.id, which includes data on community health centers and hospitals spread throughout the city of Medan, then equipped with the coordinates of each community health center and hospital. This health center data will be used as ambulance station node data. Health center data can be seen in Table 1. The J sampling approach node coordinate point data using ArcGIS is shown in Figure 1. Meanwhile generating the coordinate points for ambulance requests using the sampling approach using ArcGIS is shown in Figure 2.

One category of data collection is numerical data. The data source used in this research was obtained from the Benchmark in the Instance Journal of Advanced Transportation Research Article: distribution-free model for ambulance location problem (2018) as seen in Table 1.

Table 1. Ambulance base data

No	Name base	Digital address	Number of ambulances
1	Amplas health center	3.5450924542584383, 98.71168599439129	1
2	Belawan health center	3.778605895449408, 98.68216530788484	1
3	Bestari health center	3.589108606836923, 98.6655922502117	1
4	Bromo health center	3.573630555902878, 98.7214996790476	2
5	Darussalam health center	3.586171499938483, 98.65277262137572	1
6	Desa Binjai health center	3.5541862522462373, 98.70835068089919	1
7	Desa Lalang health center	3.5935270434821853, 98.61738069439151	1
8	Desa Terjun health center	3.711439941988507, 98.64725789439225	2
9	Glugur Darat health center	3.614961853649137, 98.68165645206355	2
10	Glugur Kota health center	3.607070338304988, 98.67378140230142	2
11	Helvetia health center	3.6123090144943726, 98.6321315213759	1
12	Kampung Baru health center	3.5508385862920138, 98.68740198132943	1
13	Kedai Durian health center	3.519689254471271, 98.68383332322706	2
14	Kota Matsum health center	3.5765599028710935, 98.69388729624316	1
15	Mandala health center	3.5864897607089654, 98.7210412287826	1
16	Martubung health center	3.6986944829827495, 98.68581423794916	1
17	Medan Area Selatan health center	3.5784316706174466, 98.70206301952398	1
18	Medan Deli health center	3.6769180786188738, 98.66465241952459	1
19	Medan Denai health center	3.5713076964661314, 98.72515577719585	2
20	Medan Johor health center	3.5445181294420087, 98.67969789439125	1
21	Medan Labuhan health center	3.723384651026294, 98.67801528275193	1
22	Medan Sunggal health center	3.5766377302883217, 98.6117972642376	3
23	Padang Bulan health center	3.560454758986014, 98.66234017904756	1
24	Selayang health center	3.5522043773624397, 98.63871190788338	1
25	Pasar Merah health center	3.5684305330105546, 98.70619499624306	1
26	Pekan Labuhan health center	3.7358092653551425, 98.67630307904855	1
27	Polonia Health center	3.5693479649326023, 98.66812138089927	2
28	Pulo Brayan health center	3.62281616648908, 98.67006716555576	1
29	Rantang health center	3.5935721054189327, 98.65563179253985	1
30	Rengas Pulau health center	3.697684778350496, 98.65097443486859	1
31	Sei Agul health center	3.6159145132566093, 98.6666893674074	1
32	Sentosa Baru health center	3.6004600112810246, 98.70141465021182	1
33	Sering health center	3.60831622343445, 98.6964947060321	1
34	Sicanang health center	3.757073629142989, 98.65553375021274	1
35	Simalingkar health center	3.5145007359370264, 98.63144210892845	1
36	Simpang Limun health center	3.5575571678261064, 98.69837098089918	1
37	Sukaramai health center	3.583507714281114, 98.70534516370381	1
38	Tegal Sari health center	3.579819764691465, 98.71909357428767	1
39	Teladan health center	3.563117625969271, 98.69321321158684	1
40	Titi Papan health center	3.6840602496206794, 98.67203980973596	1
41	Tuntungan health center	3.4925593287288916, 98.56832401587397	1

