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A Novel Approach for Resource Allocation in Emergency Department of Hospitals

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Abstract— Emergency unit plays vital role in the hospital which is used to treat the patient who needs an immediate treatment. Critical patients need to be treated immediately, which requires sufficient resources. Resource planning is a most important scenario which needs to be considered while treating the patients in Emergency Department (ED) of hospitals by providing sufficient resources. Using simulation-based metamodels optimal resource allocation with minimum waiting time can be obtained. In this paper Monte Carlo Sampling (MCS) approach for efficient selection of training data has been proposed. Then experimentation for decision support using metamodels has been proposed to allocate resources and thereby address accuracy and robustness of the corresponding metamodels. This concept has been extended, in the proposed work to reduce the average waiting time of patients in need of emergency treatment.

Keywords— Emergency department, Resource planning, Simulation-based-metamodels, Decision support, Monte Carlo Sampling, waiting time.

I. INTRODUCTION

A resource [1] is a source or supply from which benefit is produced. Typically resources can be materials, energy, services, staff, and knowledge, or anything else that must be in order to do all of the activities that planned for. Every activity in activity list needs to have resources assigned to it. Before assigning resources, know their availability. Resource availability includes information about what resources are participating, when they are available, and the conditions of availability. Resource allocation is the process of assigning and managing assets in a manner that supports an organization's strategic goals.

Many emergency departments in hospital are critically overcrowded [2] and unable to respond to day-to-day emergencies, let alone disasters and acts of terrorism. Crowding is a crisis that results from the practice of boarding, or holding, emergency patients who have been admitted to the hospital in emergency department. Congestion in EDs occurs when there are more patients than can be seen in a timely fashion by the staff in the department. Crowding occurs when the identified need for emergency services exceeds available resources for patient care in the emergency department, hospital, or both. The practice of crowding endangers patient's life and results in delays in care and ambulance diversion. This has a significant negative effect on patient safety, comfort, and satisfaction. It also ties up resources, rendering emergency staff unable to care for additional patients from the waiting room or from an ambulance.

EDs act as a window [3] into the functioning of the entire health care system. Monitoring ED performance provides information to assess whether there is:

- Healthy flow of patients within the hospital
- An appropriately sized acute inpatient bed base
- Timely access to community and residential care services
- Effective links to primary health care, home and community support

This paper combines decision support system with suitable metamodels to relieve congestion in ED. Simulation-based-metamodeling optimization process as the core part of this decision supports system because it is important in cases especially where the time and the respective cost for reaching a feasible or optimal solution is really important. Since EDs are quite complex systems and it is difficult to model thorough analytical methods, computer simulation is widely used for modeling of these systems [3], [4]. Simulation is adopted to imitate the current state of any process. Simulation enables decision makers to imitate the behaviour of the system and provides a test bed to assess changes in operations and managerial policies and examine different alternatives. Even though, the simulation is not an optimization technique and to find the optimum value of decision variables, simulation-based optimization methods should be used [5]. In recent years, the iterative methods, especially a combination of simulation models with heuristics are used for planning and optimization in healthcare systems.

II. LITERATURE SURVEY

In the work of S. Trzeciak, E. Rivers [6] the various scenarios of the EDs have been described. Some of them include long waiting time for patients and congestion in ED [7], [8] which may lead to non availability of resources.

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As it was reported in the United States [9], ED visits went up about 20% between 1995 and 2005 while 381 EDs have been closed because they were not economically justified and the insurance companies could not repay their liabilities.

In the work of Horwitz et al [10] and sprivulis et al [11] it has been observed that overcrowding in EDs lead to intractable problems like long waiting time, diverting ambulance, forcing patients to vacate, and inflated workloads on the hospital staffs. a survey shows that in 2005 where 381 EDs have been closed due to resources in budget constraints.

