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Hybrid model for optimization of ambulance allocation relocation in smart cities

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ABSTRACT

To increase the percentage of survival of citizens both in normal times and in times of emergency or Emergency Medical Services (EMS) which is one of the main pillars in a smart city, among the most important is ambulance management. A hybrid model between LR-MEXCLP is a model that combines local activity estimation with the TIMEXCLP model by achieving maximum coverage on MEXCLP which then this hybrid model can lead in solving a series of ambulance facility placement problems more accurately. This model was developed by establishing an integration model between the ability to estimate local activity and maximum completion coverage and with the shortest response time, so as to create a reliable ambulance service in a smart city.

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1. INTRODUCTION

A smart city or smart city is a city that is able to know early (has smart, preventive elements) the real needs of its citizens so that they can always be met / anticipated public desires through various applications and information technology innovations (Indrajit, 2012). Smart cities are cities that have used intelligent computing technology to integrate critical components of city infrastructure and services, such as city administration, education, health, public safety, real estate, transportation and other municipal needs, where the overall use must be done intelligently, interconnected and efficiently (Wijaya, 2018). While smart city planning based on environmentally friendly technology is basically a cooperation planning that involves various agencies in the planning process, for example through integration, dissemination of information and interaction of environmental spaces within the city (Hartama et al., 2017).

Smart City will become disabled if there is no emergency medical service (EMS). One of the entities on an EMS is an ambulance. Ambulance is a vehicle equipped with medical equipment to treat patients during transportation to health institutions such as special hospitals and public hospitals (Karkar, 2019). Where in the context of EMS there is a decision-making process that plays a very important role because some decisions greatly impact the patient's health. This work focuses on the operational level by solving the problem of ambulance delivery and relocation. Dispatch decisions assign ambulances to emergencies and relocation issues decide at which base available ambulances should be (re)assigned. To improve effectiveness and efficiency in EMS response, an integrated optimization approach is proposed: mathematical models and heuristic pilot methods. The goal is to maximize system coverage using a time readiness measure that allows relocation to any base (Carvalho et al., 2019)

The problem that then arises in the case of ambulances in smart cities is how to use IoT to identify and diagnose the condition of patients, the concept of Assisted Living is used for the elderly who live alone who need remote health monitoring. Data from sensors installed in the home to monitor the person is processed and sent to the cloud via a mobile app for viewing by the person monitoring the patient (Abdelgawad et al., 2017; Ashmawy et al., 2019).

In recent years search algorithms query the location of an entity quite accurately, particularly Taboo Search (Glover, 1989), coupled with the growth of parallel computing (Reeves, 1975) has given rise to a new stream of research that effectively tackles the dynamic nature of these issues. With the latest models and algorithms, large-scale problems can be solved quickly and dynamically in real time, with a high degree of accuracy. There is a lot of literature on emergency vehicle seating models. Survey by(Serra & Marianov, 2011) provides an overview of the most important models published up to that point (Brotcorne et al., 2003).

2. RESEARCH METHOD

The author introduces a hybrid model between the Local Reliability-based Maximum Expected Covering Location Problem (LR-MEXCLP), which is a model that combines the estimation of busyness in local reliability (Local Reliability) and Maximizing Expected Coverage (Maximum Expected Coverage) model with the TIMEXCLP model, which is a model of the location of the maximum expected coverage with time variation (Maximum Expected Coverage Location with Time Variation). The LR-MEXCLP model allows ambulance forecasts to vary from one area to the next depending on the number of vehicles and the level of demand in each local area. This strategy is more aligned with the heterogeneous distribution of geographic demand that characterizes large areas of urban areas, and therefore tends to result in more effective location decisions. In addition, this model introduces a new system performance matrix referred to as reliability (Chuang & Lin, 2007).

LR-MEXCLP method hybrid model that combines local busyness estimates in the MALP model with the maximum coverage objective in MEXCLP

$$MAX\,Z = \sum_{i=1}^{n}\sum_{k=1}^{p} d_i q_{i,k} Y_{i,k} \qquad (1)$$

In this formulation, the objective function (9a) serves to maximize the number of request completions, for all nodes, of the request rate multiplied by the reliability of the coverage. That for each node, the specific reliability measure chosen is the one where the corresponding Yi,k value is set to 1(Sorensen & Church, 2010).