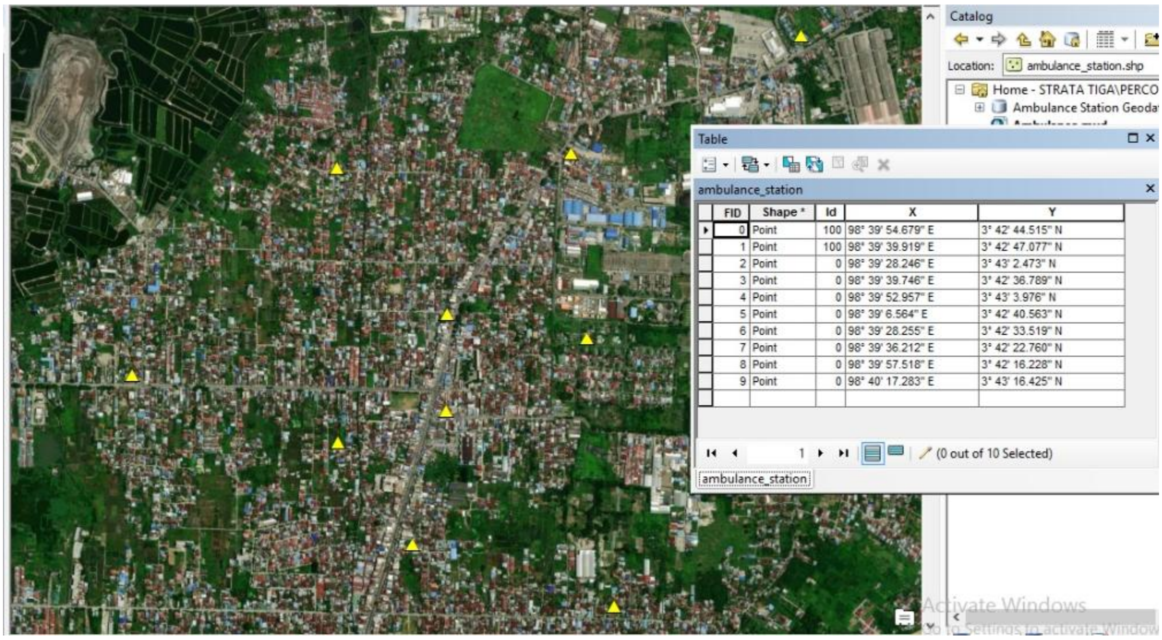

Figure 1. Node *J* as an ambulance base

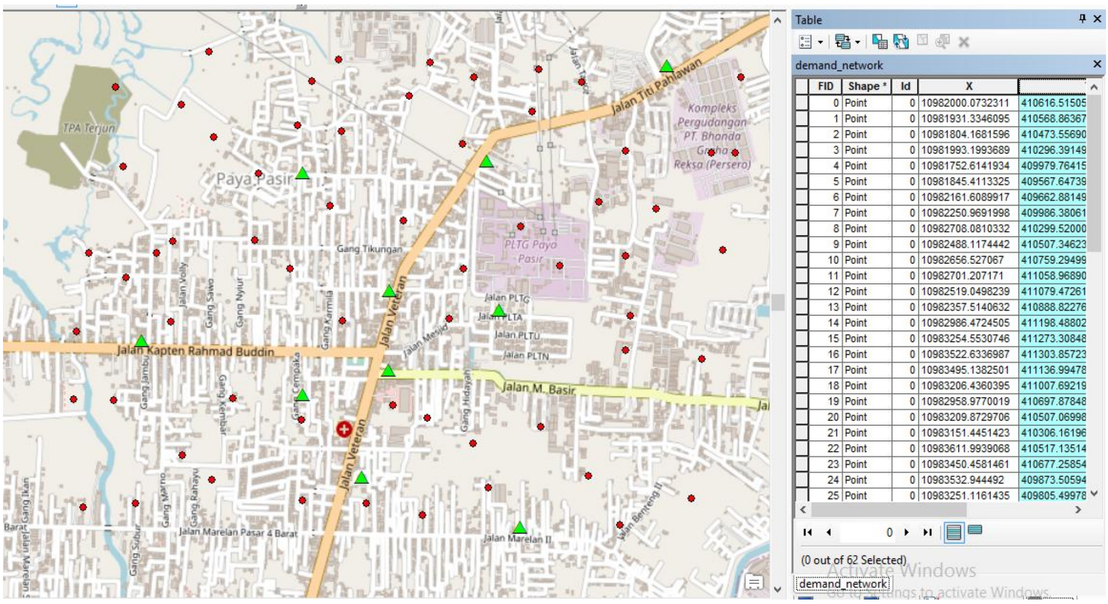

Figure 2. Node *I* as the point of request for an ambulance

3. RESULT AND DISCUSSION

One of the weaknesses of this model is that it needs to consider dynamic travel time factors. The model only considers the fixed travel time between two locations, which may not represent the actual conditions on the road. Traffic, weather, and road conditions can affect travel time and, therefore, may affect the availability of an ambulance at the right location at the right time. In addition, this model also does not consider other factors, such as the patient's severity, specific medical needs, or the ambulance's ability to handle different situations. One of the weaknesses of the relocation model for ambulance facilities is the constraints in (4). Constraint (4) ensures each client is served by at least one ambulance. This constraint only checks the existence of at least one ambulance serving each client without considering whether the number of available ambulances is sufficient to meet all client needs effectively.

Model development to overcome this weakness can be done by adding new constraints that consider the capacity of the ambulance. One of the mathematical forms of developing the model can be stated as (13):

$$\sum_{j=1}^{m}\sum_{l=1}^{p}\delta_{ij}\,y_{jl} \geq \frac{d_i}{c}, \forall v_i \in V \tag{13}$$

where d_i is the number of requests for a client, and I and c are the maximum capacity of each ambulance. In this constraint, the number of ambulances serving each client must be sufficient to handle requests, at least as many as the number of requests divided by the maximum capacity of each ambulance. Thus, the model that has been developed can ensure that each client is served by a sufficient number of ambulances so that the public's health needs can be met more effectively.

