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Carbon Footprint in Emergency Departments: A Simulation-Optimization Analysis

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Abstract

It is globally accepted to act against global warming through the reduction of carbon dioxide. Carbon footprint is historically defined as the total emissions caused by an individual, event, organization, or product, expressed as carbon dioxide equivalent. Healthcare system consumes large amount of energy in order to provide health services to patients who have to pass a series of treatment processes at each care unit, which each one of them needs different medical equipment in hospital that they cause consuming of electrical power, and the more electrical power consumption, the more greenhouse gases, specifically CO_2. The discrete-event simulation has been applied to develop the model of the treatment process and the estimation of carbon dioxide in the treatment process. By the knowledge that the simulation is not an optimization method in itself, the OptQuest optimization method has applied to reduce greenhouse gases and carbon footprint in the patients' flow in the emergency department by considering leveling off the waiting time and length of stay as constraints to leveling up patient's satisfaction. The results comparison of simulation and OptQuest show that the OptQuest is an efficient technique for patient flow optimization.

Keywords: Emergency Department, Discrete-Event simulation, Carbon Footprint, Greenhouse Gases

1. Introduction

It is globally accepted to act against global warming through the reduction of carbon dioxide [1]. There is a wide range of greenhouse gases (GHGs), including nitrogen oxide, methane, F-gases and also carbon dioxide (CO_2) proportionally responsible in GHG, for example, the share of nitro oxide is about 8% while methane is blamed for 16% of GHG.

The earth's climate is changing, owing to greenhouse gas emissions resulting from human activities. These human-generated gases derive from aspects such as building construction and operation, land-use planning, and transportation systems and infrastructure [2]. Climate events place a great burden on health systems such that responsibility that lies with health systems in the face of climate change is enormous. For this purpose, strengthening public health services must be a central component of all nations' climate change adaptation measures and policies. The intensification of these events have a direct or indirect effect on human health by disrupting ecosystems, agriculture, food, water quality and availability, air quality, and damaging infrastructure [3].

The direct effects of global warming and climatic change are heat-related illnesses, infectious diseases, cardiovascular diseases, injuries, and respiratory diseases leading to premature deaths. Due to the fact that increasing GHGs threaten the environment and healthcare, authorities encounter considerable challenges to reduce carbon footprint in health systems. To help in decision making for both cost and carbon in the healthcare, Pollard, et al. [4] proposed a bottom-up modeling framework. Research findings confirm that a bottom-up model is an efficient tool in the process of estimating and modeling the carbon footprint of healthcare.

Emergency Department (ED) is a primary healthcare department, the main entrance to the hospital, and a key component of the healthcare system. EDs are overcrowded and the length of stay (LOS) of patients has increased, whereas the quality of service has decreased. The overcrowding of EDs is a worldwide issue, and a national crisis in US [5]. Many researches have been done on ED overcrowding since 20 years ago [6]. Despite that EDs are under this overcrowding phenomenon, they suffered from budget reductions. Therefore, new techniques and should be found in order to deal with such an overcrowded condition. ED managers require different and fresh solutions because society demands not only care, quality and service, but also the best care, quality, and service. A direct solution to this issue is increasing the size of EDs. However, this straightforward solution is limited by facility, number of staff and services, and it is not the best approach. Also,

healthcare managers have to maximize the use of healthcare resources, i.e. to optimize the performance of the ED in order to increase the satisfaction of the patients. Nevertheless, the increasing use of healthcare resources leads to an increasing carbon footprint in the patient flow.
Cabrera et al. [7] presented an Agent-Based modeling and simulation to design a decision support system for the operations of EDs.
The aim of this chapter is to find the optimal ED staff configuration, which consists of doctors, triage nurses, and admission personnel. For this, two different criteria, to minimize patient waiting time, and to maximize patient throughput, were proposed and tested. Solutions obtained applying an exhaustive search technique, yield promising results and a better understanding of the problem. Results of this research enable health service providers to provide a more reliable reference for their decisions.
Zhao and Lie [8] proposed different discrete event models of ED to enable managers to predict the future number of resident patient in each department/ward.
Bhattacharjee et al. [9] classified the existing approaches related to modeling patient flows in hospitals focusing on the recent advancements to identify future research avenues. They proved a generic framework for patient flow modeling and performance analysis of hospital systems. Zhecheng [10] proposed and developed an online prediction procedure based on discrete-event simulation to predict the bed occupancy rate in a short term period. Simulation results showed that the predicted values were closer to the actual values with a narrower confidence interval compared to the offline approach. Zhu et al. [11] presented a discrete event simulation (DES) model to help the healthcare service providers determine the proper ICU bed capacity which strikes the balance between service level and cost-effectiveness. The simulation results and the actual situation shows that the DES model accurately captures the variations in the system, and the DES model is flexible to simulate various what-if scenarios.
There are a wide variety of indicators to improve service delivery and patient satisfaction to evaluate the effectiveness of different parts of the hospital. Among these indicators, patients' length of stay, waiting time and number of discharges are of particular importance. In addition, by changing the community's expectations of the hospital, patients are no longer willing to tolerate poor quality treatment and their look at the system is like that of a customer, so the concept of service has shifted from optimizing the use of resources to finding a balance between quality of service to patients and operational efficiency for health providers. Therefore, while reducing the

