Proceedings of the Fourth Australian International Conference on Industrial Engineering and Operations Management, Melbourne, Australia, November 25-27, 2025

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AU04.20250073
Published: November 25, 2025

Analysis of the Location of Emergency Ambulances in the City of Sorocaba-Brazil Using Generic Data Generation and Clustering Methods

Rodrigo Luiz Gigante
Industrial Engineering Department
Engineering School
Facens University, Sorocaba-SP, Brasil
rodrigo.gigante@facens.br

Aníbal Tavares de Azevedo
Faculty of Applied Sciences
University of Campinas (UNICAMP), Limeira-SP, Brasil
atanibal@unicamp.br

Takaaki Ohishi
Faculty of Electrical and Computer Engineering at the State University of Campinas
University of Campinas (UNICAMP), Campinas-SP, Brasil
takaaki@unicamp.br

Abstract

This paper analyzes the optimization of ambulance base locations in the city of Sorocaba, São Paulo, Brazil, through clustering methods and synthetic data generation. Sorocaba currently operates with a single SAMU ambulance base, located near the city center, which results in long travel distances and potentially delayed emergency responses. To address this issue, synthetic datasets of emergency calls were created to simulate incidents across the city, maintaining confidentiality while ensuring realistic data. Four clustering techniques—K-means, Gaussian Mixture Model (GMM), Agglomerative Clustering, and Spectral Clustering—were applied to identify alternative base configurations and compare them to the existing single-base system. The evaluation considered maximum and total distances traveled to respond to calls. Results showed that implementing multiple bases significantly improved system performance, reducing both total and maximum distances by more than 50% compared to the current setup. For instance, with four or more clusters, the total distance decreased from 11,084.75 km to less than 7,000 km, and the maximum distance dropped from 26.422 km to below 11 km, depending on the method used. Among the clustering approaches, K-means and GMM provided the most consistent balance between total and maximum distance reduction. These findings demonstrate the potential of clustering-based approaches to redesign emergency medical service systems and highlight the advantages of using synthetic data to overcome limitations in obtaining sensitive real-world datasets. The publicly available synthetic data generator developed in this study enables replication and adaptation to other urban contexts, providing a valuable tool for researchers and decision-makers. In addition, the paper recommends advancing the analysis by applying multi-criteria decision-making methods to define the optimal number of bases and discrete-event simulation to determine the appropriate number of ambulances required. The contributions of this research provide practical evidence that relocating ambulance bases using clustering methods can enhance emergency response efficiency, reduce travel distances, and potentially increase survival rates in urban populations.

Keywords
Emergency Medical Services, Ambulance Location, Clustering Methods, Synthetic Data Generation, Urban Healthcare Optimization.

1. Introduction
With the constant population growth in large cities, it is necessary to correctly size emergency and urgent care services, select the correct types of vehicles for assistance, and allocate resources at geographically distributed bases throughout the cities. In Brazil, there are two main public emergency and urgent care services: SAMU (Mobile Emergency Care Service) 192 and the Fire Department (Fire Department) 193. In many cities, these services have separate, unintegrated call centers. If an accident occurs on a public road with several witnesses, two witnesses may call different services and request two emergency vehicles. Furthermore, these services have different ambulance configurations, which can be of different types depending on the specific needs of each region, making call handling and classification crucial to the proper functioning of the system, and increasing the citizen's chance of survival. Public ambulances are used to treat people in urgent and emergency cases and are also used in hospitals, emergency rooms, and health departments to meet the demands of the municipal health system for internal patient transportation needs. Thus, an ambulance can be used to transport patients to other cities for appointments or exams, or to transfer them from one hospital to another. (Andrade, 2012)

Ambulance positioning is a critical factor in the emergency system, with the various types of ambulances and their configurations. Examples include: (i) the motorcycle ambulance, staffed by a licensed motorcyclist with the necessary equipment for initial care in cases where the individual's transportation is not necessary; (ii) the Basic Support Unit (USB), staffed by nurses and/or nursing technicians; (iii) the Advanced Support Unit (USA), staffed by a doctor and a nurse/nursing technician; and (iv) Mobile ICUs, which are vehicles with more technology and equipment for the most serious cases. Calls to advanced support units and Mobile ICUs are generally fewer (Figure 1).

This paper presents a study on the approximate distance between the vehicle locations and incidents in the city of Sorocaba, São Paulo, Brazil. Data were generated for this study using a synthetic data generator. The data generator is available for use at:
https://colab.research.google.com/drive/1aYC2A8aaD-0Ze6NXxZtU4238QS9UepvY?usp=sharing,
and the generated data can be found on Drive:
https://drive.google.com/file/d/1p7L_xVoSPbdlMX2fG4YuehSjkKI9teA0/view?usp=sharing

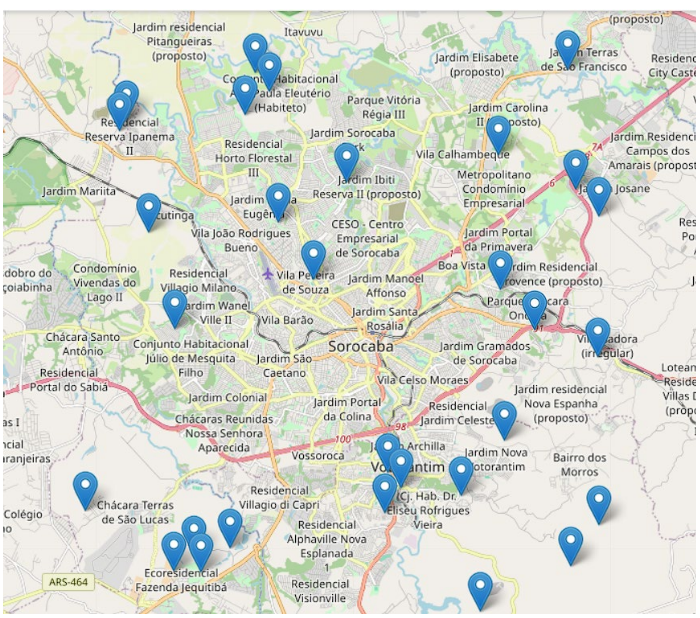

Figure 1. 30 artificially generated calls

The SAMU base in Sorocaba is located near the city center, slightly offset to the northern region, which is the most populated area. The coordinates of the base are latitude -23.4784923353165 and longitude -47.4760365108656. The city currently has a single base for locating vehicles, from which they are dispatched according to calls. Figure 2 below shows the route calculations for 50 random calls.

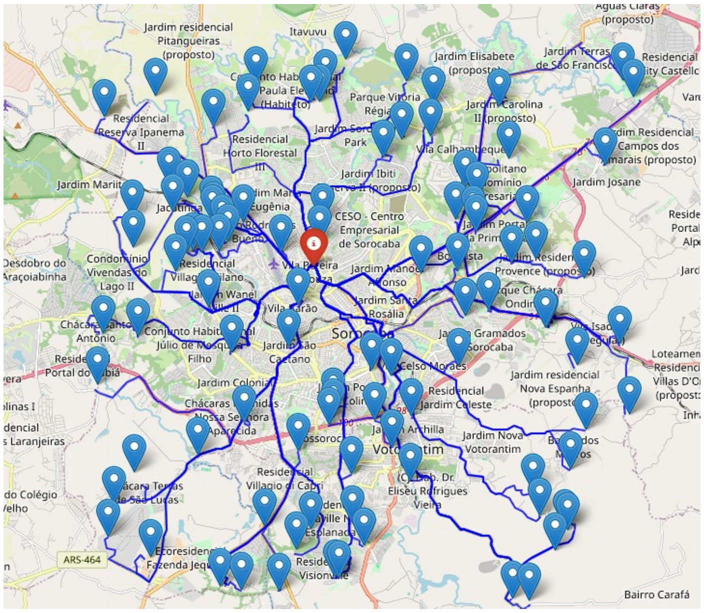

Figure 2. Routes from the base to the calls

1.1 Objectives
This study aims to compare the base location of ambulances in SAMU Sorocaba with the use of more bases through clustering methods. The maximum distance will be used to compare the number of bases and methods.

2. Literature Review
To analyze the state-of-the-art in vehicle location problems using clustering, multicriteria decision-making, and discrete-event simulation, the Springer, ScienceDirect, Web of Science, and Scopus databases were consulted. A total of 177 papers were used in this work, of which five articles serve as the basis for the study. The Figure 3 describes the prism methodology process used in the systematic literature review.