Constraint (13) is an extension of the basic model to correct the weakness in constraint (4), where all locations must be served by at least one ambulance. Constraint (13) adds a parameter that determines the number of patients served at the location I, and c is the maximum capacity of the ambulance service. However, the drawback of constraint (13) is that it only provides a lower bound for the number of ambulances needed to serve a location and does not provide an upper bound. In other words, there is no guarantee that the number of scheduled ambulances will be sufficient to treat all patients at that location, significantly if the number of patients is within the maximum capacity of the ambulance service. In addition, this constraint also ignores other factors that can affect the number of ambulances needed, such as travel time and traffic density, so the model can still be improved. One of the improvements that can be made to model (13) is to consider the distance factor between the patient's location and the location of the ambulance facility. This can be done by adding a distance variable to the model and setting a maximum distance limit between the patient and the ambulance facility that can be served. For example, a maximum distance limit of R for each ambulance facility can be set. In this case, the model can be modified by adding the binary variable z_{ij}, which indicates whether patient i is served by ambulance facility j or not based on distance. In addition, the maximum distance limitation can also be applied to the δ_{ij} variable so that only patients within R distance from the ambulance facility are considered. Thus, the model can be modified as (14)-(17):

$$\sum_{j=1}^{m}\sum_{l=1}^{p}\delta_{ij}\,y_{jl} \geq \frac{d_i}{c} * z_{ij}, \forall v_i \in V, \forall v_i \in W \quad (14)$$

δ_{ij}=0, if t_{ij}=>r_2 or distance ij>R (15)

z_{ij}=1, if distance ij≤R (16)

z_{ij}=0, if distance ij>R (17)

By adding distance variables and maximum distance limitations to the model, the weaknesses found in the initial model can be overcome so that the model can provide better and more accurate solutions for relocating ambulance facilities.