number of patients lost, patient satisfaction should be increased by increasing the quality of their treatment and reducing waiting times, each of which is costly and should be treated with caution. The previous research focus has been addressed towards classical-based objectives while ignoring environmental-based objectives. In his research is considered an environmental-based objective besides classical objectives.

The remainder of the chapter is organized as follows: in the next section green approaches in healthcare are reviewed, Section 3 introduces Emergency Department, Section 4 proposed case Study, Section 5 proposed the research methodology and simulation model. Section 6 presents the OptQuest optimization method of the simulated model and its experiments. The discussion and conclusions that can be drawn from our analysis do exist in section 7.

2. Green Approaches in the Healthcare

The Green Guide for Healthcare [2] identifies opportunities to enhance environmental performance in the following domains: site selection, water conservation, energy efficiency, recycled and renewable materials, low-emitting materials, alternative transportation, daylighting (the use of natural light in a space to reduce electric lighting and energy costs), reduced waste generation, local and organic food use, and green cleaning materials. Some decisions, such as site selection, occur during the planning and construction phases; other decisions, such as food sourcing and cleaning practices, are primarily questions of operation after a building is completed. Commitments to energy conservation, renewable resource use, and similar principles must be made and reinforced throughout the life cycle of a facility, from building conception through operation and replacement. According to [12] use of green technologies to reduce CO_2 is can be categorized as an environmental oriented sustainability action.

The consumption and generation of energy are associated with significant damages for the climate, the environment and, consequently, the economy. Greenhouse gas emissions have a decisive factor in climate change and global warming. The delivery of healthcare services produces remarkable greenhouse gas emissions. Some researchers have addressed the environmental effect of medical gases. To illustrate, Gilliam et al. [13] estimated direct CO_2 emissions from laparoscopic surgeries. In another research, Ryan and Nielsen [14] determined the 20-year global warming potentials of three common anesthetic gases including sevoflurane, isoflurane, and desflurane. As a consequence, they applied these gases to clinical scenarios in order to estimate the impacts of them on the environment.

According to climatological reports of the National Oceanic and Atmospheric Administration (NOAA) in 2018, human activities have been known as the main causes of the increase in global temperature. Carbon dioxide and methane are among the GHGs that have the dominant impact on warming up and temperature rise-up on the earth. GHGs directly affects human health through both diffusions of diseases and pandemics and food shortages around the globe [15]. Based on FAO[1] reports, climate change has decreased agricultural production. WHO[2] claims that pollution, diseases, such as malaria and cholera that spread in most areas of the planet, and severe heat causes cardiovascular disease are of GHGs effects. In 2013, the US healthcare sector was announced to be responsible for significant fractions of air pollution emissions and impacts, including acid rain (12%), greenhouse gas emissions (10%), and smog formation (10%) criteria air pollutants (9%), stratospheric ozone depletion (1%), and carcinogenic and non-carcinogenic air toxics (1–2%).

From the management point of view, the resources of the health sector are an important issue. In a rough estimation, 5% of GNP[3] and 5 to 10 percent of government costs are allocated to this sector [16]. Due to the importance of complicated equipment and technologies at the process of treatment in health systems especially hospitals, CO_2 emission must be managed in direct and indirect manners [17, 18].

Healthcare system like other industries has been required to improve its environmental performance in past decades, and many new healthcare facilities have been built worldwide based on this view [19]. The amount of GHGs emitted by the use of electrical equipment in the hospital's intensive care unit is calculated by Pollard et al. [20] with a precise estimation of the power consumption. Given that climate change is one of the most important problems related to public health, so reducing greenhouse gas emissions from health care is one of the key responsibilities of the health system in preventing global warming.