Making decisions about ED's resources is a tedious task that has significant impact on ED's performance [12]. Any decision flaws can have serious consequences on patient's emergency service. The decision what we are taking should be analyzed and the hospital resources should be allocated more efficiently. Since EDs are stochastic environments and have time-dependent behavior based on patients this cannot be a straight forward one. The variations in the patient's arrival rates and service rates have greater impact on EDs performance. So the state of EDs is continuously monitored and their resources are planned to enhance system performance and reach to predefined standards.

Since EDs are quite complex systems and it is tedious to model thorough analytical methods, computer simulation widely used for modeling of the systems. The simulation is only an approximation technique not an optimization technique and to find the optimum value of decision variables [12]. Simulation models with heuristics are used for planning and optimizing in health care systems. In the work of Baesler and Sepulveda [13] simulation optimization model is used to improve patient flow in a cancer treatment canter.

Ahmed and Alkhamis [14] combined simulation with optimization to design a decision support tool for the operation of an ED at governmental hospital in Kuwait. In their work they focus was on providing optimal resource allocation which thereby provided 28% increase in patient throughput and an average of 40% reduced waiting time for the same resource(s).

Response Surface Modeling (RSM) is a popular metamodel used for over 50 years to optimize operations in a chemical engineering units. It uses second order polynomials in which pertinent co-efficient are estimated by minimizing the total residual error between fitted and target values [15].

On the other hand Radial Basis Function (RBF) can be used in the number of decision variables and the amount of non linearity in response increases and RSM becomes less applicable [15].

Artificial Neural Network (ANN) is another popular metamodel that can be used for training dataset in a simulated environment [15].

III. PROPOSED SYSTEM

The ED centre consists of two main sections, "Cardiac Care Unit (CCU)" for patients with heart problems and "General" for other patients. The patients are assessed [15] at the triage for the Emergency Severity Index (ESI) and categorized from ESI-1 to ESI-5 according to the severity level of patients. ESI-1 who are severely unstable patient, must be attended immediately by physician, often requires an intervention to be stabilized, ESI-2 are potentially unstable patient, must be seen promptly by a physician within 10 minutes, often requires laboratory/radiology testing/medication, ESI-3 are stable patient, should be seen urgently by a physician within 30 minutes, often requires lab/medication and usually is discharged. ESI-4 are stable patient, may be seen non urgently by a physician (or) midlevel provider, requires minimal testing or a procedure, and expected to be discharged and ESI-5 are stable patient, may be seen non urgently by a physician, requires no testing or procedure, and is expected to be discharged after a consultancy. The various level of ESI are categorized for better service delivery for cardiac patients Since resource planning to reduce total average waiting times of patients is more critical for CCU. The key resources in ED are depicted in table I.

Table I Decision Variables And Associated Resources

S.NO	Name of the resources	Name of decision variables
1	Triage nurses	x_1
2	Receptionist	x_2
3	Nurses	x_3
4	Heart Residents	x_4
5	Beds	x_5

The process begins when a patient arrives through the ED entrance door and ends when a patient is discharged from the ED or admitted into the hospital inpatients units. Based on the ESI, patients are categorized from 1 (most urgent) to 5 (least urgent) levels by triage nurses.

The triage system identifies:

(1) The acute level of patients
(2) Pathway each patient type goes through
(3) The corresponding resources

ESI-1 is the patients with urgent conditions. These patients are immediately admitted in CPR (Cardio Pulmonary Resuscitation) where they can be resuscitated. If CPR treatment is successful, the patient is transferred to CPU for further treatment. Then, ESI-2 patients skip the reception without waiting and directly go to CPU for treatment. ESI-3, ESI-4, and ESI-5 go through the receptionist who collects the patient's personal information and locates their files, where, the

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ESI-3 and ESI-4 patients go to the CPU to receive their services and ESI-5 patients go for a general physician for consultation and treatment then discharged from ED.