The weakness of the model (5) is that it is less flexible because it only considers one threshold value α for all λ_i. This constraint can also limit the variation of the λ_i value due to the α threshold. In addition, the use of this equation also cannot consider the situation where some λ_i have a more significant contribution than others in influencing the functional value given by $\sum_{i=1}^{n}\lambda_i x_i$. One of the developments that can be made to improve the weaknesses of the model constraint (5) is to add tighter constraints on the value of α to minimize the difference between the values of λ_i and αλ_i. In addition, constraints can also be added to ensure that α is a realistic value and meets business requirements. For example, a hospital may need at least 80% of its available ambulance capacity at any given time to ensure a rapid response to an emergency. In this case, the model can be modified by adding constraints like (18):

$$\sum_{i=1}^{n}\lambda_i\,x_i^l \geq \alpha\sum_{i=1}^{n}\lambda_i \text{ and } \alpha \geq 0.8, \forall vi \in V \quad (18)$$

With the addition of these limits, the model can ensure that at least 80% of the available ambulance capacity will always be available to respond to emergencies, thereby minimizing the risk of errors in ambulance dispatch. The disadvantages of constraint (18) are as:

- Tight constraint: this constraint is quite stringent because it forces each facility to handle a certain minimum number of patients. This can limit the flexibility of the solution and result in sub-optimal solutions.
- Sensitivity to α: this constraint is very sensitive to the selected α value. A value that is too high can result in a solution that is impossible or unrealistic, while a value that is too low can result in a solution that is too loose and inefficient.
- Does not consider cost: this constraint does not consider cost, which is an important factor in the planning and operation of health facilities. Therefore, the resulting solutions may be uneconomical or too expensive to implement.

To overcome these weaknesses, model development can be carried out by adding other constraints that consider the cost and flexibility of the solution, as well as reducing the tightness of the minimum number of patients that must be handled by each facility. One of the improvements that can be made is to add variations to the value of α, so that it is not always tied to a value of 0.8. For example, α can be used as a decision variable that is subject to boundary constraints so that the value of α can vary depending on the conditions of the problem at hand. In addition, these constraints can also be changed to make them more flexible by replacing them with constraints that allow variations in the ratio between the assignment of variable x at level l and other levels. For example, we can replace the constraint with:

$$\sum_{i=1}^{n}\lambda_i\,x_i^l \geq \alpha\sum_{i=1}^{n}\lambda_i\,x_i^k, \forall v_i \in V, l \neq k \quad (19)$$

where k is a level other than level l. In this case, α is still a parameter that controls the ratio between the assignment of variable x at level l and other levels, but with more flexibility because the ratio is not always tied to a fixed value. From the results of model development, a new model is obtained as (20):

$$\gamma_{ij} = \begin{cases} 1, t_{ij} \leq r_1 \\ 0, other \end{cases} \quad (20)$$

and

$$\delta_{ij} = \begin{cases} 1, t_{ij} \leq r_2 \\ 0, other \end{cases} \quad (21)$$

$$\max\sum_{i=1}^{n}\lambda_i\,x_i^2 - \sum_{j=1}^{m}\sum_{l=1}^{p}M_{jl}^t\,y_{jl} \quad (22)$$

Constraint,

$$\sum_{j=1}^{m}\sum_{l=1}^{p}\delta_{ij}\,y_{jl} \geq \frac{d_i}{c}, \forall v_i \in V \quad (23)$$

$$\sum_{j=1}^{m}\sum_{l=1}^{p}\delta_{ij}\,y_{jl} \geq \frac{d_i}{c} * z_{ij}, \forall v_i \in V, \forall v_i \in W \quad (24)$$

δ_{ij}=0, if t_{ij}=>r_2 or distance ij>R (25)

z_{ij}=1, or distance ij≤R (26)

z_{ij}=0, or distance ij>R (27)

$\sum_{i=1}^{n}\lambda_i\,x_i^l \geq \alpha\sum_{i=1}^{n}\lambda_i\,x_i^k$, ∀v_i∈V, l≠k (28)

$$\sum_{j=1}^{m}\sum_{l=1}^{p}\gamma_{ij}\,y_{jl} \geq x_i^l + x_i^2, \forall v_i \in V \quad (29)$$

$$x_i^2 \leq x_i^l, \forall v_i \in V \quad (30)$$

$$\sum_{j=1}^{m} y_{jl} = 1, l = 1, \dots, p \quad (31)$$

$$\sum_{l=1}^{p} y_{jl} \leq p_j, \forall v_j \in W \quad (32)$$

$x_i^l = 0$ or 1, $\forall v_i \in V$ (33)