Considering the importance of patient's flow into emergency departments on occupying medical equipment that needs consuming electrical power for running, the patient flow has been studied in Bushehr Heart Hospital (BHH). Since this study attempts to estimate carbon dioxide produced by

[١] United Nation's Food and Agriculture Organization

[٢] World Health Organization

[٣] gross national product

electric equipment in a health center in order to preserve the environment and reduce the trend of carbon increase, it could be a significant step towards managing produced CO_2 and small steps to prevent it.

3. Emergency Department

The ED is the first point of access for many hospital visits and a major source of unplanned episodes of patient care. EDs are open and staffed 24 hours per day, 365 days per year, including holidays. The main functions of the ED include treatment of the acutely unstable and unwell, and also those with nonlife-threatening conditions requiring immediate attention. EDs are large, complex and dynamic units that have to increase their resources to attend all of those cases.
The process begins by entering patients to ED by random or Non-intermittent in two forms. Directly is the patient referring to ED by itself or using ambulance. Vital signals of the patient will be control by nurse's time entering to triage and looking for whether patient needs hospitalization or not, if no the diagnose is outpatient and the process is over, if yes the process will be continued and based on acuteness of the patient's condition and nurse's opinion patient will be classified and to determine the level of treatment [21].

ED classifies patients into five levels. Level 1 that is in a less percent, are patients who do not have often awareness and are at the highest emergency level for surviving their life. Level 2 are patients with dangerous signals and severe pain and peril of falling into coma, thus they cannot wait, level 3, are patients with two or more emergency treatment actions, 4, needs one treatment action and finally in level 5 are patients who does not have demand for instantaneous treatment and can wait. This class of Referrals refers to located clinic in the hospital by nurses.

4. Case Study

Our case study is the emergency department of Bushehr Heart Hospital, in southern Iran. The data gathered from August 2016 to August 2017, covers all patients who have visited the hospital during this period. The total number of patients who referred to the hospital was almost 7807. About 5% of them diagnosed to have ESI1 and 5% for ESI2, 30% for ESI3, 30% for ESI4 and 30% of patients categorized to be ESI5.
Using the patient's arrival records time in the ED database the distribution of interarrival times founded to be an exponential distribution with an average of 67 minutes. In doing this, a sample

of the obtained data tested by Chi-Square (χ^2) and Kolmogorov-Smirnov test in the input analyzer arena and SPSS software. According to Table 1, the distribution of patients' arrival to triage considered to follow an exponential distribution.

Table 1: The goodness of fit results of patients' arrival pattern

	Sample	Test type	Statistical test	p-value	Distribution
Arrive in ED	150	χ^2	0.723	0.423	Exponential

The other required data is the occupation of each equipment which has been used in the treatment process, to do this some cited statistical procedure has been applied and the results show that equipment occupation time has a triangular distribution with parameters and for each device. Table 2 presents the set of medical equipment and time distribution used for treatment processes.

Table 2: Information on medical equipment in ED

Department		Medical Equipment	Number of electrical equipment	Demanding time to use electrical equipment per patient (triangular Distribution)			constant rates of electricity consumption (kilowatt-hours)
				Min	Ave	Max	
Emergency Department	Triage	Monitoring of Vital Signs	1	1	2	3	0.14
	CPR	CPR Beds	1	45	82	120	2.64
		Monitoring of Vital Signs	1	45	60	90	0.14
		Syringe Pump	3	30	50	75	0.025
		General Motorized Suction	2	20	30	40	0.15
		Electro Shock	2	15	20	30	0.22
	IED	Portable Ventilator	1	10	50	80	0.529
		Blood Gas Analyzer	1	5	7	10	0.016
		IED Beds	7	240	300	360	0.5
		Monitoring of Vital Signs	7	240	300	360	0.14
		Syringe Pump	7	240	300	360	0.025
		Electrocardiograph	2	3	4	5	0.14
		Echocardiograph	1	15	17	20	1

Simulation is performed for all units of ED in one year, two days warm-up period with 10 runs. The warm-up period is set for simulation run to eliminate any bias at the early stages of the process. The described patient flow in ED and its flowchart is shown in Figure 1. Following the process patients in levels 1 and 2 refer to the CPR department 3, 4 and 5 refer to the medical visit room and can be discharged if they had stable and normal conditions, by prescribing medications, otherwise medical tests, hospitalization or radiology, based on specialist doctors. There is probability for patients to revisit doctors based on test results and demanded treatment process.

