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Hospital selection problem for Emergency Medical Services: Simulation and metamodeling of transport time

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Abstract

Emergency Medical Service (EMS) is a prehospital medical service. EMS faces many challenges to ensure efficient, effective, and equal service. Hospital selection is an important decision that impacts EMS performance, especially whiten an Emergency Department (ED) overcrowding context. The present paper aims to develop an EMS simulation model, a Design of Experiment (DOE) and an Artificial Neural Network (ANN) model as the first steps in developing a metamodeling-based optimization approach for optimizing hospital selection decisions. The simulation model was designed, validated and used to generate 3 different data sizes that serves as input for ANN model. The ANN model performances are compared and analyzed for different values of hyperparameters. Metamodels gives promising results in terms of accuracy and robustness. They may be used as surrogate model to optimize hospital selection decision, transport time, and improve the patient overall health care experience

Keywords: Hospital selection, Emergency medical service, Discrete Event Simulation, Design of Experiment, Artificial Neural Network.

1. Introduction

Emergency medical service (EMS) is the prehospital care service. It provides on-scene necessary care to stabilize patients and transport them to the hospital (if required). EMS quality impacts directly the patient's welfare. Ensuring efficient, effective, and fair EMS service is compulsory to secure patient care experience (Aringhieri et al., 2017).

EMS is a complex process marked by stochastic nature. Due to the multiple stakeholders (i.e., patients, human resources, government..) involved and their interrelationships. Analytical approaches like mathematical programming and queueing theory are difficult to use to express this complexity. As a result, simulation has been widely employed in the literature since this method enables accurate, detailed models of patient flow via the Emergency Medical Service (ECS) that account for complexity and stochasticity(L. Aboueljinane et al., 2013; Cimellaro et al., 2011)

Simulation techniques are descriptive techniques to support decision-making. However, simulation techniques are time and data-consuming. Furthermore, they present many scenarios without any optimality proof (Defraeye & Van Nieuwenhuyse, 2015; Vanbrabant et al., 2019). To overcome these drawbacks Simulation-Based Optimization (SBO) is used. The method uses optimization techniques to determine optimal solutions then it evaluates them through simulation;

Simulation-Based Metamodeling (SBM) is a common SBO method. SBM seeks an explicit expression

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(i.e., metamodel) that modal simulation inputs/outputs relationship. The metamodel is a model that describes another modal. The metamodel expression is used as an objective function.

EMS faces many challenges on the strategic, tactical, and operational levels. The main crucial decisions are ambulance location, relocation, dispatching, routing, and hospital selection (Aringhieri et al., 2017; Lee, 2014). The ambulance location problem seeks an optimal ambulance base location. Relocation problems adjust ambulance location with temporal and geographical demand changes. Dispatching decision assigns ambulance to an urgent call. The call is directly assigned if the ambulance is available. If not call is queued until the unit is available. After reaching the emergency site, the ambulance serves the patients and transfers them to the hospital (if necessary). The hospital selection problem seeks appropriate hospitals that optimize transfer time. After reaching the hospital, the ambulance is unavailable. It waits for an idle ED bed to discharge the patient. The waiting time until an ambulance is available is called turnaround time or offload time (Lee, 2014; Leo et al., 2016).

ED is the main hospital entrance. ED treats accident victims as well as medical and surgical crises. ED overcrowding problems extend the waiting time and threaten patient life (Yousefi et al., 2018). ED performance cannot be enhanced just by resource scaling; sophisticated prioritization methods as well as innovative organizational designs may prove to be more successful than straightforward capacity planning (Leo et al., 2016). Thus, selecting an appropriate hospital is a crucial decision that should be managed.

According to the literature, Hospital selection is one of the least researched topics in EMS literature (Lee, 2014). Most studies focus on ambulance's location, relocation, dispatching, and routing policies (Caicedo Rolón & Rivera Cadavid, 2021). The objective of this paper is to investigate the impact of hospital selection policy on transfer time.

Furthermore to apply SBM to hospital selection problems. To the best of our knowledge, no study tackles hospital selection through the SBM approach.

The paper is organized into 7 sections. Section 2 presents available literature reviews on EMS hospital selection. Section 3: present the EMS process. Section 4: present DOE. Section 5 depicts the SBM model. Section 6 presents and discuss results while Section 7 sums up the study and highlights future research directions.