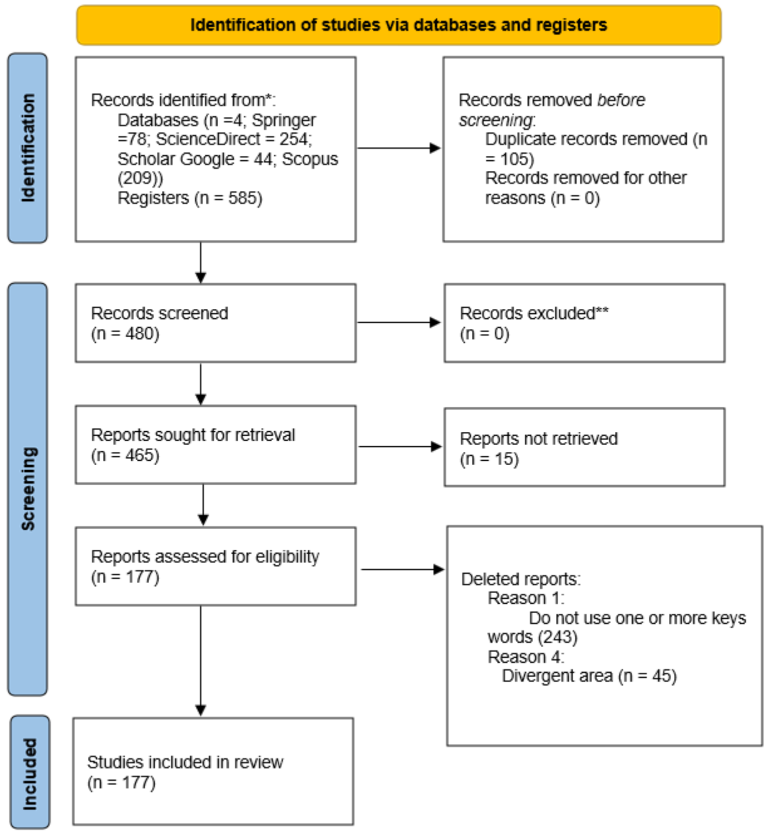

Figure 3. Prisma diagram

The paper presented by Stummer, Doerner, Focke, & Heidenberger (2004), entitled "Determining Location and Size of Medical Departments in a Hospital Network: A Multiobjective Decision Support Approach," uses a two-phase solution method. First, they developed a mathematical model to represent the problem, then applied a multiobjective tabu search to determine the best location for medical departments. This was followed by clustering to determine the best size and location for departments in a hospital network.

To validate the proposal, the authors solved a numerical problem using data from hospitals in a large German city. Four objectives were analyzed for the problem: distance: represents the distance the patient must travel to the hospital; beds: represents the number of beds available for the patient; rejection: provides the probability that the patient cannot be treated due to exceeding the hospital's capacity; and finally, rejection: represents the number of beds that will be reduced after system restructuring. The authors considered only five hospitals, three major types of departments (internal medicine, surgery, and gynecology), a constant number of beds for each planning unit (10), a maximum of 50 planning units (500 beds) for each department, and a constant 10% slack needed to meet peak demand.

The work results in a modeling proposal that contributes to the analysis of multi-objective scenarios for decision-making using metaheuristics and clustering methods. However, for larger problems, this method may not be efficient. Yang, Su, Zhou, and Qin (2020), in the article "Ambulance allocation considering the spatial randomness of demand," performed a descriptive analysis of data from the Songjiang district to verify the annual geographic distribution of the data. The authors then developed a variation of the Gaussian Mixed Model to resize the specially distributed demand partitions. To validate the result, demand was generated randomly, without loss of generality, considering data from previous years. Then, a deterministic model was used to determine the best location for ambulances.

Two years of data from the Songjiang district were used to validate the proposal. Five different scenarios for the system were analyzed. Finally, the authors present some challenges to be overcome: 1) spatial randomness is a challenge and needs to be better addressed in practice; 2) the Gaussian Mixed Model method can be considered for cluster determination; 3) a better description of special randomness reduces unexpected delays in the system; 4) the occupancy fraction of each cluster and ambulance may not be equal due to the special randomness of the problem.

The authors Zhukovskaya, Beggicheva, and Zhukovski (2022) in Computer Simulation of Spatial Placement of Emergency Medical Stations in Urban Agglomerations applied a clustering method to determine the best geographic location for bases and emergency vehicles. The study used data from the Russian city of Yekaterinburg, with approximately 450,000 records. The authors then used the K-medoid method to determine the number of clusters required, considering the following constraints: 1) a target response time of 20 minutes; 2) the service area of the vehicles must be a maximum of 50 km2. Thus, 9, 10, and 11 clusters were studied for the city. To determine the optimal number of clusters, the authors decided to choose the one with the shortest total travel time possible. Thus, the model resulted in 9 clusters with an estimated total travel time of 48 minutes.

Bharsakade, More, Nandeshwar, Narnaware, & Patil (2023), in the article "Emergency Facility Location of Ambulances Using K-Means Clustering and Minimax," the authors used the k-means method along with the minimax method to determine the optimal number and location of ambulances and thus reduce the number of deaths in the city. M. Soufyane, L. Chakir, and B. Jaouad (2023) in "New approach to solve the Uncapacitated Facility Location Problem using Continuous Hopfield Network and modified K-means clustering" use the Maximum Stable Set Problem (MSSP) and the Continuous Hopfield Network (CHN) to determine the initial number of clusters. They then used K-means to create the clusters to generate the shortest possible response time. The results were compared to the exact uncapacitated solution of the problem, with satisfactory results.

3. Clustering Methods

Clustering is an unsupervised learning technique whose objective is to categorize a data set into groups (clusters). Each cluster is composed of elements that are like each other and, at the same time, sufficiently distinct from the objects in other clusters. The clustering process involves several fundamental steps:

1. Feature extraction and selection – from the original data set, the most representative variables are selected.
2. Clustering algorithm design – the algorithm is chosen or adapted considering the specific characteristics of the problem.
3. Result evaluation – the validity and quality of the obtained clusters are verified.
4. Result explanation – the clustering is interpreted pragmatically, highlighting its practical application.

In clustering evaluation, two main metrics are used:

- Distance, more suitable for quantitative data, measures how "far" two points are in a feature space.
- Similarity, more suitable for qualitative data, measures the degree of similarity between elements.

The methods used to compare the current location of the vehicles are: k-means, agglomerative clustering, spectral clustering, and Gaussian mixed model. Details of each method are presented below:

3.1 K-means

The K-means method is one of the most widely used in clustering problems. Its objective is to minimize variability within clusters (intra-cluster sum of squares) and ensure that the groups have similar variance.
The procedure follows three main steps:

1. Initialization – the initial centroids are randomly defined (the number of clusters is predetermined).
2. Assignment – each point is associated with the closest centroid, according to the distance metric.
3. Update – the centroids are recalculated, and the process is repeated until the clusters stabilize.

This method is efficient and highly interpretable, but it depends on the prior selection of the number of clusters.

3.2 Agglomerative Clustering

Hierarchical agglomerative clustering is a method that uses the opposite principle to K-means: initially, each element is treated as an individual cluster, and progressively, the closest groups are merged to form larger clusters. The most common distance metrics include:

- Manhattan (or city-block) distance – evaluates displacements considering all dimensions, such as walking block by block in a city.
- Euclidean distance – measures the straight-line distance between two points.

The main aggregation methods are:
- Single-linkage – merges clusters with the closest points to each other.
- Complete-linkage – merges clusters considering the most distant points.

This method is useful when a hierarchical representation of the data is desired, often visualized in dendrograms.

3.3 Spectral Clustering
Spectral clustering transforms the problem into a graph theory context. In it, the data is represented by a similarity graph, and a Laplacian matrix is constructed to capture the connections between the points.

Based on the eigenvalues and eigenvectors of this matrix, the data is projected into a lower-dimensional space, where the separation into clusters becomes clearer. This method is especially advantageous in scenarios involving non-linear or complex-shaped clusters, where algorithms such as K-means can have limitations.

3.4 Gaussian Mixture Model (GMM)
The Gaussian Mixture Model (GMM) considers that the data are generated by a combination of several Gaussian distributions, each representing a cluster. Unlike K-means, GMM does not rigidly assign each point to a single cluster, but rather estimates the probability of belonging to each group. The algorithm uses the Expectation-Maximization (EM) method:
- Step E (Expectation) – the probability of each point belonging to each distribution is calculated.
- M-Step (Maximization) – The parameters of the Gaussian distributions are updated to maximize the likelihood of the observed data.

This method is quite flexible, as it allows clusters to have different elliptical shapes, sizes, and orientations, better capturing the complexity of the data.

The Elbow method was used to determine the initial number of clusters in the system. This method calculates the "gain" for each cluster added to the k-means function. Thus, as the function becomes more asymptotic, the gain from adding a cluster decreases. As shown in Figure 4 below.

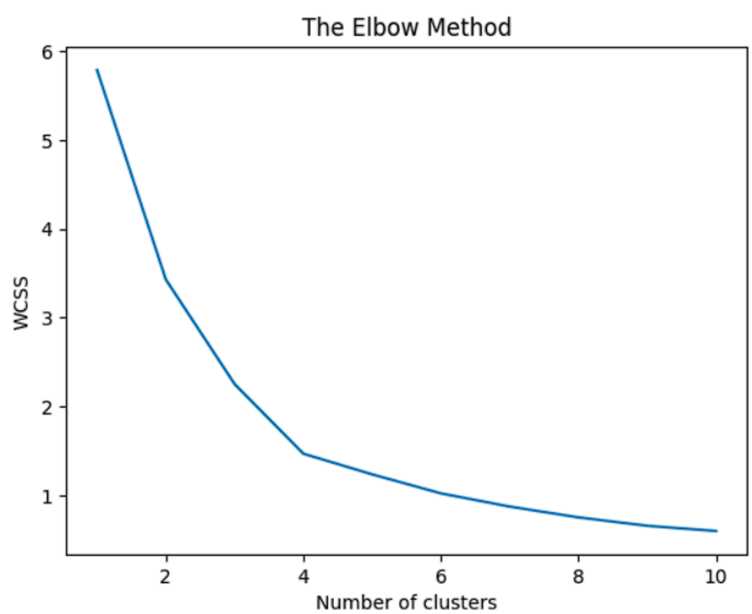

Figure 3. The Elbow Method

As a result of the Elbow method, 4 clusters were initially used, for more detailed analysis the number of clusters was increased to 6. In this way, the 4 classification methods, K-means, Gaussian Mixed Model, Agglomerative Clustering and Spectral Clustering were executed. Figure 5 below shows an example of the application of the K-means method with 5 clusters.

