

A Simulation based Imperialist Competitive Algorithm for an Emergency Department to Reduce Door to Doctor Time

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Abstract

Decision making in complex systems is a difficult task and it can be more complex when high budgets are involved. The complexity and interdisciplinarity of healthcare industry problems make this industry one of the attention centers of computer-based simulation studies to provide a proper tool for interaction between decision makers and experts. Emergency departments operate 24 hours a day, seven days a week, including holidays. Therefore, interrupting their system in order to evaluate their performance and efficiency is almost impossible. The majority of patients in public health systems are suffering from long length of stay while hospital managers are struggling with shortage in budget and resources in emergency departments. This study tries to provide a simulation based evolutionary optimization in an emergency department to allocate the resources in the best way to minimize door to doctor time subject to the problem constraints which are capacity and budget.

Keywords: Simulation, Emergency Department, Optimization, Imperialist Competitive Algorithm, Resource Planning

1. Introduction

Healthcare industry is a semi-autonomous unit that operates 24 hours a day, seven days a week, including holidays. Therefore, interrupting their system in order to evaluate their performance and efficiency is almost impossible. Healthcare industry, like most of service industries deals with humans and their interactions. Having human behavior can be considered as one of the most

important differences between manufacturing industry and service industry. The nature of human behavior makes any system more complex to be simulated. More importantly, healthcare industry in general and particularly emergency department (ED) deals with human health. Therefore, an error in ED procedures may lead to disability or death. In general, public hospitals operate under several constraints such as: budget, expert staff, tools etc. In some cases, these constraints are incompatible with each other. Patients arrive to EDs with different health issues and with different levels of acuity and EDs must provide the best service and treatment to all of them. In any stage of treatment, patients can decide to leave the ED based on their experiences or their observations and later they might come back eventually with more problems. Patients with different levels of acuity and different background might have different reactions to waiting time in an ED.

EDs are one of the most overcrowded units in healthcare industry and it has been more than two decades that this problem considered as a worldwide problem. Although this problem can be found from United States to United Kingdom and China, still there is no available comprehensive tool for analyzing EDs overcrowding and as a result, majority of patients in public health system are suffering from long length of stay while hospital managers are struggling with shortage in budget and resources in EDs.

Agent-based models (ABMs) consist of a set of agents that has their own characteristics and attributes and they can interact with each other based on a set of rules and a given environment [1]. Since these systems contain a group of agents, they are also called multi-agent systems (MASs) and agent-based-simulation (ABS) in the literature. ABSs are widely applied in different fields of study, ranging from engineering applications to social sciences and economics. Weiming et al., [2] provide a literature review on the applications of ABS in manufacturing process planning that is the process of selecting and giving priority to the procedures in a manufacturing system. Zhou et al., [3] publish a research review on analyzing electricity markets and modeling in order to investigate several agent-based tools on electricity markets.

Computer-based simulations are able to answer to numerous research questions in healthcare industry. A recent literature review of Salmon et al., [4] studies the simulation modelling applied to EDs. Pan et al., [5] provide an agent-based framework for simulating social behaviors and human behaviors during emergency evacuations. Yousefi and Ferreira [1] develop a generalized ABM combined with group decision making to simulate EDs and improve their performances. Their model was implemented using NetLogo platform and the results show that the proposed approach can be apply to different EDs after some modifications.

Most of Evolutionary Algorithms (EAs) are inspired by nature such as Genetic Algorithm (GA) that is inspired by natural selection and simulated annealing that is inspired by annealing in metallurgy.

Unlike other EAs, Imperialist Competitive Algorithm (ICA) was introduced by Atashpaz-Gargari and Lucas [6] and inspired by social-political evolution of mankind; the behavior of imperialist countries looking for more power and competing with other empires to take possession of more colonies. The population and optimization process is similar to genetic algorithm (GA) with the difference that the crossover and mutation operators are replaced by the assimilation and revolution throughout the evolution process.

ICA has shown great performance in finding global optima in numerous famous benchmarks from the literature in engineering and other fields of study [7][8]. In many cases ICA shows better performance when the results are compared to other well-known algorithms such as GA. The applications of ICA can be found in diverse engineering applications such as single machine scheduling problems, optimization in heat exchangers [8], industrial engineering, computer sciences, power systems and others.