2. Literature review

Hospital selection is one of the least researched topics in EMS literature (Lee, 2014). Most studies focus on the ambulance's location, relocation, dispatch, and routing policies (Caicedo Rolón & Rivera Cadavid, 2021).

(Caicedo Rolón & Rivera Cadavid, 2021) reviewed publications that address EMS hospital selection. They found that the primary aims are: (1) Designing a method for optimal patient assignment from ambulance to the hospital. (2) Designing a method to support Hospital Selection (HS) decision-making. (3) Developing mobile applications and information systems through the internet and exploring their implementation on HS decision-making.

According to available literature, Hospital selection decision is treated under two approaches (i.e., single and combined). In the single approach, patient assignment to the hospital is studied as the main decision. In the combined approach, HS is part of a combined decision that may include different decision levels. For instance: Strategic-operational (e.g.,(El-Masri & Saddik, 2012)), Tactical-operational (e.g.,(Lina Aboueljinane et al., 2014)), and operational-operational (e.g.,(Knyazkov et al., 2015)). HS may be included as one of the main decisions or just as part of the problem criteria. HS is studied under single or multiple HS criteria. The multiple criterion combination differs from study to study. The statistic below represents commonly used criteria (i.e., Single or a part of multiple criteria combinations). The most used criteria are closeness 83, 33%, hospital capacities 62.5%, and shortest queue or highest number of beds 45.83% (Caicedo Rolón & Rivera Cadavid, 2021).

Closeness refers to the selection of the closest hospital to the emergency scene. While the hospital capacities criterion takes into account hospital resources and specialization. Indeed, under the shortest queue or highest number of free beds criterion, patients are directed to a hospital with a short waiting room queue length. If no patient is waiting, patients are directed to the hospital with the most empty ED beds (Lee, 2014). Other criteria are considered in the literature such as quality of service (e.g.,(Leo et al., 2016)), insurance coverage (e.g.,(Enders, 2010)), patient resources (e.g.,(Velásquez-Restrepo et al., 2011)), and patient wish (Caicedo Rolón & Rivera Cadavid, 2021).

Closeness is considered a natural HS policy. In practice, the majority of the patient are assigned according to closeness criteria in either peacetime or disaster time (Auf der Heide, 2006; McCaig & Burt, 2001). The aim is to increase the chance of survival and lessen painful time. This policy may be considered suitable in the absence of ED crowding. It ensures maximum ambulance availability and the shortest time to begin service(Lee, 2014).

However, EDs are experiencing overcrowding issues. The hospital selection dilemma is becoming increasingly important (Knyazkov et al., 2015). Available literature presents different hospital selection policies to improve the patient care experience. One of which is preferential policy. It is a selection policy that uses historical data on patient transfers to a hospital to calculate the likelihood to select each hospital(Enders, 2010). Furthermore, hospital selection may be subject to jurisdiction. Thus, the hospital must respond to an emergency event that occurs in a specific predetermined area(Caicedo Rolón & Rivera Cadavid, 2021). Besides, a shorter transfer policy assigns patients to a hospital that provides the shortest transfer time (i.e. transport time plus turnaround time). The objective is to reduce the response time(Enders, 2010).

Among others, ambulance diversion is a solution to smooth the flow and improve the patient care experience. The diversion policy may be defined as an HS policy that works in tandem with the ambulance diversion. The policy is based on factors such as the number of occupied ED beds and the number of waiting room patients (Burt et al., 2006; Deo & Gurvich, 2011; Johansson et al., 2010). Ramirez-Nafarrate et al. (Ramirez-Nafarrate et al., 2011) tested two hospital selection policies under two ambulance diversion policies. Results highlight the potential of designing suitable selection and ambulance diversion policies to improve the patient care experience.

However, the ambulance diversion application produced conflicting results. It lengthens the transport time, delays care, raises the death rate, and reduces hospital revenue. As a result, many initiatives have been implemented to prevent ambulance diverts (Castillo et al., 2011; Patel et al., 2006).