$x_i^2 = 0$ or 1, $\forall v_i \in V$ (34)

$y_{jl} = 0$ or 1, $\forall v_j \in W$ and $l = 1, \dots, p$ (35)

The pseudo code of the model is as:
For each i and j, define the binary variable δ_{ij} as: if t_{ij}≤r_2, then δ_{ij}=1, if not , then δ_{ij}=0.
For each i and j, define the binary variable γ_{ij} as: if t_{ij}≤ r_1, then γ_{ij}=1, if not, then γ_{ij}=0.
Maximize the objective function as: $\max\sum_{i=1}^{n}\lambda_i\,x_i^2 - \sum_{j=1}^{m}\sum_{l=1}^{p}D_{t,k}\,y_{t,j,k}$, by selecting the appropriate values of the x and y variables.

Apply the following constraints:
a. For each v_i∈V, add up $\delta_{ij} * y_{jl}$ for all j and l and make sure their value is greater than or equal to 1.
b. Add up $\lambda_i * x_i^l$ for all i and make sure the value is greater than or equal to α * $\sum_{i=1}^{n}\lambda_i$.
c. For each v_i∈V, add up $y_{ij} * y_{jl}$ for all j and l and make sure the value is greater than or equal to x_i^l+x_i^2.
d. For each v_i∈V, make sure that $x_i^2$is not greater than x_i^l.
e. For each v_j ∈W, add up the y_{ij} for all l and make sure their value equals 1.
f. For each vj∈W, add up y_{jl} for all l and make sure the value is not greater than pj.

Constrain the x and y variables as:
a. x_i^l can be 0 or 1 for every vi ∈V and l=1,...,p.
b. x_i^2 can be 0 or 1 for each vi ∈V.
c. y_{jl} can be 0 or 1 for each vj ∈W and l=1,...,p.

This ambulance integration model can follow an algorithmic approach pattern to be applied to computer applications. The algorithm formed from this model is as:
– Define the variables to be used in the model:
λ_i: binary variable that determines whether the ith facility will be moved or not.
x_i^l: binary variable that determines whether the ith facility will be moved to location l or not.
x_i^2: binary variable that determines whether the ith facility will be moved to a new location or not (in this case, the facility is moved to the same location).
Y_{jl}: binary variable that determines whether location j will be taken by the facility that is moved to location l or not.
– Define the constraints:
$\sum_{j=1}^{m}\sum_{l=1}^{p}\delta_{ij}\,y_{jl} \geq 1, \forall v_i \in V$ (facility must be moved to new location or same location);
$\sum_{i=1}^{n}\lambda_i\,x_i^l \geq \alpha\sum_{i=1}^{n}\lambda_i$ (at least α percent of facilities must be moved);
$\sum_{j=1}^{m}\sum_{l=1}^{p}\gamma_{ij}\,y_{jl} \geq x_i^l + x_i^2, \forall v_i \in V$ (facilities can only be moved to possible locations);
$x_i^2 \leq x_i^l, \forall v_i \in V$ (if the facility is moved to the new location, the facility cannot be moved to the old location);

$\sum_{j=1}^{m} y_{jl} = 1, l = 1, \dots, p$ (each location can only be taken by one facility);
$\sum_{l=1}^{p} y_{jl} \leq p_j, \forall v_j \in W$ (each facility can only be moved to a certain location).
Note: V and W refer to the set of facilities and locations available. r1 and r2 are the time limits for moving to new or old areas. M is the cost matrix for moving the facility from location j to location l. α is the minimum percentage of facilities that must be moved.

Model testing and simulation use R Language, a statistical programming language that can be used to analyze and manipulate statistical data (statistical modeling) and graphics. The R language is used to complete the relocation model for an ambulance dispatched from each base location to each request point by minimizing response time. Researchers have succeeded in developing models and algorithms for ambulance integration modeling with an algorithmic approach that can be applied in computer applications. This algorithm optimizes the ambulance facility relocation process by considering the variables and limitations. This algorithm provides a framework for optimizing decision-making in relocating ambulance facilities by considering relevant variables and constraints. Through this model, users can make the best decisions in moving ambulance facilities by considering the limitations and objectives. Implementing this algorithm in a computer application can help simplify and speed up the ambulance relocation decision-making process efficiently.