2. Structural Model

To make a reliable ED simulation model, a reliable data collection is needed. The main data collection elements in this simulation are as follows: the amount of time each service takes (e.g. admission, triage, laboratory, etc.), patient arrival rate and the number of each type of patients in the ED. The patients flow in an ED can be seen in Figure 1 (For more details see [9]). Patients arrive to the ED by walk or with an ambulance and then, patients wait until they will be attended by a receptionist in admission to register their personal information. This step can be skipped in case that the patient is in police custody and the patient directly goes to the triage room. The process of arriving patients to the ED is a non-homogenous Poisson process with 24 intervals that is shown in Figure 2.

Data analysis showed that 44% of patients go to the yellow zone, 30% go to the orthopedics section, 7.8% go to pediatrics and 7.0% go to surgical emergency, while the suturing section and clinical emergency rates are 6.2% and 5.0% respectively.

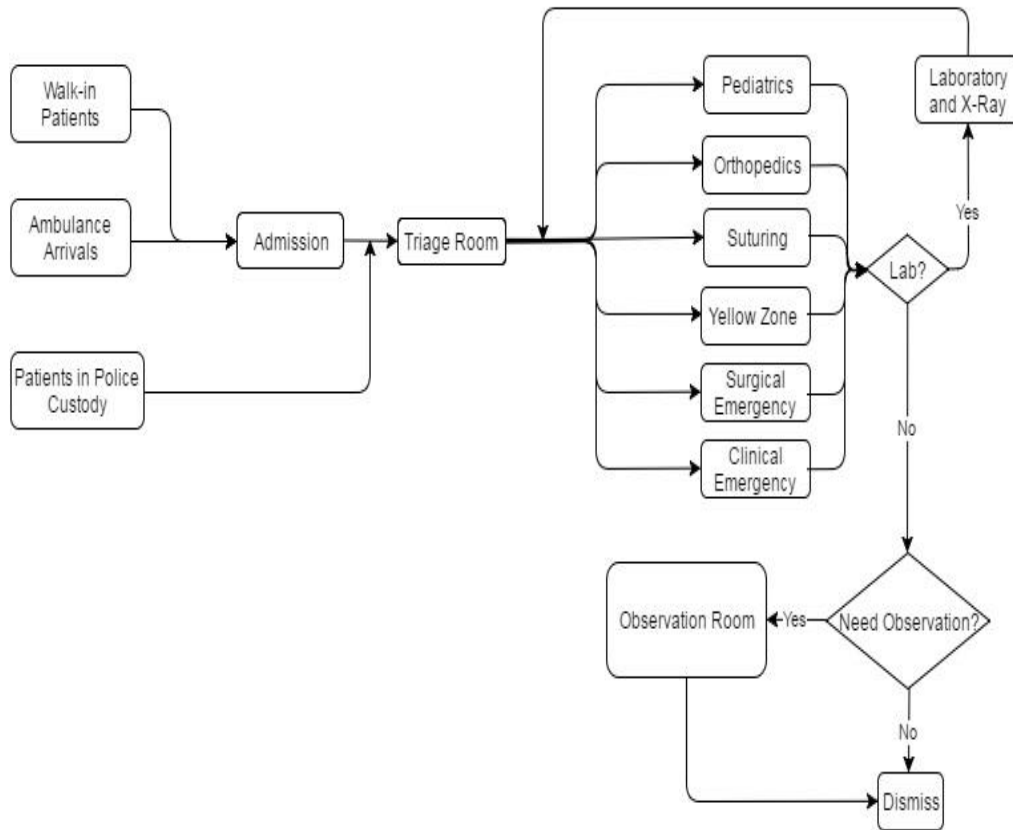


Figure 1. Patient Flow in an Emergency Department.