In the same perspective, (Lee, 2014) investigated the effects of four HS policies (i.e. closer, deviation, join the shorter queue, and shorter transfer time) on response time. Then, they proposed a new policy based on three decision principles. So, the hospital selected is the closer, the less congested, and the more centrally located. Results show that the new policy outperforms the four policies. It reduced the response time by 90%, 68, 8%, 99, 6%, and 67, 7% over the diversion policy, JSQ, closest policy, and STT respectively. However, results show that regarding the transfer time, the 3C policy‘s performance is not better than the other policies. The trade-off may be reached by adjusting the weight parameter w, which is operational scenario dependent.

EMS performances are improved from two. The first is the system view that considers resource utilization, the number of patients received, etc. The second is the patient view that considers the care experience efficiency (length of stay) and effectiveness (survival rate) (Wears & Winton, 1993). The most used HS performance metrics are transport time and waiting time (i.e.,) with 33.33% each followed by mortality rate, resources utilization, and response time 8.33% each (Caicedo Rolón & Rivera Cadavid, 2021). Transfer time combines travel time (i.e., time to travel to hospital) and turnaround time (i.e., Period from arrival to hospital to Ambulance departure).

Machine learning (ML) is a powerful decision tool. To the best of our Knowledge only one paper tackle hospital selection by using Machine learning(Caicedo Rolón & Rivera Cadavid, 2021).Therefore, there is no SBM application for hospital selection. In the present paper, we will develop Discrete Event Simulation (Section 3), DOE (Section 4) and the Artificial Neural Network metamodel (Section e 5) as first steps of simulation-based metamodeling process in order to explore and optimize hospital selection policy to reduce the EMS patient transfer time.

3. The DES model

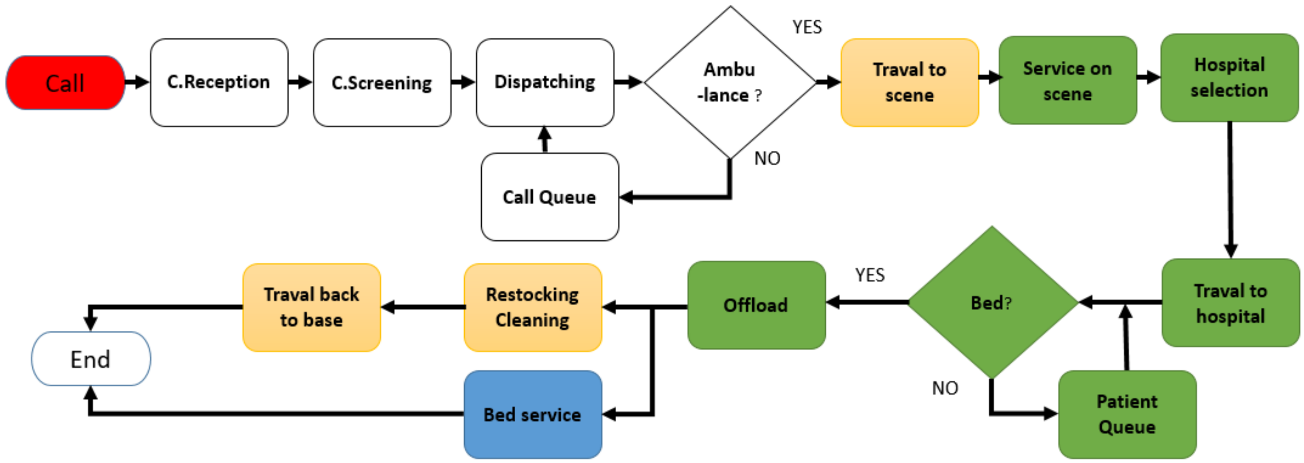

Figure 1: EMS process.

3.1. EMS system

In this article, we modelled the EMS/ED process from the reception of the emergency call until the discharge of patient from the ED of the hospital. Figure 1 depicts this process in several steps.

The process is triggered by an emergency call. The receptionist receives the call and screens it into an urgent and non-urgent call. Non-urgent calls do not require any action, the receptionist rejects them. Urgent calls are dispatched according to the ambulance dispatching policy.

According to the literature, ambulances are dispatched following common practice: greedy policy (i.e., closest available)(Alanis et al., 2013; Dean, 2008). The dispatcher allocates the patient to the closest available ambulance. Otherwise, patients wait for an idle ambulance in a queue managed by FCFS policy. Ambulances are located in EMS bases. Dispatched ambulances are prepared and then directed to the emergency scene location. Patients receive on-site care, then travel to the selected hospital.