Once a patient enters the CCU, ECG (Electrocardiography) is assigned which measures the electrical conduction system of the heart is taken by a nurse. Following this, the patients wait for availability of heart residents who should decide whether the treatment is enough or not. If the treatment is enough, patients should leave the ED, or should be admitted to an inpatient care unit. If not, patients receive further treatment (such as lab tests, medical advice, monitoring and another ECG after a few hours). If there is any queue occurred for receiving different services except for CPR, then all predetermined staff should temporarily interrupt their tasks and give the needed services to this patient. The proposed decision support system can be used for creating guidelines in strategic, tactical, and operational management practices.

A. Problem Definition:

EDs require sufficient resources to meet the fluctuating demand [3] for emergency and after hours care, and well-developed connections with the rest of the health care system to effectively support their patients.

Here are some key resources such that it minimizes the patient waiting times subject to budget and capacity constraints. The optimization problem can be mathematically expressed in equation (1) and (2):

$$\min Z = f(x_1, x_2 \ldots\ldots x_n) \tag{1}$$

$$\sum_{i=1}^{n} c_i \;\; x_i \tag{2}$$

$$l_i \le x_i \le u_i \text{ , for i = 1.....5 and } x_i \text{ for i = 1.....5}$$

Where

- Z represents the total average W.T of patients
- $(x_1, x_2, \ldots, x_5)$ are decision variables .
- c_i is the monthly cost of each resource,
- B is the monthly budget value and
- l_i and u_i are the minimum and maximum capacity levels, respectively

All values of these parameters are determined by the managerial considerations.

B. Optimization:

Determines the values of the variables that minimize or maximize the objective function while satisfying the constraints. A good mathematical model of the optimization problem is vital in research. The objective of simulation is to minimize the total average waiting times of patients. Furthermore, only some important resources in the ED such as triage nurses, receptionists, nurses, residents and beds which can directly and significantly affect the waiting time. There are different methodologies in terms of mathematical formulation and the way of finding their parameters using the respective design points are considered. A proper metamodel could improve the accuracy and superiority of optimization results which can considerably influence the ED performance.

C. Metamodels:

Used to improve the efficiency of ED in the proposed work is as follows:

1. Response surface modelling (RSM)
2. Radial basis function (RBF)
3. Artificial neural networks (ANN)

1) Response surface modeling: Response Surface Models was initially developed over fifty years ago to determine the optimal operating conditions in chemical processes. All relevant studies usually prefer to use the lower order polynomials (e.g., the second order one); the difference is in the type of error generated by the response. In RSM, the errors are assumed to be random. The application of RSM to design optimization is aimed at reducing the cost of expensive analysis methods (e.g. finite element method or CFD analysis) and their associated numerical noise. The mathematical formulation of the second order response surface is described is expressed in equation (3)

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \sum_{j=1}^{k} \beta_{ij} x_i x_j + \varepsilon \tag{3}$$

Where k is the number of variables, β is regression coefficients and ε is error. The advantages of using RSM metamodels are the availability of known techniques for experimental designs, easy estimation of unknown parameters, and simple to interpret and assess. It is quite suitable and effective in a case study with a limited number of design variables and with not-highly-nonlinear response.

2) Radial basis functions based metamodel: There are multiple radials symmetric functions in Radial Basis Functions which are cantered at different points of design space. As the number of variables and the amount of nonlinearity in the responses is increased, the RSM becomes less applicable and RBF metamodels would be therefore a proper alternative technique. To have a suitable RBF which appropriately represents the nonlinear response, the basic functions should be cautiously chosen. Although there are various basic functions and each of them has their own characteristics, Gaussian functions are widely used in the recent studies. Furthermore, due to the diminishing influence of the radial points on the objective function by getting farther from the reference point, a given k centres $c_{1,} c_2, \ldots\ldots c_k \in R^d$ mathematical form of the radial basis function interpolation is expressed in equation (4)

$$Y = \sum_{i=1}^{k} W_i \varphi(\|x - c_i\|) + \varepsilon \tag{4}$$

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Where ‖.‖ is the Euclidean norm, u is the Gaussian function, and wi Є R for i = 1, . . . , k are coefficients. The RBF solver can be written in any programming language. MATLAB2 software is used to do programming and to find the best values of the parameters.