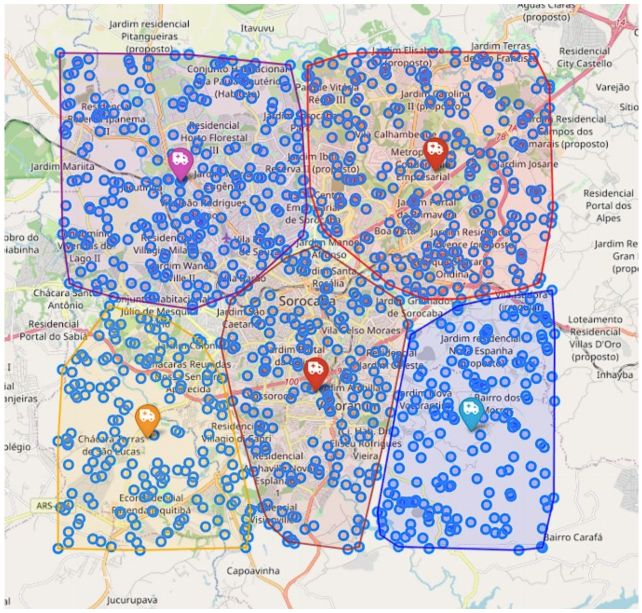

Figure 5. K-means with 5 clusters

After clustering, the routes for responding to each call were calculated, and the maximum distance and total distance traveled were entered into a table. Figure 6 below shows an example of route calculation for a k-means model with four clusters.

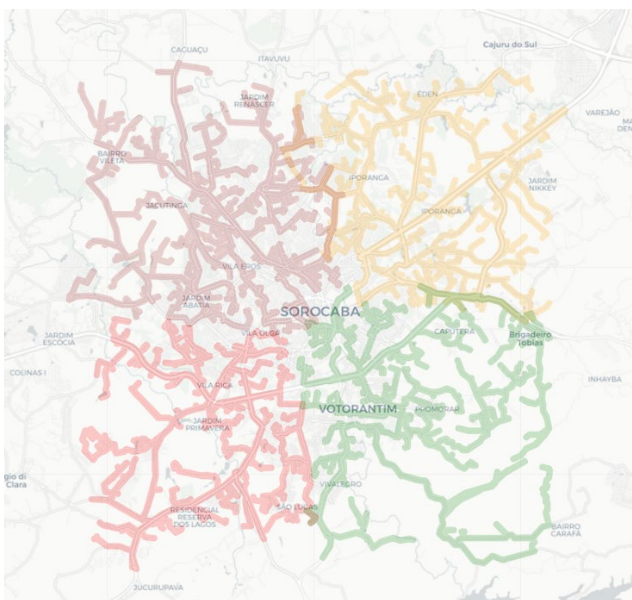

Figure 6. Routes of k-means with 4 clusters

4. Data Collection

Due to the difficulty in obtaining data from city halls in large cities without exposing citizens and, at the same time, maintaining the reliability of the information, synthetic data generation was used as a tool in this article. The data was collected through the generator available at: https://colab.research.google.com/drive/1aYC2A8aaD-0Ze6NXxZtU4238QS9UepvY?usp=sharing, and the generated data can be found on Drive:

https://drive.google.com/file/d/1p7L_xVoSPbdlMX2fG4YuehSjkKI9teA0/view?usp=sharing this data was published in Zenodo with the title: A database for determining the location and quantity of ambulances that must be available in a emergency medical care.

The data are available to any researcher and can be regenerated for any city in greater or lesser quantities and at different call intervals.

5. Results and Discussion

The results of applying the clustering methods, with the calculated distances between the suggested base, which is the center of the clusters, and the calls, are presented in Table 1 below. The table shows the total distance traveled for all calls and the maximum distance within the cluster. For all methods, the number of clusters found the smallest maximum distance.

Table 1. Results of clustering methods

Method	Number of Clusters	Total Distance	Maximal Distance
K-means	4	8221.416	18.314
	5	7438.079	12.205
	6	6905.452	10.213
Gaussian	4	7344.023	15.445
	5	7704.144	10.811
	6	6739.056	10.331
Spectral	4	7549.886	20.036
	5	9277.677	14.988
	6	6582.574	18.002
Agglomerative	4	7949.257	12.525
	5	6951.584	14.331
	6	6597.876	11.542

In the city's current situation with a single base, the total distance is 11,084.75 km, and the maximum distance is 26,422 km. The results in Table 1 demonstrate that the use of any additional base will result in a reduction in the distance to service by more than 50%.

As a recommendation for progress in this study, multi-criteria decision-making methods will be applied to define the optimal number of bases, as well as discrete event simulation to determine the number of vehicles that should be present in the system.

6. Conclusion

This study successfully compared the current single ambulance base location in SAMU Sorocaba with the use of multiple bases determined through various clustering methods, fulfilling its primary objective. The comparison utilized the maximum distance as a key metric to evaluate the efficacy of different base configurations.

The results conclusively demonstrate that implementing additional bases, as suggested by clustering methods, leads to a substantial reduction in both total travel distance and maximum distance to service incidents. Specifically, using even a minimum of four clusters (additional bases) resulted in a reduction of over 50% in service distance compared to the city's current single-base configuration, where the total distance is 11,084.75 km and the maximum distance is 26,422 km.