Our modal is based on a specific HS policy. The territory is segmented into 10 demand areas. Each demand zone is assigned to a specific hospital. A hospital may be assigned to one or more emergency zone. However, a demand zone is assigned to one hospital. The total number of hospitals is four. The initial assignment is based on the minimum distance between the hospital and the emergency zone.

After reaching the hospital, if a bed is available, the patient is transferred immediately and the ambulance is discharged. Otherwise, the patient waits in a queue. After patient's discharge, the ambulance is restocked and cleaned to prepare for a future emergency. The ambulance is then considered available and can serve queued emergency calls according to FCFS policy. If the queue for ambulance is empty, it travels back to the ambulance base. We assume that the territory contains one central base.

Hospital capacity is an important criterion that influences HS policy. According to literature, bed is the primary resource impacting ED overcrowding (Lee, 2014). The present model includes hospital capacity constraints by including ED bed numbers in each hospital: 2, 3, 3, 4 beds in hospital 1, 2, 3 and 4, respectively.

We assume that the four hospitals receive walk-in patients at the same rate. Walk-in patients share hospital beds with ambulance patients. Ambulance patients are prioritized over walk-in patients. We do not consider any other patient prioritization rule (e.g., severity of injury).

This study aims to analyze the effect of hospital selection policy on transfer time (i.e. time from the departure of ambulance with the patient from the scene, until the end of ambulance offload in the hospital.

3.2. The DES model design

The DES conceptual model of the EMS system was implemented in the simulation tool ARENA 14.0 on a laptop Intel CORE i5. The Arena model translates the EMS process depicted in Figure 1. To construct a realistic model, we used data of Fez EMS published in (Frichi et al., 2022) to determine travel times. We also inspired our EMS model parameters' from other studies(Almehdawe et al., 2016; Lee, 2014; Leo et al., 2016).

Table 1: summarizes the model data.

Period of time	Distribution
Dispatching time (min)	0.5+ ERLA(1.57,3)

On-site service time (min)	0.999 + GAMM(12.2, 6.57)
Offload time (min)	UNIF (5 , 10)
Bed service time ()	EXPO(150)*(taux2+1)

3.3. The DES model verification and validation

Simulation model verification and validation are important steps. To complete this step we followed. (Kleijnen, 1995) recommendations. We started by verifying the model step by step. After we verify the intermediate outputs. Then we launch the Arena animation to trace and verify the overall system behavior.

To validate the DES model, we performed a sensitivity analysis by varying the following input parameters of the DES model: arrival rate, number of beds, length of stay, and number of ambulances. We assess the impact of these changes on the following indicators: Queue for the ambulance, queue for beds in each hospital, transfer time, and resource utilization. We defined initial values based on real data, then we varied the values using the Arena tool: Process Analyzer (PAN). We increased sequentially the controls; the variation is in the range [+0%, +100%] with step 25%.

When we rise the arrival rate the ambulance queue time rises considerably to reach an explosion point when durations become unacceptable from realistic, efficient, and effective perspectives.

Also, the variation of bed number impacts the ED's Length Of Stay LOS, and the transfer time. The variation in the number of ambulances affects the ambulance queue time durations.

The verification and validation steps show that the model represents accurately the real system for the particular objectives of the study.

4. The Design of Experiment

Simulation-based metamodels or surrogate models are simplified models that capture the relationship linking the simulation model input and output. The mathematical estimation of metamodels is defined using a sample of input/output points obtained from the simulation model. The choice of this sample is important to ensure efficiency of the metamodel. It is usually based on the Design of Experiment (DOE). DOE is a robust data-gathering and analysis tool that may be applied to a wide range of experimental scenarios. Within a simulation experiment, DOE determines the factor to be investigated, the levels of each element, and the number of simulations runs to ensure efficiency.

Indeed, (Sanchez et al., 2018) advocate using DOE to convert a simulation study into a DOE-based simulation experiment that provides the most information about the dynamics of the system under study while executing an appropriate number of simulation runs in a relatively short period. The resulting input/output database will subsequently be utilized to fit and validate metamodels.