While the TIMEXCLP model is very concerned about the problem of response time where a number of studies have shown a directly proportional relationship between decreased response time and the number of service deaths in EMS. This makes the exact location of the ambulance an important issue for EMS planners. This model provides EMS planners with a solution by carefully estimating service levels and allowing them to reinvent the size of the number of active vehicles that change over time to respond to demand variability. The model is developed and integrated with simulation into a Decision Support System (DSS) to help EMS planners allocate vehicles to demand nodes. Scheduling decision rules embedded in decision support systems for emergency ambulance scheduling consider criteria on average response time and percentage of ambulance requests responded within 15 minutes (Zhen et al., 2015).

We remember that decisions to be made in our issues include the number and location of bases and ambulances. However, when drawing up such a plan, we can go further by also deciding how to allocate an ambulance to the point of demand in case of an emergency call. Nevertheless, since demand is stochastic, we can, at most, consider a two-stage decision process. In the first stage (here-and-now) we make decisions about the location of the bases and the number of ambulances to be included in each base. Then, depending on how the uncertainty is resolved (observed requests), we decide how to allocate ambulances to different calls. Naturally, such allocations depend on the observed demand (Nickel et al., 2016).

Previous ambulance location optimization models have used a day as a unit of time in the model. However, analysis of Louisville data suggests that significant variations in the spatial distribution of demand can occur within a single day. To capture this aspect of the demand pattern, the expected requests are partitioned into a two-dimensional matrix of time period T and K request nodes. For the size of the St vehicle fleet in time period t, the average probability of system width over period t randomly selected vehicles will be busy can be expressed as the ratio of expected service time to total available service time. The system-wide probability of a busy ambulance is an estimate of any ambulance that is busy if the assumption of independence is met. If we define you as the average service time in minutes, and m as the length of the time period t in minutes, we can express this probability, Pt, as:

$$P_t = \sum_k \frac{(C_{t,k})(u)}{S_t(m)} \qquad (1)$$

Where
u = Average service time in minutes.
m = Minutes in period t

Where the expected coverage of the stain is represented by an item of possible ambulance availability during that time period and the portion of demand located on that node during that coverage period. The complete formulation of TIMEXCLP is:

$$Max \sum_t^T \sum_k^K \sum_j^{S_t} (l - P_t)(P_t^{j-i})(D_{t,k})(Y_{t,j,k}) \qquad (2)$$

Constraint to:

$$\sum_j^{S_t} Y_{t,j,k} = \sum_i (X_{t,j})(a_{t,i,k}) \ \forall \ k \ dan \ t \qquad (3)$$

$$\sum_i X_{t,i} = S_t \ \forall \ t \qquad (4)$$

Where Xt,i is an integer and

$$a_{t,i,k} = \begin{cases} 1 \text{ Where Xt, i is an integer and} \\ 0 \text{ Other wise} \end{cases}$$

In the development of objective functions, equation (2), Yt,j,k represents whether the j-th vehicle added to the fleet during period t includes node k. Since it is reasonable to expect that some nodes cannot cover other nodes, the values of Yt, i, k depend on where the j-th vehicle is located. If all nodes can cover each other, it makes no difference where the ambulance is. The problem is just one of minimizing fleet size. The system's ability to provide inter-node coverage is represented by a coverage matrix. The coverage matrix is then used to limit the Yt,j,k values to zero when unfeasible coverage alternatives are evaluated (Repede & Bernardo, 1994).