3) Neural networks based metamodel: Artificial Neural Networks (ANNs) are another popular type of metamodel which should be trained using a set of training data provided through simulation. ANNs have evoked great interest to be used as a metamodel because they are really powerful to learn the complex nonlinear functions in an efficient way. Typical feed forward networks with one hidden layer and sufficient neurons in other layers can be used for any kind of input–output mapping problems. Each subsequent layer has a connection from the previous layer, and the final layer produces the network's output. A mathematical form of a network with three layers can be expressed in equation (5)

$$Y = \sum_{j=1}^{l} W_j f\left(\sum_{i=1}^{k} v_{ij} f(x_i) + \alpha_j\right) + \beta + \varepsilon \tag{5}$$

k is the number of variables, f is the transfer function defined by the user, v_{ij} is the weight of the connection between the i^{th} input neuron and j^{th} hidden neuron, a_j is the bias in the j^{th} hidden neuron, w_j is the weight of connection between the j^{th} hidden neuron and the output neuron, l is the total number of hidden neurons, b is the bias of the output neuron, and e is the error. Three predetermined parameters of ANNs are:

(1) Hidden layers
(2) Neurons in each layer and
(3) Transfer functions

D. Sampling:

After choosing candidate metamodels, the training data should be processed through one of the sampling methods such that these samples could cover all important points. Sampling is a complex part of fitting a suitable metamodel. The sampling process depends on the function under study, metamodel used and constraints. In this work, Monte Carlo sampling approach is used for the selection of data's from the available training data sets. Monte Carlo methods (or Monte Carlo experiments) are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results. They are often used in physical and mathematical problems and are most useful when it is difficult or impossible to use other mathematical methods. Monte Carlo methods are mainly used in three distinct problem classes: optimization, numerical integration, and generating draws from a probability distribution. In principle, when the probability distribution of the variable is too complex, mathematicians often use a Markov Chain Monte Carlo (MCMC) sampler. The central idea is to design a judicious Markov chain model with a prescribed stationary probability distribution. Monte Carlo methods vary, but tend to follow a particular pattern:

1. Define a domain of possible inputs.
2. Generate inputs randomly from a probability distribution over the domain.
3. Perform a deterministic computation on the inputs.
4. Aggregate the results.

In this problem, three data sets including 20, 40, and 70 points are generated with the MCS function that generates *n* design points for *p* variables. Furthermore, the corresponding objective function for each design point is generated through simulation. Here addressed the advantages of Better handling of the large volume of data and improved emergency resource planning with the consideration of efficient sampling approach which were far quicker to use than the tables of random numbers that had been previously used for statistical sampling.

E. Meta model selection for decision support:

To choose the appropriate metamodel and to find the suitable size of samples, two indicators including accuracy and robustness should be initially defined. The accuracy criterion, which is usually measured by the Root Mean Square Error (rmse) in equation (6)

$$\text{rmse}=\sqrt{\frac{1}{k}\sum_{i=1}^{k} (y_i-\hat{y}_i)^2} \tag{6}$$

It indicates the average deviation of the metamodel outputs ($\hat{y}_i$) from the simulation output (yi). The robustness criterion is also measured using the standard deviation of one metamodel error value across different problems. In the next step, on performing cross validation techniques to find the total error of all nominated metamodels and to choose the best of them using the above-calculated indicators. It is worth mentioning that k-fold cross validation is widely used; however, k is generally an unfixed parameter that should be predefined. In this type of cross validation, the training data set are split into k subsets and the metamodel should be individually trained using each of these subsets and tested with the remaining subsets (called validation subset). Finally total errors are calculated for each metamodel. Before constructing the metamodels, all the respective decision variables and the objective function should be scaled therefore, it might cause a significant improvement in the process of objective function approximation.