The DOE choice is metamodel's type dependent. In fact, (Alam et al., 2004) claim that the choice of DOE influences metamodel's accuracy. They studied Artificial Neural Networks (ANN) using various DOEs to investigate this effect. They determined that when the metamodel is generally smooth (e.g., polynomial regression models or similar), typical experimental techniques may be appropriate. When the metamodel is more sophisticated and non-linear, traditional DOE is ineffective. As a result, the authors recommended a modified Latin hypercube DOE with a knowledge domain.

Latin Hypercube Design (LHD) is popular in the computer experiment(Viana, 2016). LHD requires fewer data than other DOE (e.g., full factorial design) while ensuring a good space covering. Indeed, LHD samples each factor once at each level. Besides the relationship between the number of design points and variables is linear, rather than exponential(Syberfeldt et al., 2008). LHD is recommended when the number of factors is high and the underlying function is unknown (Kleijnen, 2005). For more information about LHD see (Viana, 2016). In our study, we implement LHD in a tool MATLAB through the function lhdisign (n,p). We constructed three samples of sizes (200, 500, and 1000). We run the sampling plan on our simulation model. We used the resulting database to feed our ANN metamodel.

5. The ANN metamodel

Metamodel choice is based on widely known, considered, and documented tools. ANN is a popular metamodel set using data provided through simulation. ANN can learn complex non-linear functions effectively (Zeinali et al., 2015). These networks are usually composed of numerous layers. Each subsequent layer has a connection to the previous layer. The first is connected to the network input, and the final layer produces the network's output. To improve the prediction and classification quality, the ANN adjusts the weights of each layer during the learning process(Kamber & Han, 2018).

Before implementation, we pre-possessed data to optimize the learning performance. We encode categorical data and scale variables to state in a range [0, 1]. We split data into a training set and a validation set (i.e., 20%, 80%). Then we tune ANN hyperparameters.

ANN is sensitive to hyperparameter tuning. According to the literature, there is no consensus about hyperparameter tuning. Generally, modelers follow a trial-and-error approach. We based our tuning on widely used values and the remaining on trial and error. **Error! Reference source not found.** depicts the ANN hyper-parameters and the corresponding widely used values.

Table 2: **Metamodel's hyperparameters.**

Metamodels	Hyperparameters	Range	Frequent	Our model choices
Artificial Neural Networks	Transfer function	{RBF, linear, sigmoid, quadratic error, hyperbolic tangent, ReLU.}	Sigmoid	Sigmoid
	Training function	{ levenberg-marquardt, backpropagation, feedforward}	Backpropagation	Backpropagation
	Learning rate	[0.1; 0,9]	0.45	0.1
	Epochs [200; 800000]	[200; 800000]	1500	30000
	Number of layers	[1; 4]	1	5
	Number of neurons	[1; 66]	10	
	Momentum	0.1	0.1	0.5

To implement our ANN metamodel, we use WEKA tool. It is important to validate a metamodel before it is used in an SBM approach (Wang & Shan, 2007). The choice of metrics is dependent on the metamodeling purpose and application (Barton, 2020). For our study, we validated our ANN through the following accuracy metrics: Correlation Coefficient (CC), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Root-Relative Error (RRE) and Root Relative Squared Error (RRSE). The tuning validation loop is repeated until reaching satisfactory results.

6. Results and discussion

ANN metamodels are context dependent. We have to lead our trial and error test to determine suitable hyperparameter values under the hospital selection context using 3 databases of different sizes (i.e., 200, 500, 1000). To avoid underfitting and overfitting, each scenario was tested according to 10 cross-validation tests. We first started the tuning by using Weka's default hyperparameters (i.e.; Scenario SD). Then we tuned according to the literature widely used hyperparameters values (i.e.; Scenario SW). The first scenarios did not give promising results, as the coefficient of correlation CC is very low. We concluded that the strength of the relationship between variables was very low. Furthermore, error values were very high. Thus, to improve the metamodel's performance, we tested more than 100 tuning scenarios, with different hyperparameter combinations selected according to trial and error approach guided by expert's recommendations. Tables 3 depicts some of the scenarios that respect or are near the performance thresholds (i.e. S3 to S11). Tables 3 to 6 and Figure 3 show the multilayer perceptron's performance under different scenarios.

