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Chaotic genetic algorithm and Adaboost ensemble metamodeling approach for optimum resource planning in emergency departments

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ABSTRACT

Long length of stay and overcrowding in emergency departments (EDs) are two common problems in the healthcare industry. To decrease the average length of stay (ALOS) and tackle overcrowding, numerous resources, including the number of doctors, nurses and receptionists need to be adjusted, while a number of constraints are to be considered at the same time. In this study, an efficient method based on agent-based simulation, machine learning and the genetic algorithm (GA) is presented to determine optimum resource allocation in emergency departments. GA can effectively explore the entire domain of all 19 variables and identify the optimum resource allocation through evolution and mimicking the survival of the fittest concept. A chaotic mutation operator is used in this study to boost GA performance. A model of the system needs to be run several thousand times through the GA evolution process to evaluate each solution, hence the process is computationally expensive. To overcome this drawback, a robust metamodel is initially constructed based on an agent-based system simulation. The simulation exhibits ED performance with various resource allocations and trains the metamodel. The metamodel is created with an ensemble of the adaptive neuro-fuzzy inference system (ANFIS), feedforward neural network (FFNN) and recurrent neural network (RNN) using the adaptive boosting (AdaBoost) ensemble algorithm. The proposed GA-based optimization approach is tested in a public ED, and it is shown to decrease the ALOS in this ED case study by 14%. Additionally, the proposed metamodel shows a 26.6% improvement compared to the average results of ANFIS, FFNN and RNN in terms of mean absolute percentage error (MAPE).

1. Introduction

Congestion in emergency departments (EDs) has been reported for decades as a worldwide problem in the healthcare industry while demand for EDs is increasing [1]. In the U.S. the number of visits to EDs from 1997 increased up to 23% in a decade, reaching about 222 visits per minute in 2007 [2]. EDs are complex systems by nature. They operate 24 h a day, seven days a week, while high operating costs are causes of budget shortages as EDs are obligated to attend to any arriving patient. At the same time, an error in their process may be life threatening.

Resource planning in EDs requires analyzing the whole system and finding the most efficient way to allocate resources. Such analysis is a challenging task because EDs are stochastic environments due to the influence of random variables [3]. For instance, patient arrival can be influenced by weather conditions or air pollution [4]. On the other hand, applying trial and error in ED resource planning may result in irreparable consequences. In order to overcome these issues, decision-makers need to monitor the system at the operational and tactical levels.

Since it is difficult to model EDs analytically, computer simulations are vastly used as a tool to monitor ED behavior [5–7]. Various computer simulations have already been applied to study different aspects of EDs. A study by Gul and Guneri [8] provided a review of simulation applications in normal and disaster conditions in EDs. Computer simulations allow hospital managers to observe system behavior and evaluate alternative system scenarios without interrupting routine operations.

In recent years, combinations of simulation and optimization techniques have been used in abundance to find near-optimum

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values of decision variables in complex systems including the healthcare industry [8,9]. Ahmed and Alkhamis [10] presented a discrete simulation combined with optimization to provide a decision-making support system (DSS) in an ED in Kuwait to reduce waiting time and increase patient throughput. They reported a 28% increase in patient throughput and a 40% reduction in waiting time. Cabrera et al. [11] and Taboada et al. [12] presented a DSS using a pure agent-based model and exhaustive search in an ED in Spain. Yeh and Lin [13] presented a simulation model combined with the Genetic Algorithm (GA) to find the near-optimum nursing schedule in an ED in Taiwan. The study reported 43.47% and 43.42% reductions in average queue times.

Selecting a key performance indicator (KPI) in ED simulation-optimization is a controversial subject [14]. There is no rule of thumb to select a KPI and variety can be found in the literature. Although all are related to ED crowding and patient satisfaction, the most commonly used KPIs in this field of study include the number of patients who leave without being seen (LWBS) [15–20], the number of discharged patients [12,20,21,22], length of stay (LOS) [12,15,20–24], time to see a doctor [15,16,23] and average waiting time [15,16,20,23–25].

Although optimization-simulation methods have been successfully applied in different ED-related problems, reviewing the past 10 years' worth of literature shows that a common problem with these methods is that they are computationally expensive to explore the entire search space in real-life optimization problems. In this study, an attempt is made to tackle this problem by applying a robust approximation model to find relationships between the inputs and outputs of the proposed DSS and make the process as fast as possible while maintaining reliable approximation. This type of relationship between inputs and outputs is called a "metamodel" [26].