F. Resource Allocation:

The metamodel-based optimization for resource planning is shown in Fig. 1. This figure illustrates how we can incorporate the simulation metamodel into a DSS [15]. The system user initially determines when the optimization process should be implemented. In the next step, the system status should be reported in an appropriate way. The user analyses the system in addition to constructing the simulation model with a suitable metamodel.

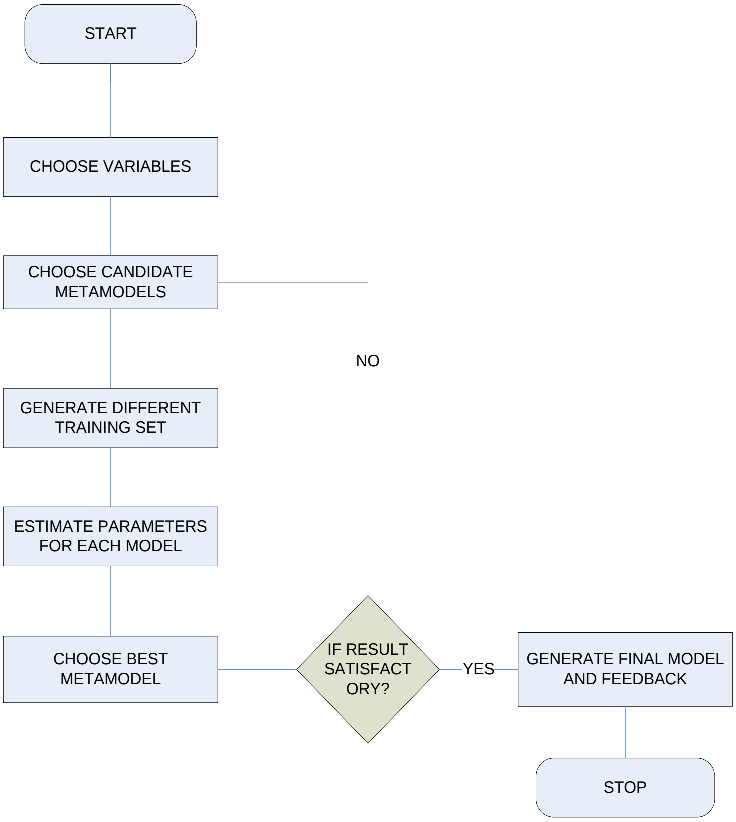

Fig. 1 Block diagram

Based on the user objectives, the user should update the simulation model. If there is a need for configuration then optimization is carried out with combination of metamodel and simulation, and finally, the optimal solutions are returned back to the simulation model for verification. This can be a repeated process for building the accuracy of the metamodel. After making the proper decision, it is implemented in system. The proposed decision support system can be used for creating guidelines in strategic, tactical, and operational management practices.

The Fig. 1 describes the meta model process by selecting the input variables , choosing a candidate metamodels generating the different training sets and estimating the parameters for each metamodel from that choosing the best metamodel according to the accuracy and robustness criterion , if the result of the metamodel is satisfactory the final metamodel is produced and the metamodel is produced and the feedback is produced, if the metamodel results are not satisfactory the process is continued from step choosing the best candidate metamodels.

IV. RESULTS AND DISCUSSION

The proposed system uses the following specifications namely MATLAB software used to do programming and to find the best values of the parameters. The RBF solver can be written in any programming language MATLAB software is used for simulation. ANN uses MATLAB for training the data set. Pentium IV 2.4 GHz processor, 80 GB hard disk, 256 MB RAM are used as hardware.

The datasets taken as training data are taken from the work of Farzad [15]. The datasets given as input to metamodels have sample size of 20, 40 and 70 respectively. The *rmse* values against the sample size are pictorially represented in Fig. 2 and Fig. 3. Where Fig.1 represents the sample datasets without using Monte Carlo approach and Fig. 2 using Monte Carlo approach. The graph reveals that the *rmse* is in fractional values when Monte Carlo approach is used for training the datasets. Thus Monte Carlo approach when used greatly reduces the error rate before the selection of metamodels.