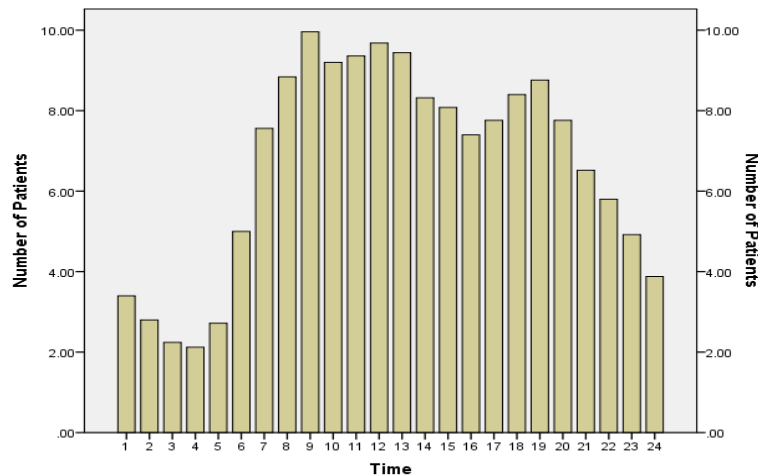


Figure 2. Patient arrival to the Emergency Department.

After being registered, patients wait for the availability of the triage room to be attended. In the triage room the acuity of each patient is checked based on the Manchester Triage System (MTS) that contains a set of different flowcharts to help the caregivers in EDs to categorize patients into five priority groups including Immediate (Red), Very urgent (Orange), Urgency (Yellow), Standard

(Green) and Non-urgent (Blue). Table 1 shows the level of priority for each category as well as the amount of time each type of patient can stay in ED before being attended [10].

Table 1. Safety minutes for patients until the first medical visit based on Manchester triage system.

Level of priority	Color	Safety minutes until first medical visit
Immediate	Red	Immediately
Very urgent	Orange	Up to 10 mins
Urgent	Yellow	Up to 60 mins
Standard	Green	Up to 120 mins
Non-Urgent	Blue	Up to 240 mins

2.1. NetLogo

NetLogo is an open source agent based simulation platform from Northwestern's Center for Connected Learning and Computer-based Modeling in Illinois, USA, and has been successfully applied in different fields of ABS [13]. Numerous extensions of the NetLogo that connect this platform to other advantageous software such as MATLAB and EXCEL and user friendly interface, makes the NetLogo an appropriate simulation platform. Moreover, the capability of the NetLogo in providing 2D and 3D views of the model makes them easier to understand. Figure 3 shows the user interface of NetLogo 6.0.2.

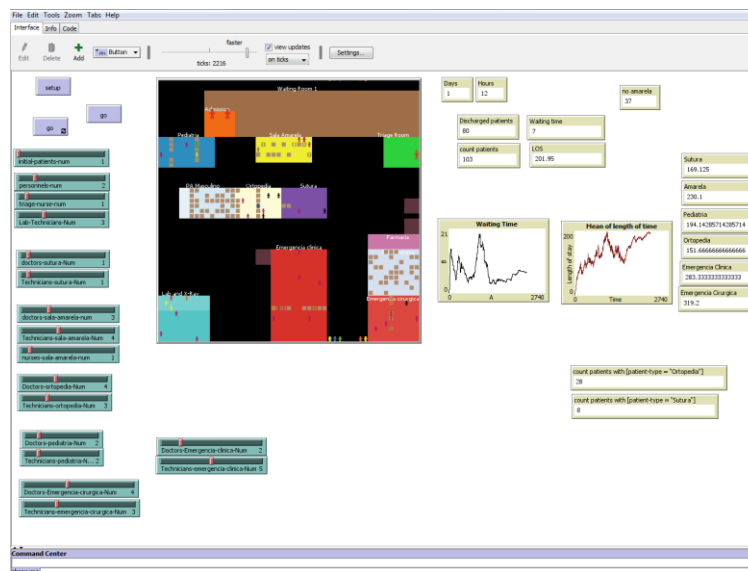


Figure 3. User interface of Netlogo 6.0.

2.2. Resource Capacity Levels in ED

Table 2 illustrates that the capacity levels have an upper bound (u_i) and lower bound (l_i), which are the maximum and minimum capacity levels with a baseline value for the resources in the current ED situation. It should be noted that the same nurses cover three sections, including the yellow zone, orthopedics and pediatrics.

Table 2. Capacity levels and relative cost of resources in each section.