All four evaluated clustering methods—K-means, Gaussian Mixture Model, Spectral Clustering, and Agglomerative Clustering—showed a decrease in maximum distance with an increased number of clusters. The methods generally yielded favorable results in identifying optimal base locations that minimize response distances.

A unique aspect of this research is the use of a synthetic data generator to simulate ambulance calls and incidents, overcoming the difficulty of obtaining real-world data while maintaining reliability and avoiding citizen exposure. This data generator and the generated data are publicly available for use by other researchers, making it a valuable resource for similar studies.

As a recommendation for future progress, the study suggests applying multi-criteria decision-making methods to precisely define the optimal number of bases and utilizing discrete event simulation to determine the ideal number of vehicles required within the system. This indicates that while the location problem has been addressed, further optimization of resources is envisioned.

The findings provide a concrete recommendation for the city of Sorocaba to reconsider its single SAMU base location, which is currently near the city center and slightly offset to the northern, most populated region. Adopting a multi-base system based on clustering could significantly improve emergency response times and potentially increase citizens' chances of survival.

References

Andrade, L. A. C. G., Heurística baseada em colônia artificial de abelhas para o problema de localização de bases, alocação e realocação de ambulâncias, Dissertação, Universidade de São Paulo, São Paulo, SP, 2012.

Aringhieri, R., Bocca, S., Casciaro, L. and Duma, D., A simulation and online optimization approach for the real-time management of ambulances, *Proceedings of the Winter Simulation Conference (WSC)*, 2018. doi:10.1109/wsc.2018.8632231

BRASIL, Portaria nº1.864, de 29 de setembro de 2003. Available: http://bvsms.saude.gov.br/bvs/saudelegis/gm/2003/prt1864_29_09_2003.html. Accessed on May 11, 2018.

Chen, A. and Lu, T., A GIS-based demand forecast using machine learning for emergency medical services, *Proceedings of the International Conference on Computing in Civil and Building Engineering*, 2014. doi:10.1061/9780784413616.203

Chen, A. Y., Lu, T.-Y., Ma, M. H.-M. and Sun, W.-Z., Demand forecast using data analytics for the preallocation of ambulances, *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 4, pp. 1178–1187, 2016. doi:10.1109/jbhi.2015.2443799

Cheng, Y.-H. and Liang, Z.-X., A strategic planning model for the railway system accident rescue problem, *Transportation Research Part E: Logistics and Transportation Review*, vol. 69, pp. 75–96, 2014. doi:10.1016/j.tre.2014.06.005

Church, R. and ReVelle, C., The maximal covering location problem, *Papers of the Regional Science Association*, vol. 32, pp. 101–118, 1974. doi:10.1007/BF01942293

Ciconet, R. M., Tempo de resposta de um serviço de atendimento móvel de urgência, Tese de Doutorado, Escola de Enfermagem, Universidade Federal do Rio Grande do Sul, Porto Alegre, RS, 2015.

Díaz-Hierro, J. et al., Evaluation of time-series models for forecasting demand for emergency health care services, *Emergencias*, 2012.

Doudareva, E. and Carter, M., Discrete event simulation for emergency department modelling: A systematic review of validation methods, *Operations Research for Health Care*, 2022. doi:10.1016/j.orhc.2022.100340

Enayati, S., Mayorga, M. E., Toro-Díaz, H. and Albert, L. A., Identifying trade-offs in equity and efficiency for simultaneously optimizing location and multipriority dispatch of ambulances, *International Transactions in Operational Research*, 2018. doi:10.1111/itor.12590

Ernst, A., Jiang, H., Krishnamoorthy, M. and Sier, D., Staff scheduling and rostering: A review of applications, methods and models, *European Journal of Operational Research*, vol. 153, no. 1, pp. 3–27, 2004. doi:10.1016/s0377-2217(03)00095-x

Farughi, H., Mostafayi, S. and Arkat, J., Healthcare districting optimization using gray wolf optimizer and antlion optimizer algorithms (case study: South Khorasan healthcare system in Iran), *Journal of Optimization in Industrial Engineering*, 2019. doi:10.22094/JOIE.2018.766.1489

Feng, W.-H., Lou, Z., Kong, N. and Wan, H., A multiobjective stochastic genetic algorithm for the pareto-optimal prioritization scheme design of real-time healthcare resource allocation, *Operations Research for Health Care*, vol. 15, pp. 32–42, 2017. doi:10.1016/j.orhc.2017.08.005

Frazão, T. D. C., Santos, A. F. A., Camilo, D. G. G., Costa Júnior, J. F. and Souza, R. P., Priority setting in the Brazilian emergency medical service: A multi-criteria decision analysis (MCDA), *BMC Medical Informatics and Decision Making*, vol. 21, no. 1, 2021. doi:10.1186/s12911-021-01503-z

Ghobadi, M., Arkat, J., Farughi, H. and Tavakkoli-Moghaddam, R., Integration of facility location and hypercube queuing models in emergency medical systems, *Journal of Systems Science and Systems Engineering*, 2021. doi:10.1007/s11518-021-5500-x

Gigante, R. L. and Azevedo, A. T., Study of the impact of the start time of work shift on the efficiency of an emergency system through a simulation model of discrete events, *Gestão e Produção*, vol. 29, pp. e4421, 2022. doi:10.1590/1806-9649-2022v29e4421

Goldberg, D. M. et al., Modeling local ambulance resource scheduling, *Proceedings of the 25th Americas Conference on Information Systems (AMCIS)*, 2019.