4. CONCLUSION

The researcher succeeded in developing a model to overcome the model's weakness in previous model by adding a new constraint that considers the capacity of the ambulance. One of the mathematical forms of developing this model can be expressed by the equation $\sum_{j=1}^{m} \sum_{l=1}^{p} \delta_{ij}\, y_{jl} \geq \frac{d_i}{c} * z_{ij}, \forall v_i \in V, \forall v_i \in W, \forall v_i \in W$ which where δ_{ij}=0, if t_{ij}=>r_2 or distance ij>R, z_{ij}=1, if distance ij≤R dan z_{ij}=0, if distance ij>R. Researchers also managed to improve the weakness of the previous model constraint by adding stricter limits on the value of α, to minimize the difference between the values of λi and αλi. In addition, constraints can also be added to ensure that α is a realistic value and meets business requirements. With the addition of these limits, the model can confirm that at least 80% of the available ambulance capacity will always be available to respond to emergencies, thereby minimizing the risk of errors in ambulance dispatch. Researchers also add variations to the value of α, so it is not always tied to a value of 0.8.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Rafiqa Dewi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓
Tulus		✓	✓					✓		✓		✓		
Muhammad Zarlis	✓			✓		✓				✓			✓	✓
Erna Budhiarti Nababan	✓	✓			✓	✓		✓		✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

We hereby declare that the authors have no conflicting non-financial interests including statements of conflicting political, personal, religious, ideological, academic, and intellectual interests. The authors also have no conflicting financial interests or personal relationships with each other.

INFORMED CONSENT

We hereby declare that we have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The principles of the Declaration of Helsinki were adhered to throughout the study. Since the study was based on regular EMS operations and confidentiality of the ambulance authorities was guaranteed, informed consent was waived. The identities of the involved parties cannot be determined using the study number.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Rafiqa Dewi was born in Pematang Siantar on November 27 1984, she is a Permanent Lecturer of STIKOM Tunas Bangsa in Pematang Siantar, North Sumatra since 2009, with a concentration in the fields of science: algorithm and programming, database management, and smart cities management analyst. She is an assistant Professor in STIKOM Tunas Bangsa since 2017. She completed her Diploma from AMIK Tunas Bangsa Pematang Siantar in 2006 and completed her bachelor of Computer Science from Sisingamangaraja XII University Medan in 2009. Her Masters of Computer Science from Universitas Sumatera Utara (USU) in 2013. She can be contacted at email: rafiqa.atb@students.usu.ac.id.

Tulus is a Professor at the Faculty of Mathematics and Natural Sciences, University of North Sumatra. He is also the Chair of the USU Research and Service Institute (LPPM) for 2016-2021 and 2021-2026. He can be contacted at email: tulus@usu.ac.id.

Muhammad Zarlis is a Professor at the Faculty of Computer Science and Information Technology at Universitas Sumatera Utara, Medan, Indonesia. Completed his Bachelor of Physics education at the Faculty of Mathematics, Universitas Sumatera Utara, Medan. Completed his Masters in Computer Science in the Computer Science study program at the Faculty of Computer Science, Universitas Indonesia, Jakarta, and completed his Doctorate program in Computer Science at Universiti Sains Malaysia (USM), Penang. Current research interests are in the fields of intelligent systems, computer security, and computation. where he is the author/co-author of more than 187 research publications. He can be contacted at email: Muhammad.zarlis@binus.edu.

Erna Budhiarti Nababan received her M.IT and Ph.D. in Computer Science from Universiti Kebangsaan Malaysia in 2005 and 2009. She completed her Doctoral studies at Universiti Kebangsaan Malaysia in 2020. She is currently a Doctoral Lecturer in Computer Science and Head of the Master's Program in data science and artificial intelligence, at Universitas Sumatera Utara. Her research interests include artificial intelligence, machine learning, and optimization. She can be contacted at email: ernabrn@usu.ac.id.