Section	Resources	Upper bound	Baseline value	Lower bound	Cost (CU)
Reception	Receptionist (x_1)	3	2	1	0.45
Triage Room	Triage Nurse (x_2)	3	1	1	0.75
Lab and X-Ray	Laboratory Technicians (x_3)	3	3	1	0.6
Suturing	Doctors (x_4)	3	1	1	2.9
	Nurse Technicians (x_5)	3	1	1	0.75
	Nurses (x_6)	1	1	1	1.1
Yellow zone	Doctors (x_7)	5	3	1	2.9
	Nurse Technicians (x_8)	6	4	1	0.75
	Nurses (x_9)	1	1	1	1.1
Orthopedics	Doctors (x_{10})	6	4	1	2.9
	Nurse Technicians (x_{11})	5	3	1	0.75
	Nurses (x_{12})	1	0	1	1.1
Pediatrics	Doctors (x_{13})	4	2	1	2.9
	Nurse Technicians (x_{14})	4	2	1	0.75
	Nurses (x_{15})	1	0	1	1.1
Surgical emergency	Doctors (x_{16})	6	4	1	2.9
	Nurse Technicians (x_{17})	5	3	1	0.75
	Nurses (x_{18})	2	1	1	1.1
Clinical emergency	Doctors (x_{19})	4	2	1	2.9
	Nurse Technicians (x_{20})	7	5	1	0.75
	Nurses (x_{21})	2	1	1	1.1

CU: Cost Unit

3. Imperialist Competitive Algorithm (ICA)

ICA is a population-based algorithm that mimics the human social evolution to solve optimization problems. Same as any other population-based approach, the algorithm begins with an initial population. Each individual in ICA terminology calls a country and the power of each country is calculated using the fitness function, the better result from fitness function, the more power for the individual (country). Although ICA same as particle swarm optimization (PSO) is continuous [7][8][14][15], the discrete ICA has shown good performances in finding near optimum solutions in short computational times in different fields of studies [16].

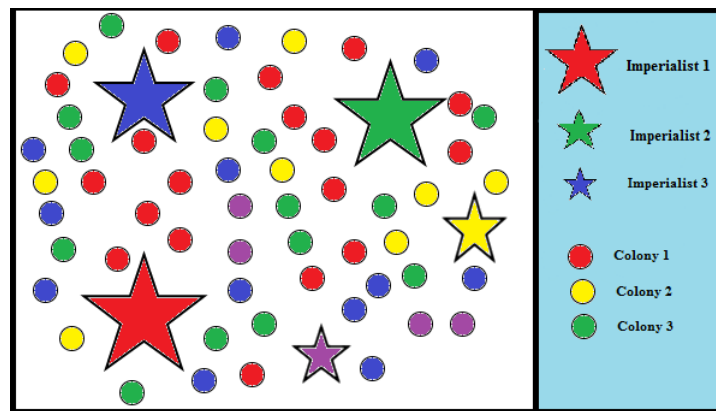


Figure 4. Creating initial population in Imperialist Competitive Algorithm.

The possible solutions (countries) in ICA are divided into two groups of countries based on their fitness function (power). Top-ranked countries are selected as imperialist countries, the weaker

countries are colonies, and they will be divided among the imperialists to create empires (Figure 5). Each empire contains an imperialist country and some colonies. In each empire (group), the members are forced to change their characteristics (culture, language, etc. in real world) towards the imperialist to improve. This process of moving a colony towards an imperialist is called assimilation that will be replaced with a two-point cross over to adapt the ICA with discrete nature of the problem. Therefore, a two-point cross over between a colony and its imperialist make the colony to be more similar to its imperialist. The original algorithm could generally be described in six steps, which are as follows.

Step 1: *Creating the initial population:* This step is already explained. 100 countries are created in this step and we select top 10 of them as imperialist and they remain as colonies.

Step 2: *Assimilation policy:* That is the process of moving a colony towards its imperialist. (Figure 6)

Step 3: *Revolution:* This concept is inspired by GA when mutation keeps the diversity of the population high to scape local optima. The same sudden change in some of the population in ICA is called revolution.