RMSE is a widely used metric to asses metamodel's accuarcy(Zeinali et al., 2015). However, RMSE values are analyzed differently. There is no consensus about RMSE thresholds. The common decision rule is the lesser is the better. To get over this limit, (Zeinali et al., 2015) combined RMSE with another metric $\frac{1}{1+RMSE}$ in order to have values in a range [0, 1]. They compare metamodel's performance for different data size, problem, and metamodels, then they choose the best metamodel among the trained metamodels (No threshold). (Singh et al., 2005) affirmed that half of the standard deviation of the measured data may be considered the maximum threshold for RMSE and MAE. Based on this recommendation another metric is developed: RMSE-observations standard deviation ratio (RSR), which divide the RMSE by the standard deviation of the observations. Similarly, no threshold is determined for RSR, the rule remains the same the lesser is the better (Moriasi et al., 2007).

To assess our metamodels, we used the following thresholds. Min = 0.5 for Correlation Coefficient CC (i.e., for moderate to very strong correlation) and_(Singh et al., 2005) thresholds as max for MAE and RMSE. For the remaining metrics, we consider the rule lesser is better.

For the database size 200, RMSE, and MAE for the first scenarios are below the thresholds, however, the other errors are very high. Moreover, the correlation coefficient is very low, the relationship is very weak for all the scenarios. The metamodels cannot be used to describe the EMS's system behavior.

For the database size 500, RMSE, and MAE are below the thresholds (i.e., the half of the standard deviation of 0.112). However, the CC is very low (i.e., under thresholds for all scenarios), and the remaining errors are very high (i.e., beyond 90%).

For the database size 1000, RMSE and MSE are beyond the thresholds, however, they are inferior to 200 and 500 cases' errors. Similarly, RAE, and RRSE values are low. Furthermore, the correlation coefficient is below the 0.6 thresholds. The relationship may be qualified as strong.

The promising scenario according to the aforementioned reasons is scenario 8. The metamodel may be used to explore the effects of changing hospital selection policy.

Table 3: Metamodel tuning scenarios.

Hyper parameters	Transfer function	Training function	Learning rate	Epochs	Number of layers	Momentum	Batch size
SD	Sigmoïd	Back propagation	0.3	500	5	0.2	100
SW	Sigmoïd	Back propagation	0.45	1500	1	0.1	100
S3	Sigmoïd	Back propagation	0.1	500	5	0.5	32
S4	Sigmoïd	Back propagation	0.1	500	5	0.5	64
S5	Sigmoïd	Back propagation	0.1	1000	5	0.5	64
S6	Sigmoïd	Back propagation	0.1	10000	5	0.5	64
S7	Sigmoïd	Back propagation	0.1	20000	5	0.5	64
S8	Sigmoïd	Back propagation	0.1	30000	5	0.5	64
S9	Sigmoïd	Back propagation	0.1	40000	5	0.5	64
S10	Sigmoïd	Back propagation	0.1	35000	5	0.5	64
S11	Sigmoïd	Back propagation	0.1	35000	1	0.5	64

Table 4: Metamodel performance results (Size: 200).

Scenarios	SD	SW	S3	S4	S5	S6	S7	S8	S9	S10	S11
CC	0.1344	0.0132	0.031	0.031	0.0307	0.0757	0.0808	0.0799	0.0804	0.08	0.027
MAE	0.1416	0.1075	0.1337	0.1337	0.1436	0.173	0.182	0.1878	0.1904	0.1892	0.0895
RMSE	0.196	0.1923	0.1888	0.1888	0.2049	0.2671	0.2891	0.302	0.311	0.3071	0.144
RAE (%)	179.1791	136.053	169.1837	169.1837	181.6	218.9768	230.3831	237.6825	241.0293	239.4372	113.25
RRSE (%)	152.1841	149.273	146.5993	146.5993	159.07	207.3791	224.4222	234	241.449	238.3712	111.82281
T	0.187	0.187	0.187	0.187	0.187	0.187	0.187	0.187	0.187	0.187	0.187

Table 5: Metamodel performance results (Size: 500).