3. RESULT AND DISCUSSIONS

From the LR-MEXCLP and TIMECLP models, it can be obtained that there are three entities that can be integrated, namely (1) ambulance requests located in the local area, (2) an ambulance node at (3) a certain time. The n*3 coverage matrix is used to limit the value of Y_t,j,k to 0 when non-feasible coverage alternatives are evaluated. In potential locales, suppose the number of nodes of the location of the viable ambulance is represented by i = 1.2 .... , I. A coverage matrix is a matrix of T * I * K whose elements a_t,i,k are valued at 1 if at time t, the k-vertex is covered by location i, and the value 0 is reverse. This coverage matrix is an assignment representation of the maximum ability of network vehicle nodes to mask request nodes. Next is the estimation of local busyness by maximizing the number of requests for all nodes, from the request rate multiplied by the coverage reliability matrix. Taking into account that for each node, a specific measure of reliability is chosen:

$$\max \sum_{i=1}^{n} \lambda_i x_i^2 - \sum_{j=1}^{m} \sum_{l=1}^{p} D_{t,k} Y_{t,j,k} \qquad (1)$$

Testing is done by varying the size of the maximum number of ambulances at the node to the destination and the number of requests. Data on ambulance demand using the Sampling Approach are shown in table 1:

Tabel 1. Ambulance arrival data generated from uniform distribution

Y	Node J	Number of Ambulances	Average Response Time	Demand
1	1	2	14.9	7
2	2	3	9.1	7
3	3	2	7.1	6
4	4	1	10.3	6
5	5	2	8.7	6
6	6	1	10.8	8
7	7	2	8.5	5
8	8	2	9.9	5
9	9	3	12.9	6
10	10	2	13.8	6
		20	10.6	62

3.1. Pseudocode for Minimization Response Time

Response time has a high level of importance to ensure patients can be evacuated in a timely manner thereby reducing the risk of death. The pseudocode to minimize the response time of an ambulance call can be written as follows:

```
Input: Number of demand, Total of facility, speed of ambulance, Time limit, Distance
Output: Average Time, Demand;
Process : Begin
Generate a Local Potential;
Calculate initial distance; (using Euclidean distance equation) Calculate Time;
Threshold Time less than Time limit;
Generate set range;
Set Max time, Demand;
for i=1 to i<total threshold of facility
Calculate:
      x i = x! + rand 0 1 × x! − mutual vector ∗ BF 1 ;
      x i + 1 = x! + rand 0 1 × x! − mutual vector ∗ BF 2 ;
Conditions:
      if x(i)=~0 then
      if x(i) less than Max time then
      Average time = x(i)
      Demand = index x(i) break;
end;
else continue;
end
End
```

3.2. Pseudocode for Optimization Allocation Relocation Ambulance

In addition to response time, another important thing in the ambulance relocation allocation process is the optimization of the placement of the number of ambulances at one node as an ambulance base. The pseudocode for ambulance allocation and relocation optimization can be written as follows:

```
Input: Total of Node, Fleet Size, RT of fleet, Average Response Time, Total
of demand, Random range, Distance, Size of Coverage;
Output: Facility Numb. and Response Time
Process:
Generate set of random demand; Calculate initial distance; travel time;
Calculating Coverage;
Threshold Time ≤ Time limit;
Generate neighbor set Local search;
Set Max time, Random Demand;
for i = 1 to i < total time limit
Calculate mutual phase:
Conditions:
if ambulance (i) available then
      if x(i) ≤ Max time; Average time = x(i);
      Demand = index x(i)
End
```

3.3. Model Optimization Calculation Results

From the calculations carried out using the algorithm on solving the minimization of response time and the optimization algorithm for the allocation of the number of ambulances on the base, an overview of the number of ambulances that have the most potential to be placed in each base is obtained. These results can be used as recommendations for government authorities in managing ambulances in the city.

Table 2. Data on the number of ambulances for allocation and relocation taking into account the number of calls and response time

Node J	Demand	Avg Time response Limit	Local Potential
1	7	10	10, 5, 1, 6, 9, 7
2	7	8	1, 5, 10, 6, 9, 7, 2, 8
3	6	12	10, 5, 1, 6, 5, 3, 7
4	6	12	2, 5, 1, 6, 4, 7, 10
5	6	10	3, 5, 10, 6, 1, 4, 8, 2
6	8	10	10, 5, 3, 2, 1, 9
7	5	8	7, 2, 5, 6, 4, 5, 3
8	5	12	10, 6, 5, 3, 8, 5
9	6	8	9, 8, 3, 5, 9, 2, 3, 4
10	6	8	6, 5, 7, 8, 3, 2, 10, 1
	62	9.8	

4. CONCLUSION

The author has developed a hybrid model to optimize the allocation relocation of ambulance management in smart city. The main feature of the system lies in the redeployment scenarios that allows city authority determine the number of ambulances for each base. The author also provides a number of computational approaches such pseudocode to facilitate the implementation of this model in the form of a decision support system (DSS) so that computational results can be showed on real data, and the proposed system can effectively solve real life instance in smart city.