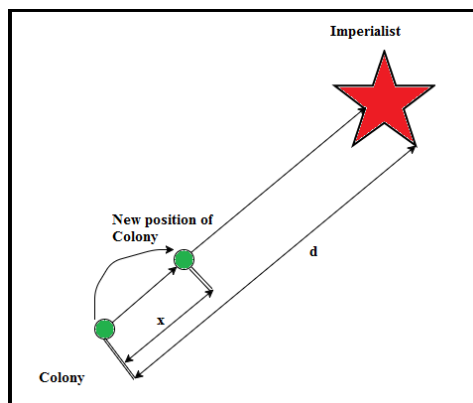


Figure 5. Process of assimilation in Imperialist Competitive Algorithm where a colony is forced to move toward its corresponding imperialist by x units.

Step 4: *Updating the state of the empire:* In any stage of the process if a colony reaches a better stage (stronger) than its own imperialist during a simulation policy, the position of colony and imperialist would change and the (more powerful) colony becomes the imperialist.

Step 5: *Imperialistic competition:* In each iteration of ICA, the imperialist participate in a competition with other empires to gain more colonies and subsequently be more powerful. We know that the total power of an empire is equal to power of the Imperialist plus power of its colonies.

Therefore, possessing more colonies help the empire to be stronger. In this process, the weakest colony of the weakest empire is chosen and all empires have a chance of taking over of it based on their power. Eventually, the weakest empire loses all of its colonies and collapse.

Step 6: Convergence: The algorithm continues until only one empire remains. The last imperialist has best fitness function (the most powerful).

3.1. Resource allocation problem

The aim of this study is to allocate the resources in the best way so as to minimize door to doctor time subject to the problem constraints which are capacity and budget. Door to doctor time is the average difference between patient arrival time and the first doctor contact with the patient. The problem can be written as follows:

$$\text{Min } Z = f(X_1, X_2, \dots, X_n) \quad (1)$$

S.t

$$\text{Min } Y = \sum_{j=1}^i C_i X_i \leq BU \quad (2)$$

$$l_j \leq X_j \leq u_j \quad \text{for } j = 1, 2, \dots, n, \quad (3)$$

$$X_j \text{ integer} \quad \text{for } j = 1, 2, \dots, n. \quad (4)$$

In Eq. (1), Z stands for the total door to doctor time in the ED and $(X_1, X_2, \dots, X_n)$ are decision variables. In fact, Z has no analytical form and it is the output of the simulation model mentioned in previous sections when the decision variables change. The cost of each resource and the budget are denoted by C_i and B respectively. In Eq (2) the budget is sum of number of each resource multiplied by the relative cost unit and it is limited to the budget of the ED. The other constraints of this optimization are shown in Eq (3) where l_j and u_j stand for lower bound and upper bound respectively for resource j.

4. Computational results

4.1. Parameter setting

The parameters of metamodeling approach are same as Yousefi et al., [9] and Yousefi [12]. The parameters of ICA are selected based on the recommendations from Atashpaz-Gargari and Lucas [6], β , γ and revolution rate values are set to $2, \frac{\pi}{4}$ and 0.1 respectively. In the process of assimilation $\beta > 1$ makes the colonies to get closer to the imperialist from both sides. Also, in the initial population one out of 10 countries is selected as initial imperialist. To select the number of initial

population the algorithm is executed several times with different initial populations and the respected results for the minimum door to doctor time is analyzed. The results show that increase in the number of initial population lead to a better result when number of countries is less than 100, therefore in this study number of initial population is selected as 100 which means 10 imperialists and 90 colonies.

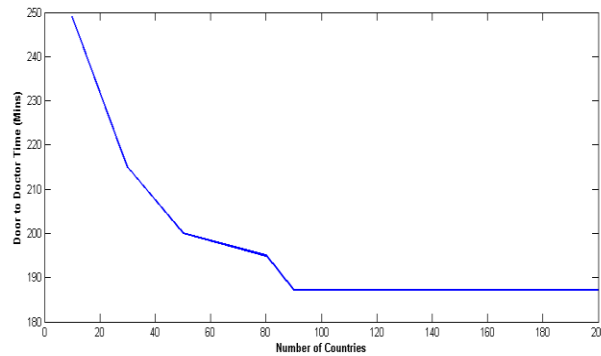


Figure 6. Effect of variation of the initial population (number of countries) on the minimum door to doctor time.