Scenarios	SD	SW	S3	S4	S5	S6	S7	S8	S9	S10	S11
CC	0.3933	0.0092	0.4351	0.435	0.4831	0.53882	0.5309	0.5234	0.5178	0.5208	0.0013
MAE	0.08	0.0772	0.0825	0.0825	0.08	0.081	0.0828	0.0831	0.0845	0.836	0.0792
RMSE	0.14	0.1447	0.1316	0.1316	0.1387	0.1788	0.1883	0.1928	0.1968	0.1948	0.1471
RAE (%)	138.4473	120.4949	128.8485	128.8485	124.86	126.5	129.2639	129.8238	131.9907	130.6	123.64
RRSE (%)	105.5	105.7704	96.2306	96.2306	101.35	130.7121	137.6312	140.9647	143.8476	142.4	107.5
T	0.1865	0.1865	0.1865	0.1865	0.1865	0.1865	0.1865	0.1865	0.1865	0.1865	0.1865

Table 6: Metamodel performance results (Size: 1000).

Scenarios	SD	SW	S3	S4	S5	S6	S7	S8	S9	S10	S11
CC	0.4861	0.0721	0.5438	0.5438	0.6539	0.799	0.8167	0.8311	0.829	0.8311	0.0722
MAE	0.0698	0.0626	0.0551	0.0551	0.0528	0.0432	0.0405	0.0384	0.0391	0.0388	0.0645
RMSE	0.109	0.1176	0.0964	0.0964	0.0879	0.0712	0.0687	0.0657	0.0663	0.0658	0.119
RAE(%)	130.91	117.3823	103.2877	103.2877	98.9552	80.9933	75.96	71.9782	73.2	72.6992	120
RRSE(%)	97.686	105.3891	86.3548	86.3548	78.7341	63.7866	61.5462	58.8273	59.4239	58.9361	106
T	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056

CC: Correlation coefficient.

T: Thresholds

7. Conclusion

This paper studies hospital selection decisions for emergency medical services. For this purpose, we first implemented a discrete event simulation that mimics the EMS process from the reception of a call until the patient's discharge from the ED. We then used the developed simulation model with LHD DOE to construct input-output databases with different sizes, that best explores the solution space. These databases were finally used to train and test ANN metamodels with different combinations of hyperparameters.

The present study was limited by many constraints. First, the problem nature. In fact, the study requires many fields: simulation, DOE, ML, ANN and so on. Furthermore, ANN tuning impacts the metamodel's performance. There are many scenarios that should be explored and tested. However, it is infeasible to explore all the scenarios, thus defining promising one is important. However, the available literature do not provides enough guidance owing to the fact that hospital selection decision is generally under looked especially under metamodeling context. Choices are generally based on trial and error.

The present study may be extended in several ways. ANN data are dependent on the modeler's choices. In fact, metamodel hyperparameter conditions the metamodel performance. According to the literature, metamodel's tuning is generally based on a trial-and-error approach. Future studies should consider developing a framework to determine optimal hyperparameters. In this context, Hyper parameters optimization may be based on more exhaustive methods such as monarch butterfly optimization(Bacanin et al., 2020b), swarm intelligence(Bacanin et al., 2020a), Bayesian optimization(Cho et al., 2020), multi-threaded training(Połap et al., 2018), evolutionary optimization(Cui & Bai, 2019), genetic algorithm(Han et al., 2020), harmony search algorithm, simulated annealing, Pareto optimization, gradient descent optimization of a directed acyclic graph and others. In addition, the mathematical expression of the developed ANN metamodel may serve to predict the performance of different input (i.e. hospital selection strategies) and provides insightful answers to what-if scenarios However, we have no proof of the scenario's optimality without proof of their optimality. Thus, the preset study may be extended to cover optimization needs by using the analytical expression of the ANN metamodel as an objective function in an optimization model. This may provide a powerful decision support tool, for hospital selection decision-making. Finally, (Aringhieri et al., 2017) claim that EMS performance should be considered from different perspectives(Aringhieri et al., 2017). They considered a tradeoff between equity, efficiency, and effectiveness. In our study, we considered transfer time as a metric for hospital selection decisions. However, considering the transfer time as metrics covers just a part of the previous aspects. Other metrics should be considered, to explore the effects of optimal transfer time on effectiveness metrics (i.e., survival rate and morbidity rate), and ensure overall performance.

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