Finally, doctors decide for prescribing, discharging or hospitalizing patients in unit, or in CCU, ICU, PCCU or surgery room, thus they exit from ED. As illustrated, patients may come on foot or by ambulance and according to his ESI, he will be routed to either CPR or the triage. Following the care procedure, a patient may leave the ED, as he does discharge (DSG) or being hospitalized for further treatments. Also, in some cases that a patient dies (the "death" symbol in the illustration).

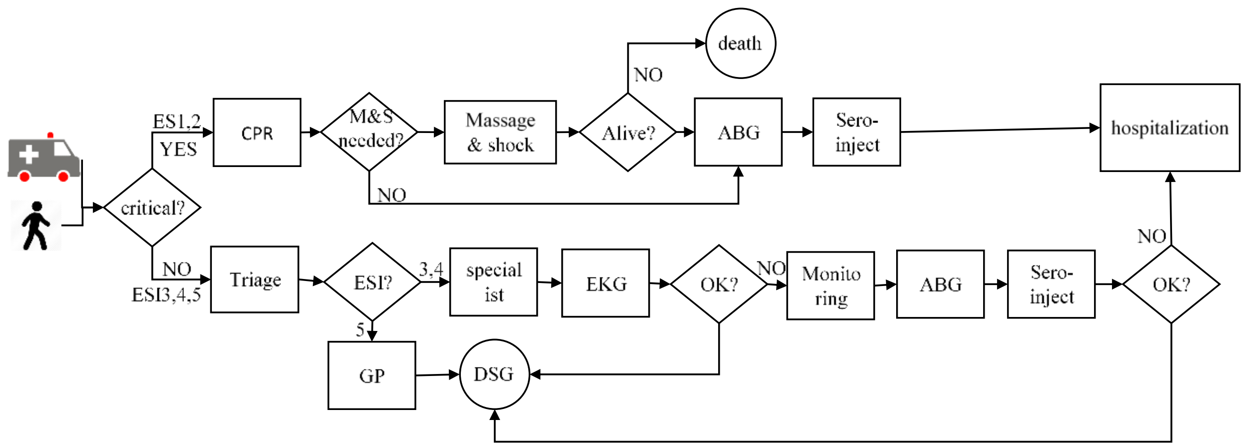

Figure 1: Patient flow in the ED

5. Research Methodology and Simulation Model

Simulation can be used as an effective analysis technique to create, maintain, evaluate or improve a system or process [22]. The ED of the hospital has three care units (workstations) including triage, cardiopulmonary resuscitation (CPR), and inpatient emergency department (IED). In this research, we take the concept of flexible job-shop scheduling (FJSP) in modeling the ED care processes. For this, we consider patients as jobs, treatment processes as operations and medical equipment as machines. The main goal of this research is to calculate and optimize the CFP in the patient’s flow, so medical equipment and the duration that is used of this equipment at each care unit are considered in the treatment process. To making the decision for patients flow in the studied hospital, discrete event simulation (DES) have been applied for this purpose, the Arena14.0 package has applied to simulate the system.

Steps of the proposed simulation-optimization framework inspired by Uriarte et al. [23]. It is based on five5 steps, understanding and data collection, simulation modeling, selection of performance criteria, multi-objective optimization, decision making. In the first step studying the intended system needs sufficient comprehension of process and systems performance. Therefore, in this step, patients' behavior in the treatment process will investigate in different units of the hospital, demanded data will be gathered and then a design of a conceptual model of patient flow. In the second step, a model of current situation has been simulated based on gathered data and conceptual model of patient flow in the studied system and finally at this step after confirmation and validation of the simulation model, a computerized model presented. In the third step, model needs criteria performance for evaluating and comparison of the system performance. At this step key performance criteria of the hospital collected. In the fourth step after creating multi-objective optimization model, simulated model by OptQuest resolved using $\varepsilon-$constraint technique. Finally, at the fifth step some recommendations are presented for improving the responsibility of healthcare system based on obtained results.

5.1 Verification and Validation of Simulation Model

The simulation model of the current conditions approved by the executive manager and validation has used to show that the simulation model is an exact representation of the real-world system. Results from validation are shown in Table 3 and Table 4.

Table 3: Model Validation Result. Total number throughput patients

Num.	Simulation	Real Data	t-Statistics	Sig.
Patient Out	7809	7812	-2.154	0.075

Table 4: Model Validation Results. Length of Stay (min.)

Care unit	Real data	Simulation	t-Statistics	Sig.
Triage	2	2.0326	0.407	0.690
CPR	82	84.70	-2.095	0.055
IED	300	310.24	-1.808	0.108

5.2 Carbon Footprint Calculation

The emission factor (EF) expressed in terms of the mass of carbon (or carbon dioxide) emitted for every unit of energy delivered. The emission factor (EF) of the country obtained through Eq. 1 as follows:

$$\mathrm{EF} = \frac{kgCO_2}{kWh} \tag{1}$$

where $kgCO2$ and kWh indicate kilograms of CO_2 and kilowatt electricity used per hour, respectively. The total amount of produced $kgCO2$ in the ED (T_{CO2}) is calculated as follows:

$$T_{CO2} = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}\left(EF * CT_{ijk} * W_{jk} * Z_{ijk}\right) \tag{2}$$

Where the related variables and parameters are including:

EF: Emission factor

CT_{ijk}: Usage time (hour) of equipment j in care unit k per patient i

W_{jk}: Power consumption rate of equipment j in care unit k (kW)

Z_{ijk}: If equipment j is used in care unit k for patient i 1; otherwise it is zero.

5.3 Simulation Outputs of Hospital Performance

Average results from simulating the status are summarized in Table 5. CFP column shows the average produced of carbon dioxide for each hospitalized patient.

Table 5: Average CFP produced in the ED for one year

Care Units		CFP (kg)
Emergency Department	Triage	7
	CPR	119
	Inpatient ED	17670
Total CFP		**17796**

6. Simulation Optimization

Simulation optimization is a modeling method applying for problems that objective function or some of the constraints can only be evaluated by simulation, for example, optimization model includes functions that are not able to be evaluated analytically. Simulation optimization purpose is gaining the best framework of system to attaining a specific goal with scarce resources in one hand and in the other one, while conducting real-world systems, evaluation some of them is highly time taking [36]. Considering simulation results for CFP in patient's flow which is not totally optimized, OptQuest has been used.

6.1 OptQuest

OptQuest is an optimization software embedded in simulation packages like Arena. It increases the analysis abilities by providing searching optimized solutions [37]. In fact, OptQuest is a simulation-optimization engine, built on a unique set of powerful algorithms and sophisticated analysis techniques including Tabu-search, neural networks and scatter search meta-heuristic algorithms. OptQuest searches, adjusts and analyzes input values and identifies the best possible outcomes with unparalleled efficiency. This method has been applied to studying the treatment system [24-27]. In this chapter, OptQuest has been used to estimate the optimal control levels for optimizing of ED simulation model.

6.2 Optimization Model

In this study, four objective functions are evaluated, that is, the minimum produced CO_2 (f_1), the minimum length of stay in ED (f_2), the minimum waiting time (f_3), and the maximum number of patient being fully treated (f_4). The mathematical model of the multi-objectives is proposed as follows. Then, OptQuest is used to obtain an optimized framework of ED resources, for more hospital responsibility (decrease in waiting time and LOS, and increase patient throughput), and reduces in produced CO_2 amount.

$$Min \quad f_1(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}) \tag{3}$$

$$f_2(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}) \leq 310 \tag{4}$$

$$f_3(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}) \leq 10.51 \tag{5}$$

$$f_3(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}) \leq 7809 \tag{6}$$

$$x_{1L} \leq x_1 \leq x_{1U} \tag{7}$$

$$x_{2L} \leq x_2 \leq x_{2U} \tag{8}$$

$$x_{3L} \leq x_3 \leq x_{3U} \tag{9}$$

$$x_{4L} \leq x_4 \leq x_{4U} \tag{10}$$

$$x_{5L} \leq x_5 \leq x_{5U} \tag{11}$$

$$x_{6L} \leq x_6 \leq x_{6U} \tag{12}$$

$$x_{7L} \leq x_7 \leq x_{7U} \tag{13}$$

$$x_{8L} \leq x_8 \leq x_{8U} \tag{14}$$

$$x_{9L} \leq x_9 \leq x_{9U} \tag{15}$$

$$x_{10L} \leq x_{10} \leq x_{10U} \tag{16}$$

$$x_{11L} \leq x_9 \leq x_{11U} \tag{17}$$

$$x_{12L} \leq x_{10} \leq x_{12U} \tag{18}$$

$$x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11,} x_{12} \in Z^+ \tag{19}$$

In this optimization model, the amount of CO_2 produced in the patient flow (Eq. 3) has been considered as an objective function. f_1 , f_2, f_3 ,and f_4 are functions of the vector x_i representing decision variables including medical equipment in ED. Equations 4, 5 and 6 display constraints where f_2, f_3 ,and f_4 are the minimum length of stay, the minimum waiting time, and increase patient throughput, respectively. The right-hand side of constraints (4-6), have been found using simulation. Equations 7-18 are the number of medical equipment in ED that determined by hospital management and supervisors. In addition, f_2 ,f_3 , and f_4 are randomized functions. That is, they do not have any analytical form and they can be only evaluated by simulation. Eq. 19 indicates that the mathematical model is an integer problem. Table 6 presents the lower and upper bounds of variables.

Table 6: Bounds of Variables

Variable	Variable Name	Low	Up
x_1	ElectroShock in CPR	1	3
x_2	Hospital Bed in CPR	1	2
x_3	Monitoring of Vital Signs in CPR	1	2
x_4	General Motorized Suction in CPR	1	3
x_5	Portable Ventilator in CPR	1	2
x_6	Syringe Pump in CPR	2	5
x_7	Electrocardiograph	1	3
x_8	Echocardiograph	1	2
x_9	Hospital Bed in IED	6	9
x_{10}	Monitoring of Vital Signs in IED	6	9
x_{11}	Syringe Pump in IED	6	9
x_{12}	Monitoring of Vital Signs in Triage	1	2

To solve the model, while having multi-objective function, one of objectives will be set as the objective function while the others set to be constraints. The right-hand side of those constraints should be carefully set, to ensure that the optimal solution to the SOOP guarantees the MOOP solution.

Since the OptQuest implemented for single-objective optimization problems, the Epsilon-Constraint (ε-constraint) technique [28] has been used to transform the multi-objective optimization problem (MOOP) into a single objective optimization problem (SOOP). The OptQuest is implemented for all optimization problems with 10 runs and 10 repetitions. Four objective functions $f_1, f_2,$ f_3 and f_4 cannot be met simultaneously, because CO_2 minimization constraint in treatment process is in conflict with the increase in patients throughput.

Table 7: Result of OptQuest for minimizing f_1 by considering f_2, f_3 and f_4 as constraints

Solution Status	Solution	Configuration (Number of Medical Equipment)											
		x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}
Infeasible	17793.78	2	1	1	2	1	3	2	1	7	7	7	1
Infeasible	17653.52	2	2	2	2	2	4	2	2	8	8	8	2
Infeasible	17616.66	2	2	2	2	2	5	2	2	9	9	9	2
Infeasible	17729.16	1	1	1	1	1	2	1	1	6	6	6	1
Infeasible	17616.66	3	2	2	3	2	5	3	2	9	9	9	2
Infeasible	17653.52	3	2	2	3	2	4	3	2	8	8	8	2
Infeasible	17616.66	3	1	1	2	2	2	3	1	9	9	8	2
Infeasible	17729.16	2	2	2	3	1	5	1	2	6	7	6	1
Infeasible	17729.16	3	2	1	3	2	5	1	1	6	8	8	1
Infeasible	17729.16	1	2	2	1	2	4	3	1	6	8	9	1

Table 8 shows the OptQuest output for solving single and multi-objective problems. According to Table 8, comparing results from both simulation and the OptQuest f_1, f_2, f_3, and f_4 have been improved by 0.89%, 0.97% , 67%, and 1.13%, respectively.

Table 8: Results of OptQuest for Single/ Multi-objective Optimization Problems

Objective Function		Constraint (s)	SS	Answer	Configuration (Number of Medical)											
					x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}
One Objective	f_1	-	F	17636.86	2	2	2	2	2	5	2	2	9	9	9	2
	f_2	-	F	307	1	1	1	2	1	3	1	2	7	7	7	1
	f_3	-	F	3.41	2	2	2	3	2	5	2	3	9	9	9	2
	f_4	-	F	7897	1	2	1	3	1	5	2	2	6	8	6	2
Two Objectives	f_1	f_2	F	17616.66	2	2	2	2	2	5	2	2	9	9	9	2
	f_1	f_3	F	17616.66	2	2	2	2	2	5	2	2	9	9	9	2
	f_1	f_4	**NF**	17729.16	1	1	1	1	1	2	1	1	6	6	6	1
	f_2	f_1	F	307.127	2	2	2	2	2	5	2	2	9	9	9	2
	f_2	f_3	F	306.97	2	2	2	3	2	5	2	3	9	9	9	2
	f_2	f_4	**NF**	307.27	2	1	2	2	1	5	2	1	9	7	6	1
	f_3	f_1	**NF**	3.41	2	2	2	2	2	5	2	2	9	9	9	2
	f_3	f_2	F	3.44	2	2	2	3	2	5	2	3	9	9	9	2
	f_3	f_4	**NF**	3.63	2	1	2	2	1	5	2	1	9	7	6	1
	f_4	f_1	**NF**	7836	2	2	2	2	2	5	2	2	9	9	9	2
	f_4	f_2	F	7814	2	2	2	3	2	5	2	3	9	9	9	2
	f_4	f_3	F	7836	2	2	2	2	2	5	2	2	9	9	9	2
Three Objectives	f_1	f_2, f_3	F	17616.66	2	2	2	2	2	5	2	2	9	9	9	2
	f_1	f_2, f_4	**NF**	17653.52	2	2	2	2	2	4	2	2	8	8	8	2
	f_1	f_3, f_4	**NF**	17729.16	1	1	1	1	1	2	1	1	6	6	6	1
	f_2	f_1,f_3	**NF**	307.127	2	2	2	3	2	5	2	3	9	9	9	2
	f_2	f_1,f_4	**NF**	307.127	2	2	2	3	2	5	2	3	9	9	9	2
	f_2	f_3, f_4	**NF**	307.127	2	2	2	3	2	5	2	3	9	9	9	2
	f_3	f_1,f_2	**NF**	3.44	2	2	2	3	2	5	2	3	9	9	9	2
	f_3	f_1, f_4	**NF**	3.411	2	2	2	2	2	5	2	2	9	9	9	2
	f_3	f_2, f_4	**NF**	3.63	2	1	2	2	1	5	2	1	9	7	6	1

	f_4	f_1,f_2	**NF**	7814	2	2	2	3	2	5	2	3	9	9	9	2
	f_4	f_1,f_3	F	7836.4	2	2	2	2	2	5	2	2	9	9	9	2
	f_4	f_2, f_3	F	7836.4	2	2	2	2	2	5	2	2	9	9	9	2
Four Objectives	f_1	f_2, f_3, f_4	**NF**	17729.16	1	2	2	1	2	4	3	1	6	8	9	1
	f_2	f_1, f_3, f_4	**NF**	307.127	2	2	2	3	2	5	2	3	9	9	9	2
	f_3	f_1, f_2, f_4	**NF**	3.44	2	2	2	3	2	5	2	3	9	9	9	2
	f_4	f_1, f_2, f_3	**NF**	7814	2	2	2	3	2	5	2	3	9	9	9	2

Note . SS, F, and NF stand for Solution Status, Feasible and Infeasible respectively.

7. Conclusions and Future Insights

Accounting produced CO_2 stems from the equipment in care units is a basic step for greenness and lowering climate change rates. Therefore, considering the produced CO_2 using a discrete-event simulation approach in care units in the proportion of the consumption amount of electricity that holds concerns to efficiency, control and optimized performance of the equipment. By the knowledge that the simulation is not an optimization method in itself, the OptQuest optimization method has been used for optimizing cardiovascular patients flow, based on multi-objectives such as minimizing the produced amount of CO_2, waiting time, length of stay, and increasing patient throughput. A comparison of the outputs obtained from the current position and OptQuest optimization confirms that this technique is efficient for optimizing the patient's flow and decreases produced CO_2.

The production of carbon footprint in hospitals is related to energy consumption and for the reason to make it more realistic, it can be a good idea if it is considered in material based. Discrete-event methodology in this chapter has been used and based on its performance for solving this kind of problems, to enhance the performance of the simulation; agent-based methodology can be applied. Also by the knowledge of restrictions of OptQuest for multi-objective optimization, it would be better to apply a meta-heuristic algorithm to reduce CO_2 and waiting time.

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