As it can be seen in the iteration process of ICA (Figure 7), the objective function significantly decreases in the first 15 decades (iterations) and after 80 decades the changes in the target function is negligible. Due to the stochastic nature of evolutionary algorithms, each execution may reach to a different result, therefore the best solution out of 10 executions is chosen as the output of the algorithm. Although there is no improvement after 80 decades, the number of decades is set at 100 to cover the stochastic nature of ICA.

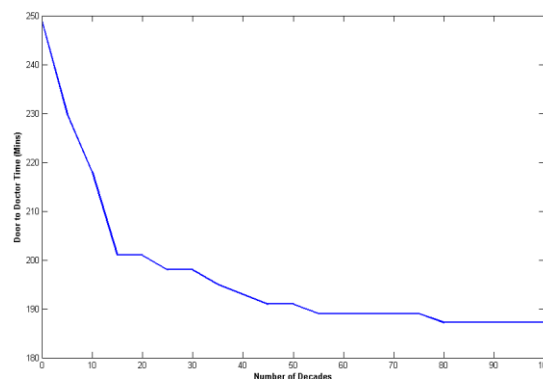


Figure 7. Convergence of the objective of minimum door to doctor time.

4.2. Results

For the case study from Risoleta Tolentino Neves hospital ED in Belo Horizonte, Brazil, the optimization goal is minimizing the total average time that patients spend to see a doctor which is

called door to doctor time. The best solution out of 10 executions of the algorithm is shown in Table 3. The average door to doctor time showed a %24.82 reduction from 249 mins to 187.2 mins.

Table 3. Near optimum resource allocation to reduce average door to doctor time.

Section	Resources	Upper bound	Baseline value	Optimization	Lower bound	Cost (CU)
Reception	Receptionist (x_1)	3	2	2	1	0.45
Triage Room	Triage Nurse (x_2)	3	1	2	1	0.75
Lab and X-Ray	Laboratory Technicians (x_3)	3	3	1	1	0.6
Suturing	Doctors (x_4)	3	1	1	1	2.9
	Nurse Technicians (x_5)	3	1	1	1	0.75
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Yellow zone	Doctors (x_7)	5	3	5	1	2.9
	Nurse Technicians (x_8)	6	4	6	1	0.75
	Nurses (x_9)	1	1	1	1	1.1
Orthopedics	Doctors (x_{10})	6	4	2	1	2.9
	Nurse Technicians (x_{11})	5	3	3	1	0.75
	Nurses (x_{12})	1	0	0	1	1.1
Pediatrics	Doctors (x_{13})	4	2	2	1	2.9
	Nurse Technicians (x_{14})	4	2	2	1	0.75
	Nurses (x_{15})	1	0	0	1	1.1
Surgical emergency	Doctors (x_{16})	6	4	3	1	2.9
	Nurse Technicians (x_{17})	5	3	3	1	0.75
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Clinical emergency	Doctors (x_{19})	4	2	3	1	2.9
	Nurse Technicians (x_{20})	7	5	3	1	0.75
	Nurses (x_{21})	2	1	1	1	1.1

The value for nurses in orthopedics (x_{12}) section and nurses in pediatrics section (x_{15}) is equal to zero, because as it can be seen in the baseline scenario in this ED the same nurse in yellow zone (x_7) can cover all the three sections. Among all sections in the ED, the yellow zone has the most increase so the number of doctors and nurse technicians reach to their upper bound. There is a decrease in the number of laboratory technicians that comes from the nature of the key performance indicator (door to doctor time). In most cases patients go to the laboratory only after being seen by a doctor, therefore; waiting for an exam does not influence the objective function.

5. Conclusions

This study provides a simulation based optimization approach in a hospital ED to find a better human resource allocation to decrease the average door to doctor time. To avoid high computational time, the output of simulation is used to train a metamodeling approach. Then a discrete ICA is applied to find a near optimum problem for the resource allocation when the budget is limited to 68 budget units. The achieved results show that the algorithm is able to reduce the door to doctor time by %24.82. The increases in the number of doctors and nurse technicians in the yellow zone section show that this section might be a bottleneck of the ED. The success rate of the algorithm to find its best solution is calculated as 59% after 100 executions of the ICA. The same approach can be applied to any other ED after some minor modifications.