Metamodels enable researchers to obtain reliable approximate model outputs without running expensive and time-consuming computer simulations. Therefore, the process of model optimization can take less computation time and cost. Simulation-based metamodels enable users to employ these tools in crisis decision-making when a case is serious and there is only a very short response time to manage it [27,28].

Machine learning methods have proven to be efficient in finding the nonlinear relation between the inputs and outputs of simulation models. While machine learning, and in particular neural networks, have been successfully employed for constructing metamodels in recent years, there has not been much effort on systematically increasing metamodel efficiency. The literature has shown that the performance of neural network-based metamodels (or predictors in the case of forecasting problems) can be improved, in some cases drastically, by utilizing an ensemble of different metamodels based on their individual performances [29]. Nevertheless, the potential of ensemble metamodeling has not been explored for the problem at hand. In this study, a robust ensemble algorithm is constructed through a systematic method. Three power machine learning approaches, namely ANFIS, FFNN and RNN are used to build the ensemble metamodel through two well-known ensemble approaches: bootstrap aggregating (bagging) and adaptive boosting (AdaBoost).

In this paper, an agent-based simulation is designed and constructed based on a real case study at an ED in a teaching hospital in the capital of the second largest Brazilian state by population. After verifying and validating the computer simulation model, different metamodels are used to find the metamodel with less error. A GA with a chaotic mutation operator is introduced to decrease the average length of stay (ALOS) in the ED while budget and capacity are considered the problem constraints.

The remainder of this paper is organized as follows: In Section 2, a detailed description of the case study and the problem definition are presented. The proposed metamodel approaches and GA are introduced in Section 3. The results from the simulation-based metamodeling approach, a comparison with other methods and the optimization results are given in Section 4. Finally, Section 5 presents the conclusions and future works.

Table 1
Manchester Triage System (MTS).

Priority level	Color	Safe time until first medical visit
Immediate	Red	Immediately
Very urgent	Orange	Up to 10 min
Urgent	Yellow	Up to 60 min
Standard	Green	Up to 120 min
Non-urgent	Blue	Up to 240 min

2. Risoleta Tolentino Neves emergency department

2.1. System description

Risoleta Tolentino Neves Hospital (RTNH) is a teaching hospital in the capital of Minas Gerais state of Brazil, Belo Horizonte. The ED of RTNH operates 24/7 and receives 162 patients a day on average. The ED contains different sections: pediatrics, orthopedics, suturing, yellow zone and emergency rooms (surgical and clinical). Each of these sections provides services for patients based on their problems. The yellow zone and clinical emergency respectively received the most and least patients among all sections, with 44% and 5% of all patients in the first half of 2016. The main resources in this ED are as follows:

1. Receptionists
2. Triage nurses
3. Doctors
4. Nurses
5. Nurse technicians

At one time, 2 receptionists, 1 triage nurse, 22 doctors, 5 nurses and 29 nurse technicians are working in the ED. Fig. 1 demonstrates the flow of patients in the ED. The procedure starts with patient arrival to the department. Patients may arrive by themselves, by ambulance, or in police custody. All patients except for those in police custody must visit a receptionist to register their personal information. Subsequently, they go to a triage nurse in the triage room. In the triage room, the patient's acuity is checked based on the Manchester Triage System (MTS). MTS categorizes patients into five categories: red, orange, yellow, green and blue [30]. Red is for patients with the highest acuity (most urgent) and Blue is for patients with the lowest acuity (least urgent). Patients in police custody can omit registration and go directly to the triage room. Table 1 shows the levels of patient propriety based on MTS.

Following triage, patients wait for the availability of the section where they need to be treated. Except for the suturing section, all sections contain beds. Patients in any section might go to the laboratory or X-Ray section for further examination and later return to their relevant section. After treatment in each section, the patient may leave the department or, depending on necessity, they go to the observation room. The process in the ED begins with registration for admission and concludes when the patient is released.

2.2. Simulation model

To simulate the mentioned system, an open-source multi-agent modeling environment is used, namely NetLogo 5.3.1 [31]. In order to make a reliable ED simulation model, data collection is needed. The main data collection elements in this simulation are as follows: