GESTÃO & PRODUÇÃO

ISSN 0104-530X (Print)
ISSN 1806-9649 (Online)

Thematic Section

Digital Transformation, Intelligent Manufacturing and Supply Chain Management 4.0

Application of Automation and Manufacture techniques oriented to a service-based business using the Internet of Things (IoT) and Industry 4.0 concepts. Case study: Smart Hospital

Aplicação de técnicas de Atomação e Manufatura orientadas para um Modelo de Negócios baseado em serviços, usando o conceito de Internet das Coisas (IoT) e Indústria 4.0. Estudo de caso: Hospital Inteligente

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How to cite: Cáceres Flórez, C. A., Rosário, J. M., & Amaya Hurtado, D. (2020). Application of Automation and Manufacture techniques oriented to a service-based business using the Internet of Things (IoT) and Industry 4.0 concepts. Case study: Smart Hospital. *Gestão & Produção*, 27(3), e5416, https://doi.org/10.1590/0104-530X5416-20

Abstract: The implementation of Manufacture and Automation techniques is mandatory in the current world. Mainly, the enhancement and progress of healthcare are fundamental in wellbeing improvement. This paper points to the utilization of the Internet of Things (IoT) and Industry 4.0 concepts oriented to the optimization of a Smart Hospital using the Hospital Emergency Department (HED) as a case study. This proposal focuses on the development of a smart Hospital-based of the IoT, Industry 4.0, Health 4.0, and other current technology. On the other hand, the use of a computational simulation tool like the Discrete Event Simulation Model (DES) will allow the test, recognition, and reduction of bottlenecks in the HED workflow. The issue given by the bottlenecks is automatically controlled using an improved dynamic shift management proposal based on control theory, forecasting methods, and telemedicine. The results show an improvement in the use of the resources and a reduction of the length of stay that directly reduces the HED mortality rate, improving the service quality. The objective of this paper is to propose a simulation tool-based on DES for a selected HED, using forecasting methods of the patients' arrival in a HED using the Autoregressive integrated moving average (ARIMA) model. Following the forecasted entries, a proposal for bottleneck avoidance using a HED DES was realized. The forecasting data provided useful predictive information for the improvement of the HED workflow. As well as the analyzed data of a traditional HED system is helpful to solve the overcrowding problem. Finally, the use of simulation tools allows the test and validation of novel proposals for two smart HED optimization proposals following e-Health and Hospital 4.0 principles.

Keywords: Emergency Department; Smart Hospital; Discrete Event Simulation; Hospital 4.0; Health 4.0; Smart Decision Support Tool.

Received Apr. 2, 2019 - Accepted Nov. 29, 2019
Financial support: This work was supported by the National Council for Scientific and Technological Development (CNPq) (Ph.D. grant: 140743/2017-0).

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Resumo: A implementação de técnicas avançadas em automação e manufatura é obrigatória no mundo atual. Particularmente, no que concerne o aprimoramento e o cuidado com a saúde, são fundamentais para a melhoria do bem-estar das pessoas. Este artigo tem como propósito a utilização dos conceitos de Internet das Coisas (IoT) e Indústria 4.0, orientados na otimização de um Hospital Inteligente, utilizando o Departamento de Emergência Hospitalar (HED) como estudo de caso. Esta proposta se concentra no desenvolvimento de um Hospital Inteligente baseado nos conceitos de IoT, Indústria 4.0, Saúde 4.0 e outras tecnologias atuais. Por outro lado, o uso de uma ferramenta de simulação computacional para o Modelo de Simulação de Eventos Discretos permitirá a validação deste estudo, através da identificação e redução de gargalos que ocorrem no fluxo de trabalho do HED. Esse problema é supervisionado e gerencidado automaticamente usando uma proposta de gerenciamento dinâmico de turnos baseada na utilização da teoria de controle, métodos de previsão e telemedicina. Os resultados obtidos mostram uma otimização no uso dos recursos e uma redução do tempo de permanência dos pacientes que reduz diretamente a taxa de mortalidade do HED, melhorando a qualidade do serviço. Consequentemente este artigo tem como seu principal objetivo propor um HED inteligente baseado na utilização de uma ferramenta de simulação DES, utilizando métodos de previsão da chegada do paciente associado a um modelo de média móvel integrada autorregressiva . Após, com as chegadas previstas foi realizada uma proposta de evitar gargalos usando uma simulação do HED. Os dados obtidos pela previsão forneceram informações preditivas úteis para a melhoria do fluxo de trabalho do HED. Finalmente, o uso de ferramentas de simulação permitiu testar e validar duas propostas inovadoras de HED inteligente, seguindo os princípios de E-health e Hospital 4.0.

Palavras-chave: Departamento de Emergência; Hospital Inteligente; Simulação de Eventos Discretos; Hospital 4.0; Health 4.0; Ferramenta de Suporte à Decisão Inteligente.

1 Introduction

Nowadays, technological improvements have brought wellbeing, especially in areas like transportation, manufacturing, communications, businesses, and related areas. The service-based enterprises hold a close relationship with the healthcare systems; each of them can be modeled as a queue-based system. A Hospital Emergency Department (HED) can be considered as high risk and critical service-based business, mainly because of the nature of services related to the preservation of the users' life.

Medicine and healthcare are areas in constant improvement and renewal. Current concepts like the Internet of Things (IoT), Medical Internet of Things (mIoT), Artificial Intelligence (AI), Smart Management Tools, Robotics, Industry 4.0, Blockchain, are pointing to an improvement of healthcare, in a health revolution know as Health 4.0. This concept brings a new path for more efficient and better healthcare, based on the best practices and principles of the most advanced and efficient industries.

The hospitals are complex management and business structures, with a high risk in the offered service. The most complex area, according to unpredictability, high-risk, and management, is the HED. It is an area of primary care; its main function is to offer initial treatment of different diseases to unscheduled patients with high priority.

In any service-based business, like HED, the overcrowding appears when the demand for the service overpass the available resources. It is a generalized problem around the globe (Bittencourt & Hortale, 2009; Pines et al., 2011; Jensen, 2013). This situation, particularly in the HED, reduces the service quality, creating agglomerations, increasing the patients waiting time, reducing the staff productivity and increasing their stress levels, increasing the patients' risk of death, mortality rate and social discrimination in the queues, among other factors (Bittencourt & Hortale, 2009; Jensen, 2013; McHugh, 2013). In contrast, the overcrowding, from the economic viewpoint brings higher profits, since a service provided with overcrowding maximizes the use of resources, allowing more efficient use of the available resources (Handel et al., 2010).

For the development of the current healthcare models, Industry 4.0 and IoT are vital topics (Riazul Islam et al., 2015). On those concepts is grounded the Health 4.0 perspective. The definition of IoT according to (Bradley et al., 2015), corresponds to the use, processing, and storage of information in the cloud, that can be accessed and used autonomously by intelligent objects with a connection in the cloud through the internet With the IoT is expected a life improvement thought the connection of the different devices. On the other hand, the IoT concept has evolved into the industry, bringing the Industry 4.0 or Industrial IoT (Gilchrist, 2016). This concept aims, as in the IoT, an intelligent connection of objects in the industrial area, like information technologies and operational technologies. The goal of Industry 4.0 is improving the development, the services, and processes of each company.

In contrast, Health 4.0 was created as a response to the demographic and socio-economic changes in the last years, life expectancy is growing up, and the population is getting older. Hence the healthcare will become more expensive (Thuemmler, 2017). Health 4.0 is defined as the health approach of Industry 4.0 (Grigoriadis et al., 2017; Thuemmler & Bai, 2017). The Health 4.0 follows the design principles of the Industry 4.0: The core design principles identified for the health domain are Interoperability, Virtualization, Decentralization, Real-Time Capability, Service Orientation, Modularity, Safety, Security and Resilience (Grigoriadis et al., 2017; Thuemmler, 2017).

In the literature review was found that hospital managers were always looking for pioneering strategies to improve healthcare quality. The unpredictability in the healthcare systems bring bottlenecks, overcrowding, increased staff workload, reduced quality of care, and patient and staff dissatisfaction (Abe et al., 2016a). Between the current solutions to solve the described problems in hospitals, and especially in HED, principally are two categories of solutions: the implementation of healthcare politics or the optimization of resources using Operation Research (OR) methods.

The OR methods, using different simulation and optimization tools, have been used to enhance the effectiveness and efficiency of hospitals (Abe et al., 2016b, a, c). Lately, the healthcare area is being more used to these methods, reflected in the exponential number of researches and publications (Thorwarth & Arisha, 2009). Among the most recognized OR methods for simulation and modeling in healthcare are simulation tools like Discrete Event Simulation (DES), Agent-Based Modeling, and System Dynamics. (Oueida et al., 2016).

Critical problems in hospital management can be addressed using simulation models, handling problems such as overcrowding, surgery scheduling, shift scheduling, among others (Oueida et al., 2016). The most used simulation tool in healthcare is the DES; it is used mainly for patient admission and scheduling, patient demand planning, room allocation, workflow, workload evaluation, staff allocation, staff scheduling, and others (Oueida et al., 2016; Abe et al., 2016b, a, c).

Also, it was found that some research projects in healthcare are introducing different forecasting methods to predict the demand for their services in order to predict their requirements and improve their planning. The goal of this researches is to improve the profit and optimize the utilization of the resources by the identification of possible future scenarios. Forecasting methods are widely used in different situations like the prediction of Patient Length Of Stay in an HED (Gül & Güneri, 2015), forecasting models for patient arrivals of an HED (Djanatliev & German, 2013; Aboagye-Sarfo et al., 2015; Calegari et al., 2016;

Carvalho-Silva et al., 2018; Yucesan et al., 2019), decision support tools in HED (Mapuwei et al., 2013; Demir et al., 2017; Ordu et al., 2019) and other applications (Jalalpour et al., 2015). The most remarkable works related to the development of a decision support tool for HED are done by (Demir et al., 2017; Ordu et al., 2019). They take the English healthcare system as a study case, using mostly forecasting models as Auto-Regressive Integrated Moving Average (ARIMA) and as simulation tool the DES.

According to the presented literature review, the simulation methods mainly intend to dimension future hospital facilities or optimize a current hospital efficiency, by the selection of a fixed staff number, being an unreactive solution to changes like unexpected events or population growth. On the other hand, the patients' arrival forecasting methods are mainly used embedded in decision support tools, which allows the hospital managers to take some decisions in case of abnormal situations.

As discussed before, smart hospital management using simulation tools can help solve different current problematics in the area. The objective of this work is to introduce a potential solution to improve the overcrowding problem in a chosen HED, using concepts like Health 4.0, DES, telemedicine, forecasting models, automatic control, and IoT. That improvement can be achieved through the convergence of the described concepts above and healthcare management. That convergence could be ambiguous. Still, from a broad viewpoint, healthcare management can be improved using as input data, the collected data by the IoT smart objects.

The role of the IoT philosophy is essential in the conceptual development of this work, besides the connection of different devices like computers, security cameras, security checkpoints, telemedicine rooms, and others. In a real scenario, these devices would gather the required input data for the on-site implementation of this proposal, also allowing the use of the telemedicine concept. Between the potentially collected data by the IoT devices in a HED system, can be the patients 'waiting time and the queue length in any room. This information can be processed with the help of tools like AI, in the case of video analysis, and summarized with the use of statistics to obtain the central tendency measurements of the data, allowing the knowledge real workflow state of the system.

The research gap that is intended to fill by the current work corresponds to the proposal of a preventive and reactive method that automatically takes smart staff decisions in remote diagnosis rooms to make the services in a hospital more reliable, accessible, and higher quality by the use of the technology. From the software development perspective, this concept pretends to build a bridge between the traditional simulation methods in this area, adding feedback and control on their internal processes, changing their nature from static to reactive. Also, the use of forecasting models, that allow a prediction of future events, to use that information to make preventive decisions. In practical terms, this perspective is original and innovative in the area due to the use of concepts of simulation, time-series forecasting, and the use of automatic control concepts, all embedded in a telediagnosis room system.

The current work presents a study case to validate the described hypothesis. This case study article will attempt to describe and analyze a real situation of overcrowding in a public HED in Kuwait (Ahmed & Alkhamis, 2009) and improve it. The potential solutions are validated by testing them in a DES environment, measuring and comparing its performance with the Key Performance Indicators (KPI).

Therefore, the objective of this paper is to propose a solution based on telemedicine and simulation, to solve overcrowding in reactive and preventive ways. The simulation tool follows the DES method, modeling a selected HED. The patients' arrivals are forecasted with an ARIMA model, providing useful information for a preventive workflow improvement in the HED. All this is possible, thanks to the data analysis of a traditional HED. That offers historical data of the system and the current workflow and problem to solve; in this case, the overcrowding.

This paper is organized as follows: Section 2 shows the description and development of the proposed methodology. In section 3, the results are presented, compared, and discussed. Finally, the conclusions and future perspectives of the study are present.

2 Proposed methodology

The used methodology for this work is based on the results obtained in the study case of (Ahmed & Alkhamis, 2009) to validate the proposed objectives. This work developed a DES model of a chosen HED in Kuwait to optimize the staff number, reducing the hospital budget with traditional optimization methods, giving a fix personnel number. In the current work, the named study case was reconstructed using DES, following the available data in the original publication. The reconstruction was done in Matlab 2018b, using SimEvents®, to obtain an equivalent system, comparable with the original work. The difference of the implementation is based on the use of different software simulation tools that allows testing the new hypothesis as improved response to the overcrowding problem presented in the HED.

As well, this work continues with the ideas and work performed by (Cáceres et al., 2019), which in contrast with the original work (Ahmed & Alkhamis, 2009), this work proposes a dynamic staff number selection controlled by the state of the current situation of the HED, using telemedicine concepts. Opposite, in the ongoing work, the proposal is a dynamic staff number selection with a predictive behavior, to foresee the future behavior of the system, taking the corrections before a critical situation appears. The foundation of that goal is the use of the ARIMA method to forecast the patients' arrivals.

In that order, the first step corresponded to the development of a DES for the studied HED (Ahmed & Alkhamis, 2009). Subsequently, the improvement of the traditional HED using IoT, ARIMA, Automatic control, Health 4.0, and e-health concepts are made, based on the analysis of the HED DES. The critical issue in the system is detected as a bottleneck because it reduces de HED service quality and workflow. The solution allows observing some Health 4.0 design principles like Virtualization, Real-Time Capability, and Modularity, improving some e-health characteristics like management, efficiency, and equity.

Finally, the analysis of a traditional HED (Ahmed & Alkhamis, 2009), and the solutions-based Health 4.0, like the smart-Hospital HED and smart HED with forecasting methods are compared. That comparison is realized using the KPIs indicated in Section 3, where the different changes and improvements in the system are easily observed. The solution showed that an investment in the Telemedicine Rooms and the use of teleconsulting service could improve the service quality.

2.1 Discrete Event Simulation of an emergency department

The DES of a HED as a study case is presented. The DES as a highly used model in the analysis of health services allows the possibility of modeling a HED and verify its behavior under a particular established condition. This kind of simulation presents the

KPI that grades the execution of each analyzed resource. The realization of the HED DES follows initially the work of (Ahmed & Alkhamis, 2009), followed by an implementation of (Cáceres et al., 2019). This simulation is based on the data presented in Table 1.

Table 1. Service time distributions at each stage of the process as presented in (Ahmed & Alkhamis, 2009; Cáceres et al., 2019).

Stage	Probability Distribution (Minutes)	Staff	Abbreviation	Current Staff
Reception	Uniform (5,10)	Receptionist	R (Receptionist)	2
Lab Tests	Triangular (10, 20, 30)	Laboratory Technician	T (Laboratory Technician)	3
Examination Room	Uniform (10, 20)	Physician	D (Physician Doctor)	2
Reexamination Room	Uniform (7,12)			
Treatment Room (TR)	Uniform (20,30)	TR Nurse	TN (Treatment Room Nurse)	1
Emergency Room (ER)	Uniform (60,120)	ER Nurse	EN (Emergency Room Nurse)	9

The HED has different patients' arrival processes, the patients' regular arrival, that corresponds to a non-homogenous Poisson process with an estimate of $\lambda(t)$, an example of a random day is given in Figure 1; and the ambulance arrival given by a Poisson process, with a rate of 2 patients per hour. The development of the DES follows a high-level process to know the flow of the service, for the studied HED, it is presented in Figure 2. The service flow presented in Figure 2 shows the patients' arrivals described above, normally distributed patient arrival, and ambulance arrival.

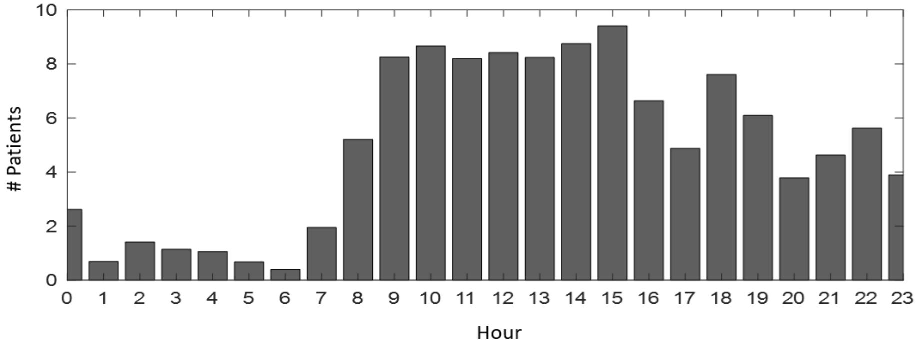

Figure 1. Estimated arrival process rate function λ(*t*), comparing the number (#) of patients and the hour of the day, following (Ahmed & Alkhamis, 2009), and used by (Cáceres et al., 2019).

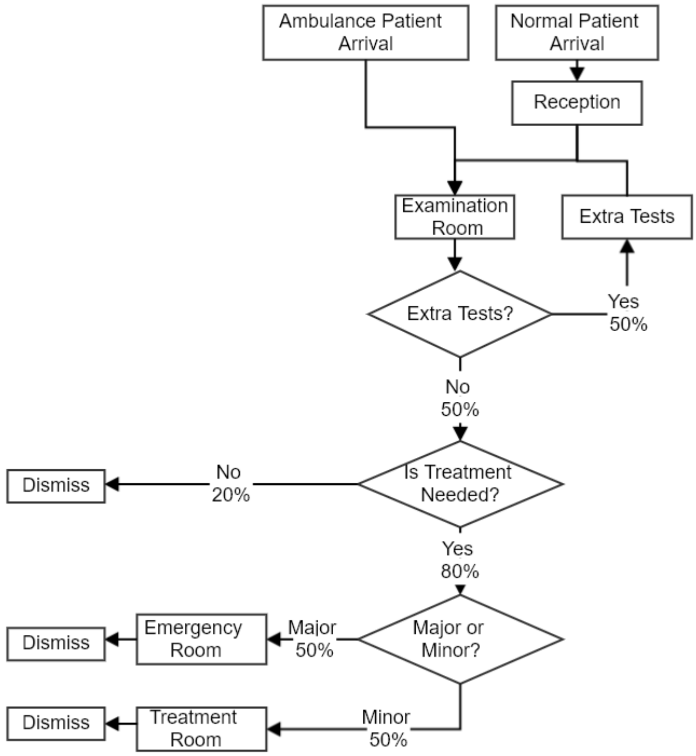

Figure 2. HED high-level process view, following (Ahmed & Alkhamis, 2009) and used by (Cáceres et al., 2019).

2.2 Optimization of the Emergency Department

To optimize the studied HED is required an analysis of the DES results. The obtained results allowed the detection of a bottleneck in the Examination Room (ER), because of its high utilization of 96±1%, as can be observed in Section 3, Traditional HED. Also, other KPIs in the ER are elevated, for example, the queue length with an average of 17,83±5,55 patients and the waiting time with an average of 84.67±25.62 minutes.

The HED optimization is based on the concept of telemedicine, specifically the use of teleconsultation and telediagnosis. The concept of telemedicine has been applied in (Latifi et al., 2007; Marconi et al., 2014). The proposal of a telediagnosis area in ER will remove the detected system bottleneck.

The smart Hospital is founded on the use of a telediagnosis room, which depends directly on the queue length. The desired queue length is of 5 patients in the waiting line, after analyzing the HED data. The chosen number of Examinations Rooms are 5: 2 physical room and 3 rooms of teleconsultation.

2.2.1 Smart HED proposal 1

The first smart HED proposal (S-HED 1) corresponds to a similar case as proposed by (Cáceres et al., 2019), being the main difference between them the tuning method, and the real-time capability. In that case, an Evolutionary Algorithm is used to tune the system, and the optimization was done twice because a new bottleneck appeared after the first improvement. In this case, a heuristic method is used, and only the optimization is done once, obtaining similar KPIs but different staff distribution.

To choose the number and the moment when a tele-physician will be requested, a concept of automatic control is required. This concept is a highly used control technique, knowns as the PID (Proportional, Integral, and Derivative) controller, widely used in many engineering areas like in (Siciliano & Khatib, 2016; Cáceres Flórez et al., 2018; Caceres et al., 2018; Chou & Juang, 2018). The PID controller corresponds to a mathematical model that tries to correct a signal of error along the time. Therefore, it can compensate the error by its action on an output variable; it follows the Equation 1, where u(t) is the control output signal, e(t) the error signal, P the proportional constant, I the integral constant and D the derivative constant. This controller was also used for the same purpose in the implementation of (Cáceres et al., 2019).

$$u(t) = P\,e(t) + I\int e(t)\,dt + D\frac{de(t)}{dt} \tag{1}$$

The controller was tuned heuristically by the response of the system, because of the nature of the system, that follows a stochastic model, and has a limited and rounded output (the number of physicians is a positive integer number). The PID implementation has limited and rounded output. Rounded, due to the positive integer number of physicians. The limits of the controller output correspond to a minimum output that is 0, and the maximum output is 5, due to the physical limitations.

The S-HED 1 corresponds to a HED with a telediagnosis room controlled by a heuristically tuned PID, as it is presented in Figure 3.

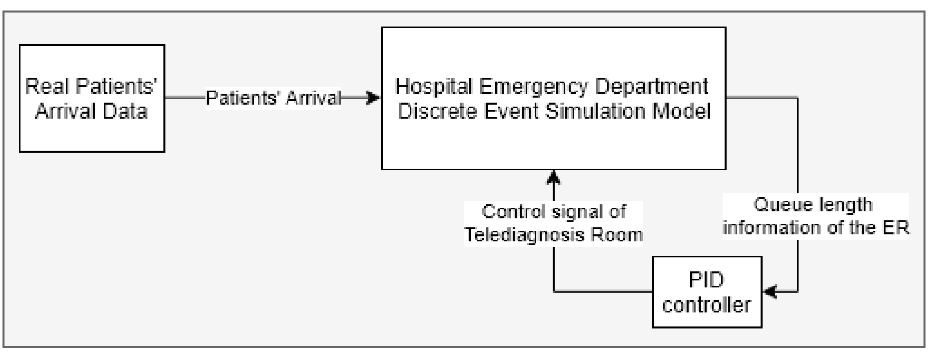

Figure 3. Schema of the first optimization method as proposed by (Cáceres et al., 2019).

2.2.2 Smart HED proposal 2

The second smart HED proposal (S-HED 2) is founded on S-HED 1, adding some enhancements. The main improvement corresponds to the use of a forecasting method, which tries to predict the patients' arrivals and their workflow behavior under that forecasted situation. This improvement influences the present decisions in the HED, considering forecasted system inputs and their operation.

The proposed improvement considers the current state of the HED and the forecasted HED as independent cases, being the input of the present model the real data, and the predicted HED inputs the forecasted patients' arrivals. The models' responses that correspond to the predicted and current values of the PID action of control of the telediagnosis room are added to integrate the present and the forecasted models.

The implemented forecasting method corresponds to the ARIMA, due to its frequent use in the area, like in the work of (Mapuwei et al., 2013; Aboagye-Sarfo et al., 2015; Calegari et al., 2016; Carvalho-Silva et al., 2018; Ordu et al., 2019). This is a statistical model highly used in the time-series modeling, like patient arrivals, and describe the autocorrelations in the data and use the following notation *ARIMA (p, d, q)*, where *p* shows the order of the autoregression process (AR), *d* corresponds to the involved differentiation degree (I) and *q* means the order of the Moving Average process (MA). The seasonal ARIMA can model a seasonal time-series, and the usual notation is *ARIMA (p, d, q) (P, D, Q)* ^{s}, where *P*, *D,* and *Q* have the same meaning as *p*, *d,* and *q*, but for the seasonal part of model, and *s* is the number of periods in a seasonal cycle (Carvalho-Silva et al., 2018).

The seasonal ARIMA model implemented in this work follows the methodology presented by (Carvalho-Silva et al., 2018) follows the Box-Jenkins methodology described in (Box et al., 2015). That methodology starts with a process for the determination and identification of stationarity of the data with a test like the augmented Dickey-Fuller test, then is realized a differentiation of the data to achieve stationarity, followed by a determination of parameters supported by the analysis of the Autocorrelation Function and the Partial Autocorrelation Function. Finally, the verification of the obtained model is done with the Ljung–Box test or plotting autocorrelation and partial autocorrelation of the residuals to identify the model misspecification, if the estimation is wrong, the process should be restarted.

The obtained ARIMA model corresponds to an ARIMA (1, 1, 1) (1, 0, 1)^{24}, similar to the result obtained by (Carvalho-Silva et al., 2018). The difference is the seasonal cycle, in this case, 24 hours, found in the autocorrelation test. The ARIMA (1, 1, 1) (1, 0, 1)^{24}, follows the structure of the Equation 2.

$$x_t = x_{t-1}(\phi_1 + 1) + x_{t-24}\Phi_1 - x_{t-25}(\phi_1\Phi_1 + \Phi_1) - x_{t-26}(\phi_1\Phi_1) + \epsilon_t + \epsilon_{t-1}\theta_1 + \epsilon_{t-24}\Theta_1 + \epsilon_{t-25}\theta_1\Theta_1 \tag{2}$$

Where x_t corresponds to the future value to forecast, x_{t-n} is a past value in n delays. The ϵ corresponds to the error terms of the Moving Average (MA) part of the equation in the different delays, as the last variable. Also, parameters of the autoregressive (AR) part of the model like ϕ_1 and Φ_1 for the seasonal part.

The obtained ARIMA model has as input the real patients' arrival data, and it can predict 3 hours, following the structure of the Equation 2, being recursive in the use of the term x_{t-1}; for the prediction of x_{t+1} and x_{t+2}.

Taking the output of the ARIMA model as input to the DES, it can be obtained a presumable future state of the HED three hours in the future. That information given by the predicted DES model is valuable to take predictive actions of control. The PID control signal of the present telediagnosis room number of physicians corresponds to the mean values obtained between the real DES (DES_t) and the predicted system (DES_{t+3}), as the Equation 3 shows. The equation constants were found heuristically.

$$PID_t = \frac{PID_t}{2} + \frac{PID_{t+3}}{2} \tag{3}$$

Figure 4 shows the structure of the S-HED 2, as described beforehand. The S-HED 2 aims to a predictive response capability by the integration of the present system and a forecasting model, to have better control of the telediagnosis room, considering the current state and the possible future situations.

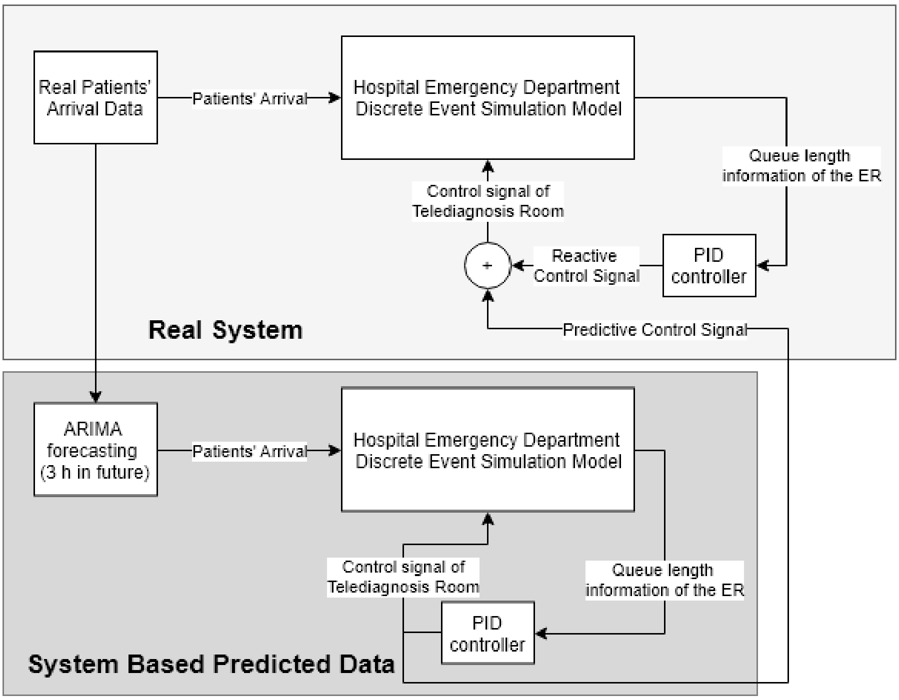

Figure 4. Schema of the second optimization method for the HED using DES using ARIMA.

2.2.3 Comparison of S-HED 1 and S-HED 2

The S-HED 1 and 2 present a clear difference in its implementations, as is shown in Figure 3 and Figure 4, and sections 2.2.1 and 2.2.2. The main difference lies in the use of forecasting methods to be more accurate and responsive under critical future situations.

The S-HED 1 and 2, in contrast with the proposed by (Cáceres et al., 2019), present some additional key features of the Health 4.0 concept like Virtualization, Real-Time Capability, and Modularity.

On the other hand, the topology and structure of the S-HED 2 is more robust than the S-HED 1. This affirmation is based on its capability to predict patients' arrival and a feasible future state of the system, allowing a better control response, because its data horizon is longer than in the S-HED 1. Under critical situations, the forecasting model can attempt to predict some abnormal behavior and try to forecast it, giving to this structure a response advantage, reducing the delayed response of the S-HED 1.

2.3 Software simulation approach

In order to accomplish a system behavior approximation under the given parameters, two simulation environments are prepared. The first simulation corresponds to the DES under normal conditions, corresponding to a traditional hospital. The second simulation corresponds to the desired smart Hospitals, the S-HED 1 and 2, which acquired some of the Health 4.0 main concepts with the implementation of the different optimization methods and ideas proposed for the study case.

The base simulation of the DES is realized according to Figure 5, it shows the DES of the HED, separating the ER in Physical Examination Room and Telemedicine Room. The simulations are done following the data of Table 1, Figure 1, and Figure 2. For each simulation environment, around 1500 simulations are done, in order to capture and visualize the stochastic nature of the DES.

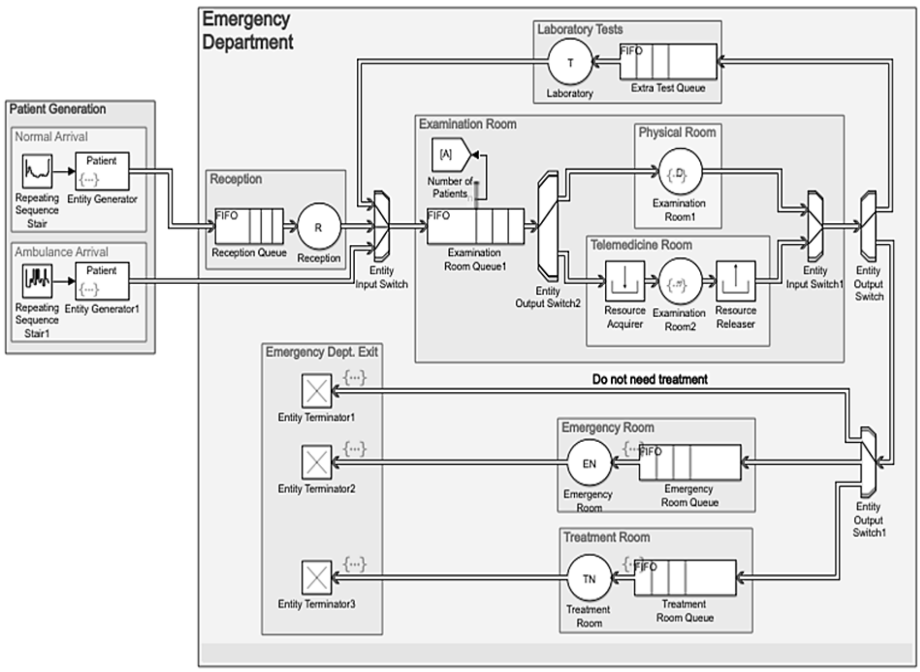

Figure 5. Discrete Event Simulation of an Emergency Department including the Telemedicine Room based in the model presented by (Cáceres et al., 2019)

After the collect the data of the HED DES, data comparison is required. The obtained KPIs for each simulation environment show resource usage in each case, allowing a comparison between a traditional hospital and an approach of the proposed smart hospitals, with and without arrival prediction.

3 Results and discussion

The obtained KPI of the developed DES of a traditional HED and S- HED1 and S-HED 2 based Health 4.0 are presented in Table 2, using the main KPIs metrics for healthcare systems. Table 3 shows the comparison between the results of Table 2, where it is possible to observe the significant difference between the results of a Traditional HED and the two optimization proposals of a smart HED. The results present the smart HED as a more effective and efficient system, with a considerable improvement of the KPIs, especially in the ER, where the traditional HED presented a bottleneck.

Table 2. KPI of a traditional hospital and the 2 proposed Smart HED.

Key Performance Indicator (KPI)	Traditional HED		Smart HED 1		Smart HED 2	
	Value	STD	Value	STD	Value	STD
Expected Time in System (h): Total	**3.68**	**0.7**	**2.73**	**0.27**	**2.69**	**0.26**
Expected Number Out (patients/ hour)	**4.66**	**0.27**	**7.55**	**0.39**	**7.55**	**0.38**
Average Waiting Time (min): Reception	0	0	0	0	0	0
Average Waiting Time (min): Laboratory	0.54	0.3	40.94	22.2	38.73	21.72
Average Waiting Time (min): Doctor	**84.67**	**25.62**	**19.35**	**0.5**	**18.89**	**0.63**
Average Waiting Time (min): Emergency Room	0.03	0.16	0.95	2.13	0.9	1.68
Average Waiting Time (min): Treatment Room	19.7	11.11	15.11	9.75	15.37	10.49
Average Queue Length: Reception	0	0	0	0	0	0
Average Queue Length: Laboratory	0.05	0.03	5.62	3.33	5.3	3.22
Average Queue Length: Doctor	**17.83**	**5.55**	**5.2**	**0.18**	**5.07**	**0.2**
Average Queue Length: Emergency Room	0	0.01	0.06	0.14	0.05	0.1
Average Queue Length: Treatment Room	0.61	0.41	0.85	0.61	0.87	0.67
Utilization (%): Reception	0.28	0.01	0.34	0.01	0.34	0.01
Utilization (%): Laboratory	0.5	0.05	0.63	0.06	0.63	0.06
Utilization (%): Doctor	0.96	0.01	0.83	0.04	0.83	0.04
Utilization (%): Emergency Room	0.34	0.04	0.41	0.05	0.41	0.05
Utilization (%): Treatment Room	0.64	0.09	0.48	0.05	0.48	0.05

Table 3. Comparison of the KPI of Table 2.

Key Performance Indicator (KPI)	Trad. HED vs S-HED 1		Trad. HED vs S-HED 2		S-HED 1 vs S-HED 2	
	Difference	Improve (%)	Difference	Improve (%)	Difference	Improve (%)
Expected Time in System (h)	0.95	26	0.99	27	0.04	1
Expected Number Out (patients/h)	2.89	62	2.89	62	0.00	0.00
Avg Waiting Time (min): Reception	0.00	-	0.00	-	0.00	-
Avg Waiting Time (min): Laboratory	-40.40	-	-38.19	-	2.21	5
Avg Waiting Time (min): Doctor	65.32	77	65.78	78	0.46	2
Avg Waiting Time (min): Emergency Room	-0.92	-	-0.87	-	0.05	5
Avg Waiting Time (min): Treatment Room	4.59	23	4.33	0.22	-0.26	-2
Avg Queue Length: Reception	0.00	-	0.00	-	0.00	-
Avg Queue Length: Laboratory	-5.57	-	-5.25	-	0.32	6
Avg Queue Length: Doctor	12.63	71	12.76	72	0.13	3
Avg Queue Length: Emergency Room	-0.06	-	-0.05	-	0.01	17
Avg Queue Length: Treatment Room	-0.24	-39	-0.26	-43	-0.02	-2
Utilization (%): Reception	0.06	21	0.06	21	0.00	0.00
Utilization (%): Laboratory	0.13	26	0.13	26	0.00	0.00
Utilization (%): Doctor	-0.13	-14	-0.13	-14	0.00	0.00
Utilization (%): Emergency Room	0.07	21	0.07	21	0.00	0.00
Utilization (%): Treatment Room	-0.16	-25	-0.16	-25	0.00	0.00

It is possible to remark the improvement of the patients' Expected Waiting Time in System, from 3.68±0.7 h in the Traditional HED to 2.73±0.27 h in the S-HED 1 and 2,69±0.26 h in the S-HED 2, showing a reduction of the patients time in the system by almost 1 h, showing a faster and higher quality service. The Expected Number Out of discharged patients (out of HED) is improved as well, from 4.66±0.27 patients/ h in the Traditional HED to 7.55±0.39 patients/ h in the S-HED 1 and 7.55±0.38 patients/ h in the S-HED 2, showing an improvement in the number of patients that are successfully attended, increasing the capacity and maximizing the utilization of the S-HED. Both KPIs indicate the general performance of the hospital. Other specific KPIs were improved, the Queue Length and Queue Wait in the General Examination Room (Physician Room). On the other hand, some KPIs are worsened because of bottleneck removal, for example, different KPIs in the Laboratory Room, Emergency Room, and Treatment Room show a minor negative effect on the service queue length and waiting time. Still, it improves the utilization of each Hospital Facility, making the system more efficient, profitable, and higher quality. Efficient due to the use of the maximization of the available resources. Profitable and more top quality, because the maximization of the available resources influences in faster service for the users and also in improving the revenues of the HED, that by now can be measured in the number of attended patients per hour, corresponding to the KPI Expected Number Out (patients/ hour).

Table 4. KPI of a traditional hospital and the two proposed Smart HED.

Key Performance Indicator (KPI)	Traditional HED		S-HED 1		S-HED 2	
	Value	STD	Value	STD	Value	STD
Expected Time in System (h): Total	**3.68**	**0.7**	**2.73**	**0.27**	**2.69**	**0.26**
Expected Number Out (patients/ hour)	**4.66**	**0.27**	**7.55**	**0.39**	**7.55**	**0.38**
Average Waiting Time (min): Reception	0	0	0	0	0	0
Average Waiting Time (min): Laboratory	0.54	0.3	40.94	22.2	38.73	21.72
Average Waiting Time (min): Physician Room	**84.67**	**25.62**	**19.35**	**0.5**	**18.89**	**0.63**
Average Waiting Time (min): Emergency Room	0.03	0.16	0.95	2.13	0.9	1.68
Average Waiting Time (min): Treatment Room	19.7	11.11	15.11	9.75	15.37	10.49
Average Queue Length: Reception	0	0	0	0	0	0
Average Queue Length: Laboratory	0.05	0.03	5.62	3.33	5.3	3.22
Average Queue Length: Physician Room	**17.83**	**5.55**	**5.2**	**0.18**	**5.07**	**0.2**
Average Queue Length: Emergency Room	0	0.01	0.06	0.14	0.05	0.1
Average Queue Length: Treatment Room	0.61	0.41	0.85	0.61	0.87	0.67
Utilization (%): Reception	0.28	0.01	0.34	0.01	0.34	0.01
Utilization (%): Laboratory	0.5	0.05	0.63	0.06	0.63	0.06
Utilization (%): Physician	0.96	0.01	0.83	0.04	0.83	0.04
Utilization (%): Emergency Room	0.34	0.04	0.41	0.05	0.41	0.05
Utilization (%): Treatment Room	0.64	0.09	0.48	0.05	0.48	0.05

Table 4 introduces a comparison between principal KPIs in each case under study. It is possible to distinguish the differences between the traditional system and the improved ones. Also, it is possible to identify the new bottlenecks created by the removal of the ER bottleneck. Following the observations, it is possible to conclude that the S-HEDs added the equivalent of a 1.4433± 0.112 tele-physician (in a day) in the first proposal and 1.4377± 0.112 tele- physician (in a day) in the second proposal. That increase in the staff number in a telediagnosis room improves the workflow of the healthcare system in different ways. Those improvements directly enhance the HED workflow, by the reduction of the patients' waiting time in the facilities by around 1 hour.

Comparing the S-HED 1 and S-HED 2, it is possible to conclude that S-HED 2 has a better KPI performance in the overall HED results, like the expected time in the system. That applied methodology shows that it is possible to optimize the use of the resources by the prediction of the patients' arrival. The comparison between the study cases is presented in Table 5.

Table 5. Comparison of the KPI of Table 4.

Key Performance Indicator (KPI)	Trad. HED vs. S-HED1		Trad. HED vs. S-HED2		S-HED 1 vs. S-HED 2	
	Difference	Improve (%)	Difference	Improve (%)	Difference	Improve (%)
Expected Time in System (h)	0.95	26	0.99	27	0.04	1
Expected Number Out (patients/h)	2.89	62	2.89	62	0.00	0.00
Avg Waiting Time (min): Reception	0.00	-	0.00	-	0.00	-
Avg Waiting Time (min): Laboratory	-40.40	-	-38.19	-	2.21	5
Avg Waiting Time (min): Physician	65.32	77	65.78	78	0.46	2
Avg Waiting Time (min): Emergency Room	-0.92	-	-0.87	-	0.05	5
Avg Waiting Time (min): Treatment Room	4.59	23	4.33	0.22	-0.26	-2
Avg Queue Length: Reception	0.00	-	0.00	-	0.00	-
Avg Queue Length: Laboratory	-5.57	-	-5.25	-	0.32	6
Avg Queue Length: Physician	12.63	71	12.76	72	0.13	3
Avg Queue Length: Emergency Room	-0.06	-	-0.05	-	0.01	17
Avg Queue Length: Treatment Room	-0.24	-39	-0.26	-43	-0.02	-2
Utilization (%): Reception	0.06	21	0.06	21	0.00	0.00
Utilization (%): Laboratory	0.13	26	0.13	26	0.00	0.00
Utilization (%): Physician	-0.13	-14	-0.13	-14	0.00	0.00
Utilization (%): Emergency Room	0.07	21	0.07	21	0.00	0.00
Utilization (%): Treatment Room	-0.16	-25	-0.16	-25	0.00	0.00

Table 5 shows clearly the comparison between the Traditional HED, S-HED 1, and S-HED 2. The notorious improvement of the S-HEDs is observed if compared with the traditional one. In contrast, S-HED 2 is a little bit better than S-HED 1, making better use of a similar amount of resources. The key to the improvement is in the predicted data and its predictive control signal, not only reactive control.

On the other hand, the performance of the developed ARIMA model compared with the database has a Mean absolute percentage error (MAPE), showed in the Equation 4, of 29.55%.

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{R_t - F_t}{R_t} \right| \tag{4}$$

Where n is the number of fitted points, R the reference value, and F the forecast value. An example of the forecasted data can be done with the random data under study, corresponding to Figure 1, where the chosen forecasting model obtained a MAPE of 7.26%, the comparison is presented in Figure 6.

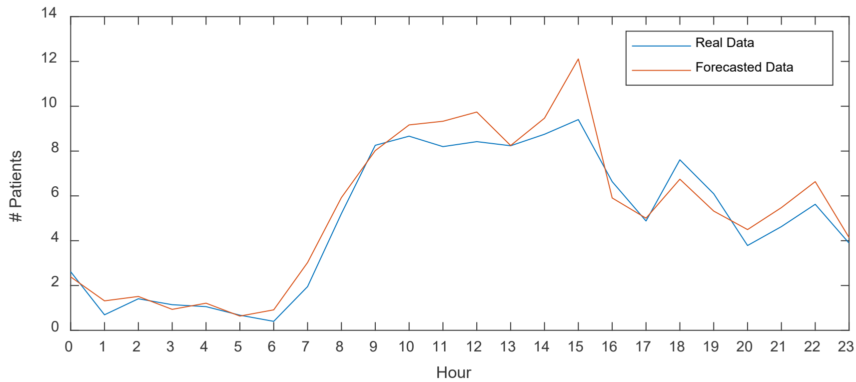

Figure 6: ARIMA forecasting results of a random day for the process of **Figure 1,** comparing the number (#) of patients and the hour of the day.

The ARIMA model presented a moderate performance with a MAPE of 29.55%, but in this case, it was possible to observe that the obtained performance was enough for the proposed analysis. The possible errors of the forecasting model correspond to many factors, between them the unusual activity of the HED, the low capacity of generalization of the forecasting method selected, the complex nature of the process to forecast, the weak temporal relationship of the collected time-series data, between others.

On the other hand, it is remarkable the process of obtaining some Health 4.0 capabilities. In S-HED 1 and S-HED 2, aspects like Virtualization, Real-Time Capability, and Modularity are acquired by the proposals. These features are key concepts of the Health 4.0 principles, as presented in the literature review in section 1. Virtualization, due to the integration of the physical world with the virtual world, with the use of Telemedicine. Real-Time Capability, due to the capability to respond instantaneously to a changing situation, being able to control the number of tele-physicians. Modularity, for the efficiency in the service quality, no matter how many real physicians will be available, the system will cover the requirements.

The implications of the current proposal from the theoretical and practical views point to the integration of different technologies and perspectives in one area and how, by the use of different current concepts and perspectives, a good result can be achieved. In the simulation, the use of closed feedback loops and automatic control concepts into the DES looks promising. It requires a deeper theoretical and practical study to see its limitations, advantages, and disadvantages. On the other hand, the practical perspective should take advantage of this connected world and how the different IoT devices can gather information to make better datasets and improve the current simulation models by the gathered data refining.

4 Conclusions and further developments

This development of the proposed smart-Hospital based on Health 4.0 features using the computational HED models will allow the avoidance and detection of bottlenecks in the HED workflow. The results show an optimization in the use of the resources and a reduction of the length of stay. These improved characteristics are associated with the decrease of the mortality rate, due to a faster treatment in high-risk or medium-risk patients, reduces the death risk, improving the service quality.

The IoT concept was introduced to improve a service-based system. The use of network-connected devices like computers, security cameras, security checkpoints, telemedicine rooms, and others, to gather live data aid the management of a service-based business. The simulation of IoT devices as ideal in a simulation environment, like DES, was vital in the conceptual proposal of this work. The used simulation tool and the proposed concepts point to a comfortable and cheap possibility to prototype and make viability tests of real IoT based solutions for service-based systems.

The improvement of the HED was successful in both proposed structures, supporting the potential use of the concept. Both proposals were software-based models, and physically they used not many additional resources and introduced concepts as telemedicine, Health 4.0, forecasting models, and IoT to improve the workflow. The proposed S-HED enhanced by 26% and 27% in the KPI that corresponds to the Expected Time in System. On the other hand, the Expected Number Out of patients per hour improved 62% in both proposals. Those significant changes were obtained by the addition of 1.4433± 0.112 tele-physicians in a day.

Finally, it was possible to present work were the IoT, IIoT, Health 4.0, automatic control, forecasting methods, simulation tools, and other concepts can be merged and obtain promising results. Also, it proposes a multidisciplinary idea that suggests a more reliable, accessible, and higher quality hospital service. It leads to a hyperconnected smart reality, where the different devices and technologies improve human well-being.

Acknowledgements

The authors thank the University of Campinas (UNICAMP) and the National Council for Scientific and Technological Development (CNPq) for its support in the development of this work.

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