References

- [1] M. Yousefi and R. P. M. Ferreira, "An agent-based simulation combined with group decision-making technique for improving the performance of an emergency department.," *Brazilian J. Med. Biol. Res. = Rev. Bras. Pesqui. medicas e Biol.*, vol. 50, no. 5, p. e5955, 2017.
- [2] Weiming Shen, Lihui Wang, and Qi Hao, "Agent-based distributed manufacturing process planning and scheduling: a state-of-the-art survey," *IEEE Trans. Syst. Man Cybern. Part C (Applications Rev.)*, vol. 36, no. 4, pp. 563–577, 2006.
- [3] Z. Zhou, W. K. Chan, and J. H. Chow, "Agent-based simulation of electricity markets: A survey of tools," *Artif. Intell. Rev.*, vol. 28, no. 4, pp. 305–342, 2007.
- [4] A. Salmon, S. Rachuba, S. Briscoe, and M. Pitt, "A structured literature review of simulation modelling applied to Emergency Departments: Current patterns and emerging trends," *Oper. Res. Heal. Care*, pp. 1–13, 2018.
- [5] X. Pan, C. S. Han, K. Dauber, and K. H. Law, "A multi-agent based framework for the simulation of human and social behaviors during emergency evacuations," *AI Soc.*, vol. 22, no. 2, pp. 113–132, 2007.
- [6] E. Atashpaz-Gargari and C. Lucas, "Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition," *2007 IEEE Congr. Evol. Comput. CEC 2007*, pp. 4661–4667, 2007.
- [7] M. Yousefi and R. M. Yusuff, "Minimising earliness and tardiness penalties in single machine scheduling against common due date using imperialist competitive algorithm," *Int. J. Prod. Res.*, vol. 51, no. 16, 2013.
- [8] M. Yousefi, M. Yousefi, and A. N. Darus, "A modified imperialist competitive algorithm for constrained optimization of plate-fin heat exchangers," *Proc. Inst. Mech. Eng. Part A J. Power Energy*, vol. 226, no. 8, 2012.
- [9] M. Yousefi, M. Yousefi, R. P. M. Ferreira, J. H. Kim, and F. S. Fogliatto, "Chaotic genetic algorithm and Adaboost ensemble metamodeling approach for optimum resource planning in emergency departments.," *Artif. Intell. Med.*, no. October, 2017.
- [10] K. Mackway-Jones, J. Marsden, and J. Windle, *Emergency triage: Manchester triage group*. John Wiley & Sons, 2013.
- [11] W. A. Knaus, E. A. Draper, D. P. Wagner, and J. E. Zimmerman, "APACHE II: a severity of disease classification system," *Crit. Care Med.*, vol. 13, no. 10, pp. 818–829, 1985.

- [12] M. Yousefi, "Designing and Building an Interactive Simulation- Based Decision Support System in Healthcare Industry," Universidade Federal de Minas Gerais - UFMG, 2017.
- [13] U. Wilensky, "NetLogo." 1999.
- [14] M. Yousefi, M. Yousefi, D. Hooshyar, and J. Ataide De Souza Oliveira, "An evolutionary approach for solving the job shop scheduling problem in a service industry," *Int. J. Adv. Intell. Informatics*, vol. 1, no. 1, pp. 2442–6571, 2015.
- [15] M. Yousefi, M. Yousefi, R. P. Martins Ferreira, and A. N. Darus, "A swarm intelligent approach for multi-objective optimization of compact heat exchangers," *Proc. Inst. Mech. Eng. Part E J. Process Mech. Eng.*, vol. 231, no. 2, 2017.
- [16] M. Yousefi, A. N. Darus, and H. Mohammadi, "An imperialist competitive algorithm for optimal design of plate-fin heat exchangers," *Int. J. Heat Mass Transf.*, vol. 55, no. 11–12, pp. 3178–3185, 2012.