Smart application design that is able to provide the hospital recommendations for patients as the final sequence for ambulance allocation relocation problems, even though it is one of the main factors to provide intelligence characteristics of an ambulance management. Although these technologies were not considered in this study, they will undoubtedly play a role in determining what system installation is recommended as a standard feature in future ambulances for future research.

REFERENCES

Abdelgawad, A., Yelamarthi, K., & Khattab, A. (2017). IoT-based health monitoring system for active and assisted living. *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST*, *195 LNICST*, 11–20. https://doi.org/10.1007/978-3-319-61949-1_2

Ashmawy, M. N., Khairy, A. M., Hamdy, M. W., El-Shazly, A., El-Rashidy, K., Salah, M., Mansour, Z., & Khattab, A. (2019). SmartAmb: An integrated platform for ambulance routing and patient monitoring. *Proceedings of the International Conference on Microelectronics, ICM*, *2019-Decem*, 330–333. https://doi.org/10.1109/ICM48031.2019.9021900

Brotcorne, L., Laporte, G., & Semet, F. (2003). Ambulance location and relocation models. *European Journal of Operational Research*, *147*(3), 451–463. https://doi.org/10.1016/S0377-2217(02)00364-8

Carvalho, A. S., Captivo, M. E., & Marques, I. (2019). Integrating the ambulance dispatching and relocation problems to maximize system's preparedness. *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2019.11.056

Chuang, C. L., & Lin, R. H. (2007). A maximum expected covering model for an ambulance location problem. *Journal of the Chinese Institute of Industrial Engineers*, *24*(6), 468–474. https://doi.org/10.1080/10170660709509061

Glover, F. (1989). Tabu Search—Part I. *ORSA Journal on Computing*, *1*(3), 190–206. https://doi.org/10.1287/ijoc.1.3.190

Hartama, D., Mawengkang, H., Zarlis, M., & Sembiring, R. W. (2017). Smart City: Utilization of IT resources to encounter natural disaster. *Journal of Physics: Conference Series*, *890*(1). https://doi.org/10.1088/1742-6596/890/1/012076

Indrajit, R. E. (2012). Ict pura. *Seri 999 E-Artikel Sistem Dan Teknologi Informasi*, 1–4.

Karkar, A. G. (2019). *Sistem Ambulans Cerdas untuk Menyoroti Rute Darurat*. 255–259.

Nickel, S., Reuter-Oppermann, M., & Saldanha-da-Gama, F. (2016). Ambulance location under stochastic demand: A sampling approach. *Operations Research for Health Care*, *8*, 24–32. https://doi.org/10.1016/j.orhc.2015.06.006

Reeves, C. (1975). Chapter 3 GENETIC ALGORITHMS Part A : Background. In *Information Sciences* (Issue May). https://doi.org/10.1007/978-1-4419-1665-5

Repede, J. F., & Bernardo, J. J. (1994). Developing and validating a decision support system for locating emergency medical vehicles in Louisville, Kentucky. *European Journal of Operational Research*, *75*(3), 567–581. https://doi.org/10.1016/0377-2217(94)90297-6

Serra, D., & Marianov, V. (2011). New Trends in Public Facility Location Modeling. *SSRN Electronic Journal*, *May*. https://doi.org/10.2139/ssrn.563843

Sorensen, P., & Church, R. (2010). Integrating expected coverage and local reliability for emergency medical services location problems. *Socio-Economic Planning Sciences*, *44*(1), 8–18. https://doi.org/10.1016/j.seps.2009.04.002

Wijaya. (2018). Menuju Konsep Smart City. *ResearchGate*, *February 2016*, 1–9.

Zhen, L., Sheng, S., Xie, Z., & Wang, K. (2015). Decision rules for ambulance scheduling decision support systems. *Applied Soft Computing Journal*, *26*, 350–356. https://doi.org/10.1016/j.asoc.2014.10.001