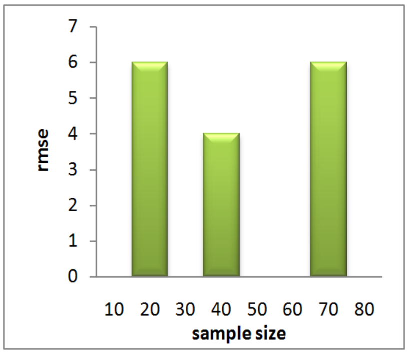

Fig. 2 Sampling of training datasets without Monte Carlo

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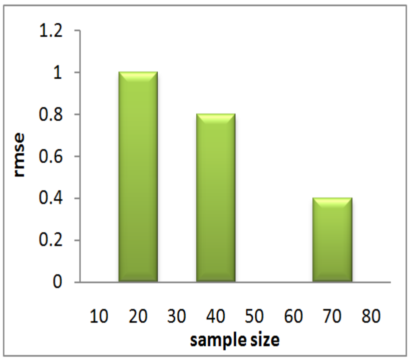

Fig. 3 Sampling of training datasets using Monte Carlo

The error rate encountered when using metamodels is represented in Fig. 4 and Fig. 5. In both the figures error rate is expressed in y-axis and type of metamodels in the x-axis. The graph reveals that ANN metamodel trained with 70 sample points have better performance in terms of both accuracy and robustness compared to other metamodels after the trained dataset is subjected to Monte Carlo approach. However, as there is a minor difference between the results of ANNs trained with 40 and 70 data points, ANN is preferred with less samples to reduce the number of evaluations which leads to reduction in running time.

The error rate encountered when using metamodels is represented in Fig. 3 and Fig. 4. In both the figures error rate is expressed in y-axis and type of metamodels in the x-axis. The graph reveals that ANN metamodel trained with 70 sample points have better performance in terms of both accuracy and robustness compared to other metamodels after the trained dataset is subjected to Monte Carlo approach. However, as there is a minor difference between the results of ANNs trained with 40 and 70 data points, ANN is preferred with less samples to reduce the number of evaluations which leads to reduction in running time.

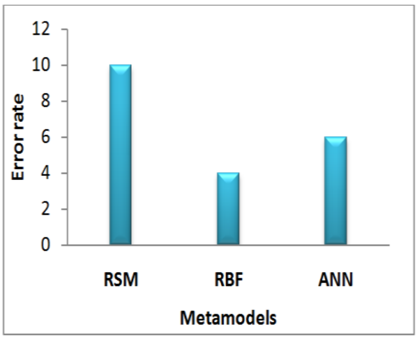

Fig. 4 Error rate of various metamodel before sampling

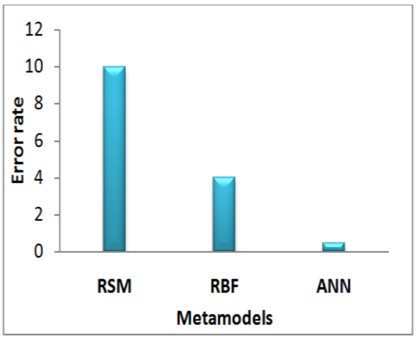

Fig. 5 Error rate of various metamodels after sampling

V. CONCLUSIONS

Simulation of training data along with selection of metamodels is a popular concept in healthcare systems. Literature reveals that the metmodels produce a fast and accurate solution along with management guidelines to optimize the performance of emergency departments in hospitals. Appropriate resources and planning is vital to promote, facilitate and sustain the functioning of the emergency department. The problem of sampling is also essential to determine efficient resource planning. In the proposed work Monte Carlo sampling approach has been extended for the selection of data from the available training data sets. Using Monte Carlo approach, variables can be approximated by taking the empirical mean of independent samples of the variables considered. In the proposed work decision support using metamodel-based optimization has been extended to allocate resources appropriately to thereby reduce the total average waiting time of patients in emergency need.

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