Hajiali, M. et al., An interactive decision support system for real-time ambulance relocation with priority guidelines, *Decision Support Systems*, 2022. doi:10.1016/j.dss.2021.113712

Harper, P. et al., Emergency medical services modelling, *Proceedings of the 3rd International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH)*, 2013. ISBN 9789898565693

Hatami-Marbini, A. et al., An emergency medical services system design using mathematical modeling and simulation-based optimization approaches, *Decision Analytics Journal*, 2022. doi:10.1016/j.dajour.2022.100059

Jagtenberg, C. J., Bhulai, S. and van der Mei, R. D., An efficient heuristic for real-time ambulance redeployment, *Operations Research for Health Care*, vol. 4, pp. 27–35, 2015. doi:10.1016/j.orhc.2015.01.001

Jánošíková, Ľ., Kvet, M., Jankovič, P. and Gábrišová, L., An optimization and simulation approach to emergency stations relocation, *Central European Journal of Operations Research*, 2019. doi:10.1007/s10100-019-00612-5

Jilani, T., Housley, G., Figueredo, G., Tang, P.-S., Hatton, J. and Shaw, D., Short and long term predictions of hospital emergency department attendances, *International Journal of Medical Informatics*, 2019. doi:10.1016/j.ijmedinf.2019.05.011

Kamali, A., Sajadi, S. M. and Jolai, F., Optimising emergency medical centres location with a response-time-decreasing approach using hybrid methods of optimisation and simulation, *International Journal of Services and Operations Management*, vol. 36, no. 1, pp. 72–91, 2020. doi:10.1504/ijsom.2020.106793

Kaveh, M., Kaveh, M., Mesgari, M. S. and Paland, R. S., Multiple criteria decision-making for hospital location-allocation based on improved genetic algorithm, *Applied Geomatics*, 2020. doi:10.1007/s12518-020-00297-5

Klein, R. W., Dittus, R. S., Roberts, S. D. and Wilson, J. R., Simulation modeling and health-care decision making, *Medical Decision Making*, vol. 13, no. 4, pp. 347–354, 1993. doi:10.1177/0272989x9301300411

Kozan, E. and Mesken, N., A simulation model for emergency centres, 2005.

Larson, R. C., Hypercube queuing model for facility location and redistricting in urban emergency services, *Computers and Operations Research*, vol. 1, pp. 67–95, 1974.

Lupa, M. et al., Emergency ambulance speed characteristics: A case study of Lesser Poland voivodeship, southern Poland, *GeoInformatica*, vol. 25, no. 4, pp. 775–798, 2021. doi:10.1007/s10707-021-00447-w

Mayorga, M. E., Bandara, D. and McLay, L. A., Districting and dispatching policies for emergency medical service systems to improve patient survival, *IIE Transactions on Healthcare Systems Engineering*, 2013. doi:10.1080/19488300.2012.762437

McCormack, R. and Coates, G., A simulation model to enable the optimization of ambulance fleet allocation and base station location for increased patient survival, *European Journal of Operational Research*, vol. 247, no. 1, pp. 294–309, 2015. doi:10.1016/j.ejor.2015.05.040

Meinzer, N. and Storandt, S., Decision support in emergency medical systems: New strategies for dynamic ambulance allocation, *Proceedings of the AAAI Workshop - Technical Report*, 2013. ISBN 9781577356752

Monks, T. and Meskarian, R., Using simulation to help hospitals reduce emergency department waiting times: Examples and impact, *Proceedings of the Winter Simulation Conference (WSC)*, 2017. doi:10.1109/wsc.2017.8248000

Muruyama, L. Y. and Souza, R. M., Identificação de regiões similares em relação ao tempo de resposta de chamados do SAMU-Bauru, *Gestão e Saúde*, vol. 9, no. 2, pp. 180–191, 2018.

Ordu, M., Demir, E. and Davari, S., A hybrid analytical model for an entire hospital resource optimisation, *Soft Computing*, vol. 25, no. 17, pp. 11673–11690, 2021. doi:10.1007/s00500-021-06072-x

Revelle, C. and Snyder, S., Integrated fire and ambulance siting: A deterministic model, *Socio-Economic Planning Sciences*, vol. 29, no. 4, pp. 261–271, 1995.

Rodriguez, S. A., De la Fuente, R. A. and Aguayo, M. M., A simulation-optimization approach for the facility location and vehicle assignment problem for firefighters using a loosely coupled spatio-temporal arrival process, *Computers & Industrial Engineering*, vol. 157, 107242, 2021. doi:10.1016/j.cie.2021.107242

Silva, P. M. S., Análise do serviço de atendimento móvel de urgência (SAMU) de Belo Horizonte via simulação e otimização, Dissertação, Universidade Federal de Minas Gerais, Belo Horizonte, MG, 2010.

Souza, R. M., Morabito, R., Chiyoshi, R. Y. and Iannoni, A. P., Análise da configuração de SAMU utilizando múltiplas alternativas de localização de ambulâncias, *Gestão e Produção*, vol. 20, no. 2, pp. 287–302, 2013. Stummer, C., Doerner, K., Focke, A. and Heidenberger, K., Determining location and size of medical departments in a hospital network: A multiobjective decision support approach, *Health Care Management Science*, vol. 7, no. 1, pp. 63–71, 2004. doi:10.1023/b:hcms.0000005399.23600.69

Toregas, C., Swain, R., Revelle, C. and Bergman, L., The location of emergency service facilities, *Operations Research*, vol. 19, no. 6, pp. 1363–1373, 1971.

Tsai, C.-W., Chiang, M.-C., Ksentini, A. and Chen, M., Metaheuristic algorithms for healthcare: Open issues and challenges, *Computers & Electrical Engineering*, vol. 53, pp. 421–434, 2016. doi:10.1016/j.compeleceng.2016.03.005

Tsai, Y., Chang, K.-W., Yiang, G.-T. and Lin, H.-J., Demand forecast and multi-objective ambulance allocation, *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 32, no. 7, 1859011, 2018. doi:10.1142/s0218001418590115

Vermuyten, H., Namorado Rosa, J., Marques, I., Beliën, J. and Barbosa-Póvoa, A., Integrated staff scheduling at a medical emergency service: An optimisation approach, *Expert Systems with Applications*, vol. 112, pp. 62–76, 2018. doi:10.1016/j.eswa.2018.06.017

Yi, H., Xu, Z., Song, J. and Wang, P., Optimize the planning of ambulance standby points by using Getis-Ord Gi* based on historical emergency data, *IOP Conference Series: Earth and Environmental Science*, vol. 234, 012034, 2019. doi:10.1088/1755-1315/234/1/012034

Yousefi, M., Yousefi, M., Fathi, M. and Fogliatto, F. S., Patient visit forecasting in an emergency department using a deep neural network approach, *Kybernetes*, vol. 49, no. 9, pp. 2335–2348, 2019. doi:10.1108/k-10-2018-0520

Zarrinpoor, N., Fallahnezhad, M. S. and Pishvaee, M. S., Design of a reliable hierarchical location-allocation model under disruptions for health service networks: A two-stage robust approach, *Computers & Industrial Engineering*, vol. 109, pp. 130–150, 2017. doi:10.1016/j.cie.2017.04.036

Zeltyn, S., Lauterman, T., Schwartz, D., Moskovitch, K., Tzafrir, S., Basis, F. and Shtub, A., Simulation-based models of emergency departments, *ACM Transactions on Modeling and Computer Simulation*, vol. 21, no. 4, pp. 1–25, 2011. doi:10.1145/2000494.2000497

Zhou, L., Wang, S. and Xu, Z., A multi-factor spatial optimization approach for emergency medical facilities in Beijing, *ISPRS International Journal of Geo-Information*, vol. 9, no. 6, 361, 2020. doi:10.3390/ijgi9060361

Zhou, Z. and Matteson, D. S., Predicting Melbourne ambulance demand using kernel warping, *The Annals of Applied Statistics*, vol. 10, no. 4, pp. 1977–1996, 2016. doi:10.1214/16-aoas961

Biographies

Rodrigo Luiz Gigante Doctoral Student in Electrical Engineering (FEEC - UNICAMP); master's in production engineering from the University of São Paulo (2010); bachelor's degree in applied mathematics and Scientific Computing from the University of São Paulo (2007); Coordinator of the Production Engineering Course and Professor at Facens University. Experience in Production Engineering, Operations Research, Simulation of Discrete Events, Scheduling, Queuing Theory, Production Planning and Control and Logistics.

Anibal Tavares de Azevedo graduation at Matemática Aplicada e Computacional from Universidade Estadual de Campinas (1999), master's at Electric Engineering from Universidade Estadual de Campinas (2002) and doctorate at Electric Engineering from Universidade Estadual de Campinas (2006). Has experience in Production Engineering, focusing on Linear, Nonlinear, Mixing and Dynamic Programming, acting on the following subjects: combinatorial optimization, operations research, systems simulation, integer programming.

Takaaki Ohishi holds a degree in Electrical Engineering from the University of São Paulo (1978) and a PhD in Electrical Engineering from the State University of Campinas (1990). He is currently a full professor at the State University of Campinas. He has experience in the area of Electrical Engineering, with an emphasis on Electrical Power Systems, working mainly on the following topics: pre-dispatch, economic dispatch, optimization, load forecasting and power systems.