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A smart healthcare reward model for resource allocation in smart city

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Abstract

Today, cities face many significant challenges, and the smart city concept is a promising means to address typical traditional city problems. The wireless e-health technologies is an evolving topic in the area of telemedicine nowadays. Mobile telecommunication and the use of multimedia technologies are the core of providing better access to healthcare personnel on the move. These technologies provide equal access to medical information and expert care leading to a better and a more efficient use of resources. Mobile and Fog computing technologies can also cope with many challenges in smart healthcare resources of mobility, scalability, efficiency, and reliability. Optimal healthcare systems are particularly critical in cities, due to the highly concentrated populations. This high population increases the potential for harm and damage in the case of negligence or improper treatment. This can lead to infections and disease outbreaks, which could become epidemic situations and require containment, which is very costly. Motivated by the need for better usage and management of healthcare resources, which is crucial for reliable healthcare delivery, this paper introduces a model that can provide improved delivery and utilization of resources. The quality reward-based model was developed to study and react to the satisfaction factors of healthcare systems, and proposes an optimization-based algorithm called the Maximum Reward Algorithm (MRA), that enhances the use and delivery of healthcare resources. The algorithm has been tested with multiple experiments and simulations, and has proved that it can provide reliability, efficiency and achieves 50.1% to 77.2% performance improvement.

Keywords Smart healthcare · E-health · Multimedia technologies · Telemedicine · Reward system · Resource allocation · Smart city

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1 Introduction

Today's cities are continually growing, and urban living poses major challenges to resource availability, allocation and optimization. The smart city concept is one of the most promising solutions for the traditional city model. With smart city, Information and Communication Technologies (ICT) and the many available connected smart systems including smart government, smart infrastructure, smart transportation and smart healthcare are key to providing innovative services to make smart cities a reality [18, 30].

The Internet of Things (IoT) plays an important role in improving smart healthcare. This is achievable by contributing to the development of more sophisticated methods of remote monitoring, tracking, digital transformation and personal robotic healthcare [1, 31]. IoT can improve the delivery of diverse services, including smart transportation, homes and grid, as well as smart governance, infrastructure and healthcare. Smart health is built on a foundation of information and resources, and its sole purpose is to connect healthcare technology and key stakeholders to improve the quality of the healthcare experience [39]. Smart healthcare can ease mobility and access to treatment, enhance the management and sustainability of healthcare resources and services, and simplify the fundamental requirements of healthcare in smart cities. However, these goals can be only achieved with involved and supportive management, enhanced processing of raw data and relevant experience. Thus, smart healthcare is a fundamental and valuable component of smart cities, as it helps enable a broad range of applications for industry, government and citizens. Similarly, smart city subsystems will communicate and enhance healthcare services by using smart city technology to make healthcare smarter and more efficient [11]. On the other hand, there are still many issues to be addressed with respect to smart healthcare services, particularly service delivery and resource utilization. In order for smart health services to be beneficial, the means of handling and managing smart healthcare resources is critical.

Mobile Tele-monitoring in healthcare or the wireless telemedicine is nowadays playing a major role in the evolution in healthcare services [26]. This evolution imposes the use of mobile telecommunication and multimedia technologies to be integrated into new mobile health care delivery systems. The use of this technology facilitates the concurrent access to medical information and expert care by overcoming the boundaries of separation that exists between different users. This can lead to a better use of available resources.

The moving network consists of a cluster of mobile nodes and a wireless gateway. The local routing device can be a regular WiFi access point or a smartphone to connect a WPAN with the wide-area network infrastructure. WPAN is a wireless personal area network used to interconnect devices using wireless connections. Since the emergency department studied consists of two separate emergency rooms, resource utilization efficiency is a must. This can be achieved using the concept of moving networks. The multi-service traffic from a moving network can be multiplexed at the local gateway before forwarded over a relay channel. Therefore, it is favorable to deploy a multi-mode gateway with multiple access capabilities. The smartphone refers to the gateway for the personal moving network and must be equipped with multiple radio interfaces for network access. At this gateway the allocation of resources is happening. The aggregation of this multi-service traffic can be relayed via a WiFi network or a cellular network.

There are various studies in the literature regarding the prevailing issues in health service delivery. Most agree that the increasing burden on healthcare facilities and the inefficiency of supplying adequate health services is due to increasing pollution and the subsequent need for treatment [6, 19]. Thus, the goal of this study is to research a novel method to effectively provide healthcare, and to develop new approaches that ensure optimal health service delivery. This paper addresses the issue from a new perspective, by considering healthcare delivery service and resources as an industrial system. We investigate degrees of satisfaction, and propose a new reward-based optimization algorithm that will enhance healthcare systems with queueing theory. Optimization is improving the operational flow of a system without interrupting the actual processes, and enhancement of complex healthcare systems must be considered to increase satisfaction levels of the three main players: patients, owner and medical resources (doctors, nurses ..etc).

In healthcare industry, patient satisfaction depends on the quality of service delivered, and healthcare systems include at least three main players: patients, owner and medical resources. Satisfied patients tend to prefer and recommend the hospital they last used, and will likely return for additional services [41]. In complex systems such as healthcare, patients express their preferences and recommend medical service when they are well treated and the service meets their expectations (i.e. fast and simple). Higher patient satisfaction levels increase service usage and market share, which implicitly also increases owner satisfaction [37]. Another factor that leads to a successful healthcare delivery is medical resource satisfaction. Services that are quick and well delivered increase the satisfaction of the medical resource involved in the delivery stage in two ways: higher pay and optimal utilization. A well-paid medical resource with an acceptable workload tends to deliver higher quality service, and subsequently imposes a positive impact on the patient's satisfaction level [29].

The proposed model in this article is an optimization based novel generic reward system that targets the satisfaction of the three parties involved in the medical care systems (Patient, Owner and Medical Resources).

The remainder of this article is organized as follows: Section 2 is related work, and smart healthcare in a smart city is presented in Section 3. The model design is examined in Section 4, and in Section 5 the proposed reward system is applied to healthcare. A new reward-based optimization algorithm is defined in Section 6, and conclusion and potential future work are presented in Section 7.

2 Related work

New technological advances in the IoT and smart health have enabled real-time monitoring of patients. However, these technologies face many challenges with respect to power efficiency, scalability and cost. A study by Granados et al. presented the benefits of combining data and power in a single process to effectively deliver both cloud connectivity and energy to medical sensors and smart hospital appliances [16]. Opportunities and challenges for IoT to realize this vision of smart healthcare are highlighted in [15]. Another study proposed two algorithms for improving the throughput of video transmission in cellular networks as a potential to satisfy the high demand for high data rates [2]. Moreover, the performance of an architecture for improving the Quality of Experience video streaming in cellular networks is presented in [3].

Resource allocation supporting a personal moving network over a heterogeneous multi-hop wireless infrastructure was studied by [42]. The personal wireless devices or medical sensors around a mobile user moving in a group together consist the personal area network such as smartphones, notebooks, personal digital assistants (PDAs), and health monitoring. Devices are the nodes constituting the personal moving network. In this study [42], different aspects of resource allocation for aggregation of multimedia and healthcare services in such a heterogeneous network scenario are investigated. The multi-radio smartphone needs to select among multiple available networks. Therefore, a stochastic Petri net model for the access selection is proposed. Different such as Bluetooth and Zigbee can be considered as WPAN options in order to construct the personal moving network.

Moreover, Mobile telemedicine is a new research area that exploits recent advances in mobile telecommunications technologies having the potential for highly flexible medical services. Telemedicine systems consist of an interface between hardware, software and communication channel in order to exchange medical information between two different locations. The hardware consists of computer, printer, scanner, video conferencing equipment etc. The software enables the acquisition of patient information (images, reports, films etc.) and resource allocation details. Today′s, Telemedicine systems are supported by state of the art multimedia technologies like Interactive video, high resolution monitors, high speed computer networks, etc. [24].

Recently, Cloud-assisted WBAN (Wireless Body Area Network) has become popular and widely applied in healthcare domains. While these platforms provide massive advantages in healthcare systems, they suffer from significant performance challenges when large media sizes are transmitted to remote terminals. These performance challenges have led [Hassan et al.] to propose their model that combines WBAN and cloud for valid data sharing [17]. Four layers are defined as the network architecture: perception layer, network layer, cloud computing layer, and application layer. Here, efficient management of patient-related data in the form of text, image, voice, etc. from various WBAN is vital for various applications. OPNET simulator is used in order to prove the feasibility of the proposed architecture in terms of transmitting a huge amount of media healthcare data in real-time under traditional IP-based network.

The IoT revolution has revealed promising technological enhancements for healthcare management. A survey conducted by researchers in the field proved the efficiency of IoT-based healthcare for a smart city. They also discussed network architectures, platforms and applications, as well as challenges to be expected due to security risks. Collecting and sharing information on continuous basis can enrich the healthcare sector and help it evolve to meet the functional requirements. Smart healthcare is implemented to support real-time recognition and treatment of medical situations. The authors [Kim and Oh] achieved this by developing a watch that detects temperature and heartbeat through integrated sensors [23, 32]. Using IoT, physical and location information are collected and analyzed. Moreover, technological development on detection intrusive sensor behavior in critical applications has shown great performance [33].

A recent study conducted by Elmisery et al. [14] proved the efficiency of the IoT to deliver healthcare services. They used digital sensors and cloud computing to shift healthcare sector from a traditional to smart environment. IoT-aware, smart architecture to transform classic healthcare into smart service was proposed by Catarinucci et al. [8]. Their model monitors and automatically tracks patients, personnel and biomedical devices in the hospital. The authors proposed a smart hospital system (SHS) that implements technologies such as RFID, WSN and smart mobile. This SHS can collect environmental conditions and patients' physiological parameters in real time, via an ultra-low power hybrid sensing network (HSN).

Mobile cloud computing (MCC) also contributes to technology for the healthcare sector, by enabling new types of services and facilities for patients and caregivers. Hence, a new mobile medical web service system to integrate MCC and Multi Agent Systems in healthcare and improve the medical process was proposed by Jemal et al. [22]. A comprehensive review on cloud computing and the benefits and challenges that could arise when adopting these technologies in the healthcare sector was presented in [4]. Chung and Park developed a cloud-based mobile health service to enhance the quality of service (QoS) of healthcare services [10]. They studied factors such as reliability and response time, to resolve broadband-communication problems and wireless network delays.

Healthcare industrial systems are typically comprised of business processes that compete for resources [43]. The complex dynamic behaviour and unpredictability of these business processes require workflow systems to control the work and guarantee effective allocation of resources. As healthcare systems, emergency departments (ED) in particular, are non-stop services with patients arriving without prior notice. Simulation modelling is necessary to examine the systems and predict malfunctions. Currently, EDs are encountering many problems that impact their daily medical service and operations [27]. The main issues are overcrowding that results in long waiting times, extended length-of-stay (LoS) and, ultimately, patient dissatisfaction [7]. A potential solution is to increase the ED capacity and provide extra resources, but these measures are not always achievable due to the intrinsic extra costs and budget constraints [40]. As per the literature, simulation modelling has proved to be a more efficient means of addressing complex problems [25].

ED simulation models have been studied by many researchers over the past few decades. All simulations are unique in terms of the characteristics and layout of the ED, including the number of units, the amount of resources, patient flow and the real input data collected from the target ED. ED performance is measured by evaluating the major Key Performance Indicators (KPI) in the literature and the length of stay (LoS), which is the total time a patient spends in the ED [38]. Experiments were conducted with this model to determine ways to improve patient flow [9, 13]. The author in a previous work [34] modelled, simulated and improved an emergency department in Lebanon using Arena software. Studies of emergency departments through the literature have shown that simulation modelling is the best way to study the system, spot the problems and enhance the operational flow.

For a cost-effective and sustainable healthcare information system, healthcare data must be effectively collected, processed and transformed into information and knowledge for future action. Unfortunately, the implementation of these systems is rather complex and challenging. To address this, Demirkan proposed a new framework to conceptualize data-driven, mobile cloud-enabled smart healthcare systems that enhance healthcare operations by providing cost-effective quality healthcare services with lower IT set-up costs and reduced risk [12].

We now know that addressing ED problems relies on improving the processes and considering the extra costs, patient safety and satisfaction and the LoS [20]. Therefore, the new reward system proposed as the main contribution of this article focuses on three satisfaction factors: patient satisfaction, owner satisfaction and resource satisfaction. Equations are provided to calculate these satisfaction levels, and new resource allocation levels to increase these metrics are simulated.

3 Healthcare at the edge of IoT and smart city

The use of multimedia technologies along with mobile edge and cloud computing is very efficient in enhancing medical services and especially resource allocation and medical information delivery. The increasing pace of IoT and edge concepts [5] and their integration in smart city systems, connected and smart health systems have emerged as integral components of the smart city and its services [21]. Thus, many entities have classified smart healthcare systems as key enablers for a smart city. With unique real-time data and the required levels of system availability, healthcare systems are not merely smart city sub-systems like infrastructure, transportation or government, but leading gateways to a more productive and livable construct that helps ensure quality of life for smart city citizens [15, 31].

Smart healthcare is also an important driver in data science (real-time big data). Data-intensive and digital-physical ecosystems of smart healthcare consolidate information from many aspects of a patient's life, and present a more comprehensive view of a citizen′s health, all in real-time. This also leads to the substantial effects that smart healthcare data will have on the healthcare industry. In order to achieve noticeable improvements, proper management of healthcare services and resources is essential. Our proposed reward model facilitates proper management for both healthcare services and resources.

Healthcare systems in the medical sector that attend to the health of an entire population highlight the need to change healthcare systems from traditional services to smart health delivery. Transforming existing healthcare systems, particularly emergency departments, into smart, reliable operations with efficient resource allocation is an extremely complex undertaking, so a smart model for optimal resource allocation is critical. This paper proposes a Maximum Resource Allocation (MRA) algorithm for resource management, which will help decision makers allocate the required resources to deliver healthcare most effectively. The algorithm is supported by a reward system that guarantees smooth operations and patient, owner and medical resource satisfaction. Balancing these three factors will lead to a unified and stable smart healthcare system. Table 1 is a dedicated table to explain the most frequently used notations in the paper.

4 Smart healthcare reward model

In the previous sections, literature review and related work were illustrated in order to clarify the relation between healthcare and IoT.

The reward system is defined by:

$$\mathfrak{R} = \Sigma_{i=1}^{3} \mathbb{W}_i \mathbb{F}_i \tag{1}$$

Table 1 Notations used in this paper

Notation	Description
$\mathfrak{R}$	Reward System
$\Sigma_{i=1}^{3} \mathbb{F}_i$	$\mathbb{F}_1 + \mathbb{F}_2 + \mathbb{F}_3$
$\mathbb{F}_1$	patient satisfaction factor
$\mathbb{F}_2$	Owner satisfaction factor
$\mathbb{F}_3$	Medical resource satisfaction factor
$\mathbb{W}_i$	$\Sigma_{i=1}^{3} \mathbb{W}_i = \mathbb{W}_1 + \mathbb{W}_2 + \mathbb{W}_3$
$\Sigma_{i=1}^{3} \mathbb{W}_i$	Equal to 1
$\mathbb{W}_1$	Weight of importance of patient
$\mathbb{W}_2$	Weight of importance of owner
$\mathbb{W}_3$	Weight of importance of medical resource
x	Average level of patient LoS in the system

The degree of importance reflects which satisfaction factor most impacts the reward system; the one with the highest weight should be the first considered for enhancement. Improving the satisfaction factors can be achieved by hiring new resources and effective resource allocation.It is essential to improve service throughput in order to increase revenue and subsequently maintain/improve owner's satisfaction. Patient satisfaction is a combination of waiting times and level of care received, while medical resource satisfaction is a factor of utilization rates and workload. Weights can be assumed or predicted from observations and site visits, and more precise values can be calculated based on management decisions and hospital preferences. This section defines the model for the proposed reward system in terms of patient, owner and medical resource satisfaction.

4.1 Patient satisfaction

Patient satisfaction, $\mathbb{F}_1$, is a factor of the average waiting time a patient spends in the system, and the level of care they receive from medical resources. Patient satisfaction is represented by:

$$\mathbb{F}_1 = \eta_1 e^{-x} + \eta_2 \mathbb{F}_3 \tag{2}$$

Where,

(i) $x = \frac{\text{(actual LoS - expected LoS)}}{\text{expected LoS}}$
(ii) η_2 is the patient-medical resource relationship
(iii) $\eta_1 + \eta_2 = 1$
η_2 is affected by the culture and utilization rate of the medical resource. Some medical resources are negatively affected by their high workload and therefore badly affect the level of care they deliver to patients.
(iv) Actual LoS is the current patient's LoS
(v) Expected LoS is the maximum expected time duration a resource spends before receiving the service

4.2 Owner satisfaction

The owner satisfaction, $\mathbb{F}_2$, is a factor of the profit and the revenue. Therefore, in order to experience an increase in the owner satisfaction, the net profit must be increased. $\mathbb{F}_2$ is represented by:

$$\mathbb{F}_2 = \frac{\text{profit}}{\text{revenue}} \tag{3}$$

Where,

(i) Revenue is system gain regardless of the cost paid
(ii) Revenue $= k *$ Payment
(iii) Payment is the money patients spend in the system
(iv) $k =$ number of patients arriving to the system
(v) Profit is the net profit after paying all the expenses for human resources, equipment, material, etc.
(vi) Profit $=$ Revenue - Total Expenses
(vii) Total Expenses represent salaries, material, equipment maintenance/replacement, etc.

The values to measure patient satisfaction are collected through meetings with management, and the proposed reward system can only be considered by decision makers with a goal of net profit. Simulation outputs can be used to propose enhancements to the actual operating system during normal workflow.

4.3 Medical resources satisfaction

Medical resource satisfaction is a factor of the levels of pay and workload. In order to guarantee high patient satisfaction, monthly wages should be increased and daily workload decreased. Medical resource satisfaction, $\mathbb{F}_3$, is represented by:

$$\mathbb{F}_3 = \Sigma_{n=1}^{m} \frac{f_n}{m} = \frac{f_1 + f_2 + \cdots + f_m}{m} \tag{4}$$

where, m is the number of different medical resource categories, such as: receptionists, actual workers, transporters, and such. The satisfaction of each category is defined by f_n where f_n is defined by:

$$f_n = \frac{\Sigma_{i=1}^{k} \mathbb{X}_i(\triangle_n)}{k} \tag{5}$$

Where,

(i) $\triangle_n$ is a certain category of medical resources
(ii) k is the number of medical resources in a same category
(iii) $\mathbb{X}$ is the balance between pay and workload for an medical resource belonging to a same category $\triangle$
(iv) $\mathbb{X}_i = (\mathbb{W}_1 * \text{pay }) - (\mathbb{W}_2 * \text{workload})$
(v) $\mathbb{W}_1 + \mathbb{W}_2 = 1$
(vi) $\text{pay} = \frac{\text{actual pay}}{\text{maximum pay}}$
(vii) $\text{workload} = \frac{\text{actual workload}}{\text{maximum workload}}$

Since each category type can have several medical resources, then,

$$f_1 = \frac{(\mathbb{X}_1(\triangle_1) + \mathbb{X}_2(\triangle_1) + \ldots\ldots. X_k(\triangle_1))}{k}$$
$$f_2 = \frac{(\mathbb{X}_1(\triangle_2) + \mathbb{X}_2(\triangle_2) + \ldots\ldots. \mathbb{X}_k(\triangle_2))}{k}$$
$$\vdots$$
$$f_m = \frac{(\mathbb{X}_1(\triangle_n) + \mathbb{X}_2(\triangle_n) + \ldots\ldots. \mathbb{X}_k(\triangle_n))}{k}$$

5 Model application

In the previous section, a new reward system is proposed in order to apply optimization. This reward system balances between three satisfaction factors: Patient, Owner and resources. Healthcare is very complex and always prone to overcrowding and bottlenecks, particularly in the ED. Therefore, ED flow must be carefully examined in order to suggest ways to improve the system without interrupting ongoing services. Previous studies mention that an effective and efficient means of enhancing ED operations is to reallocate current resources and add new ones. Thus, the three main satisfaction factors of patient, owner and medical resources are applied by the reward system as suggested in the previous section $\mathfrak{R}$. Our target ED is an emergency department in Lebanon, with several types of human resources to serve patients. ED department used in this study is constituted of 2 Emergency Rooms (ERs): ER A and ER B. The non-human resources, referred to as ’facilities’, are indirectly considered during the optimization stage, since the addition of human resources to accomplish certain tasks requires material, medical equipment and other support. The facilities resource type includes everything required to deliver care to an arriving patient, including beds and accessories, medication, medical devices, cotton, syringes and many more.

Human resources are classified into eight different categories: doctor, RN, nurse, transporter, receptionist, technician, accountant and physician. Each category type includes different numbers of allocated resources, as depicted in Table 2. Registered Nurse is responsible for all triage activities once patient arrives to the ED. RNs are the chief of all nurses. Nurse on the other hand, is responsible for collecting patients’ data information once patients enters the ED. The nurse is also responsible for preparing the patient until the doctor is available. Applying the defined reward system equations to our target ED gives the satisfaction level values presented in Table 3. The reward system for the ED is defined by: $\mathfrak{R}_{ED} = \Sigma_{i=1}^{3} \mathbb{W}_i \mathbb{F}_i$. From interviews with management and observations from site visits, the weight $\mathbb{W}_i$ of each $\mathbb{F}_i$ was found to be: $\mathbb{W}_1$ =0.6, $\mathbb{W}_2$ =0.3 and $\mathbb{W}_3$ =0.1 with the highest weight representing the patient satisfaction factor, which is the priority concern of decision makers. Profit is then considered by decreasing the cost as much as possible and eliminating waste. Finally, staff utilization rates are also decreased to address staff satisfaction. The weight values will vary for different hospitals, based on culture, hospital requirements, budget constraints, and other factors. This leads to:

$$\mathfrak{R}_{ED} = (0.6 * \mathbb{F}_1) + (0.3 * \mathbb{F}_2) + (0.1 * \mathbb{F}_3)$$

5.1 Owner satisfaction

To determine owner satisfaction, revenue and total expenses must be calculated. The consultation fee per patient is \$35, the number of system out was found through simulation with Arena is to be 60 patients and the simulation of the ED model was run for 24 hours (More details will be provided in the simulation results section). Thus, the average revenue per month is = \$6,300. Total expenses include the cost of all nine resources, both human (eight) and non-human (one), and applying the values of Table 2 gives a result of \$31,000 per month. The non-human (facilities) expenses include the cost of material required to deliver a service, equipment maintenance and replacement of medical devices such as beds. Facility Expenses are $= \eta *$ Expenses $= 0.6 *$ Expenses = \$18,600, and the value of η is different for each hospital. More medical resources assigned for a service means more facilities are

Table 2 Actual pay vs. expected pay

Resource type	Actual pay(\$)	Maximum Pay(\$)
Doctor	2000	2500
Registered Nurse (RN)	1100	1500
Nurse	850	1000
Transporter	650	700
Accountant	1000	1100
Receptionist	500	550
Physician	1200	1800
Technician	800	850
Facilities	800	Not considered

Table 3 Resource satisfaction factors

Resource type	Satisfaction factor(%)
Doctor	$f_1 = 43.6$
Registered Nurse (RN)	f_2 44.17
Nurse	$f_3 = 48.62$
Transporter	$f_4 = 27.874$
Accountant	$f_5 = 57.38$
Receptionist	$f_6 = 58.01$
Physician	$f_7 = 41.85$
Technician	$f_8 = 64$

needed to accomplish the task. Thus, the correlation between Expenses (human resources) and Facility Expenses (resource type facilities) are the Total Expenses = \$49,600. Owner satisfaction was then calculated and found to be $\mathbb{F}_2 = 20\%$. This is a very low value for owner satisfaction, so changes should be made to enhance system throughput and increase $\mathbb{F}_2$ accordingly.

5.2 Resource satisfaction

As human resources are classified into eight different categories, the satisfaction factor must be calculated for each type of resource individually to determine true resource satisfaction $\mathbb{F}_3$. Since facilities resources are non-human, they are not considered for the satisfaction metrics. The maximum utilization rate of a resource in the ED should not exceed 80% for normal flow of the system, which reflects the value of "maximum workload". "Actual load" values result are from the simulation with Arena. The "actual pay" and "maximum pay" for each resource is depicted in Table 2, where maximum pay is the average maximum wage each resource can receive, determined by investigations and observations. The calculation of satisfaction factors for each type of resource is depicted in Table 3.

Having calculated the satisfaction factors of all resources in the system, the total resource satisfaction can be deduced: $\mathbb{F}_3 = 48.19\ \%$.

5.3 Patient satisfaction

The patient satisfaction level with the current ED, $\mathbb{F}_1$, was calculated before optimization. After several observations and interviews with ED medical resources, η_2 was found to be 0.3, and η_1 to be 0.7. From the Arena simulation results, the average patient length-of-stay was 357 minutes, which reflects the actual LoS. In the literature, the expected LoS in an ED is 270 minutes. $\mathbb{F}_1$ was calculated with these values and found to be $\mathbb{F}_1 = 65.17\ \%$.

Using the calculated satisfaction factors from the previous sub-sections, the reward system for normal patient flow in the ED was $\mathfrak{R}_{ED} = 50.1\ \%$. This reward value was unimpressive to hospital management, and it is below the thresholds of 70% for a satisfied reward system and over 77% for a highly satisfied reward system. In order to increase the reward system values of the target ED, $\mathfrak{R}_{ED}$ optimization of the three factors affecting the system is crucial. The owner satisfaction factor of $\mathbb{F}_2$ is 20%, which is very low. Thus, it is essential to always consider this factor, and carefully monitor the balance between the three satisfaction factors: $\mathbb{F}_1$, $\mathbb{F}_2$ and $\mathbb{F}_3$.

6 Optimization algorithm: MRA

In the previous section, the reward system is applied to healthcare and satisfaction factors are calculated. This work proposes applying the Maximum Reward Algorithm (MRA), a new reward-based optimization algorithm based on queueing theory, to improve smart healthcare systems. MRA was applied to our target ED to enhance operational flow and maximize the reward system, $\mathfrak{R}$ under normal conditions. The MRA flowchart, shown in Fig. 1, identifies the steps to reach a near-optimal solution. Some variables used for the algorithm include:

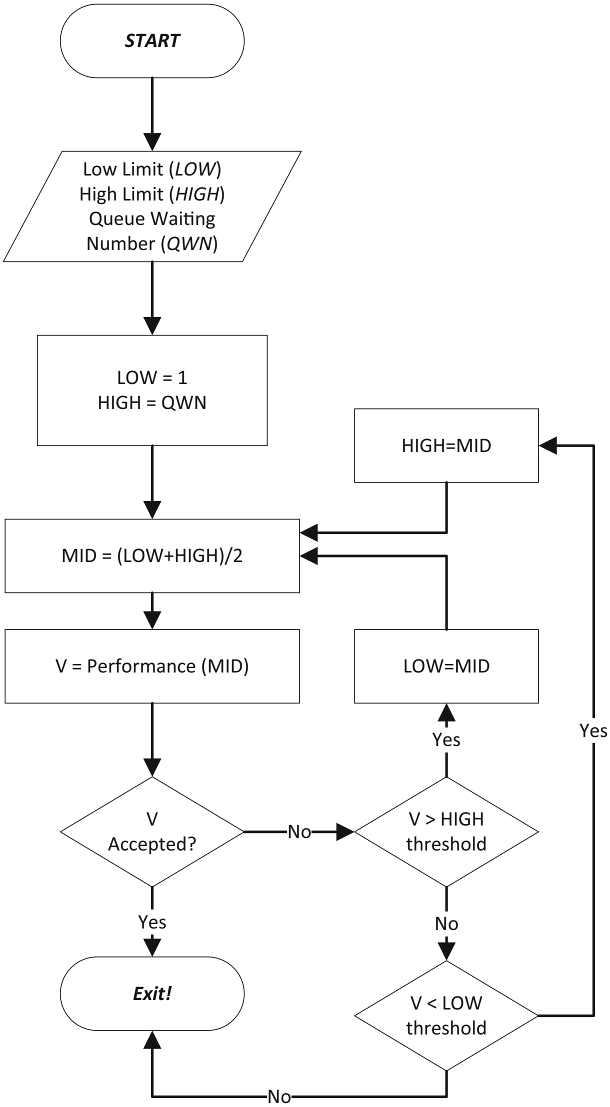

Fig. 1 MRA flowchart

1. The first type of resource to start the algorithm with is the one causing the bottleneck in the ED.
2. The next type of resource is the one with the less wage.
3. The threshold is the accepted value .
4. The algorithm is stopped when no more changes are occurring to the system.
5. The performance is the simulation results using the MID (Medium) value of a resource; it includes the performance of resource utilization rates, patients LoS and Queues waiting number.
6. The threshold value is a range between two numbers. The optimal value should be lower than the high threshold and greater than the low threshold.
7. The threshold for patients LoS: LoS should be less than 2 hours and not exceeding 4 hours.
8. The threshold for resource utilization: resource utilization rates should not be less than 20% in order to avoid wastes and not exceeding 80%.
9. The threshold for queues waiting number: the waiting number in queues should not exceed 20 and cannot be 0 in order to avoid wastes.
10. The threshold values, low and high, for each metric are represented in Table 4 and are based on ED observations and hospital's management decisions

The importance and application of simulation modelling in emergency departments was also addressed in the author's previous work [35, 36]. According to the simulation results, during normal operational flow the ED had a bottleneck in the transportation queue (refer to Fig. 2). Therefore, the MRA algorithm will start with the first resource type, the transporter. According to the simulation results, on average 23 patients are waiting in the transporter queue (Fig. 3). To begin the algorithm, the low and high values for the resource must be identified. The low values are always 1, and the high values are related to the performance. In the case of bottlenecks in more than one stage and the dependencies between the stages, the values are calculated and the model simulated using the new values of dependent bottleneck resources, in parallel with one phase of the algorithm. For example, facilities depend on the availability of doctors, nurses and other resources; if both nurses and doctors are extremely busy then the algorithm is started by considering the facilities, nurses and doctor resources together as the first phase.

Three cases are studied for the transporter resource, as follows:

1. The HIGH transporter value is equal to the number of patients waiting in the transporter queue (23), and the value to be used in the next simulation is MID = (LOW + HIGH) $\div 2 = 12$. The model was run again after increasing the number of transporters to 12. The subsequent results indicated that the waiting time decreased from an average of 598.55 min to 0 min, as per in Fig. 4, with nearly no patients waiting in transporter queues, as per Fig. 5. Also, the LoS decreased from six hours to 1.74 hours, as shown in Fig. 6). As shown by the resource utilization rates in Fig. 7, if the workload of all the resources is minimal, the threshold of a resource utilization rate should average in the

Table 4 Threshold details

Metrics	Low	High
Patient LoS	2 Hours	4 Hours
Resource Utilization Rate	20%	80%
Queue Waiting Number	0%	20%

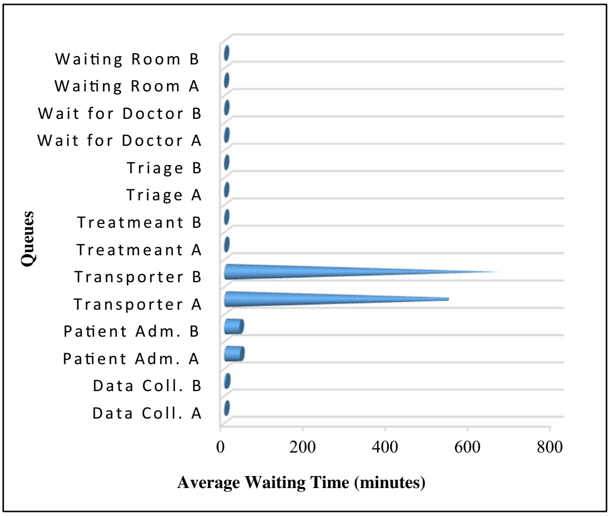

Fig. 2 Queues waiting time

range of 20% to 80%. This means the number of transporters should be decreased to reduce waste. Performance here is dependent on the QWN and utilization rates.

2. As the new HIGH value = MID = 12 is below the threshold after performance V, the MID = (1+12) ÷2 =6.5. The model was run again with seven transporters, and the results showed an average system LoS of 118.6 min, which is equivalent to two hours. Hospital management specified a reliable optimization algorithm for the ED system with a LoS of less than two hours. Therefore, a new value for the transporter resource is required. Performance here is dependent on the LoS.
3. The new LOW value of = MID = 7 after performance V is greater than the threshold, and calculating this value gives nine transporters. Running the model again with the

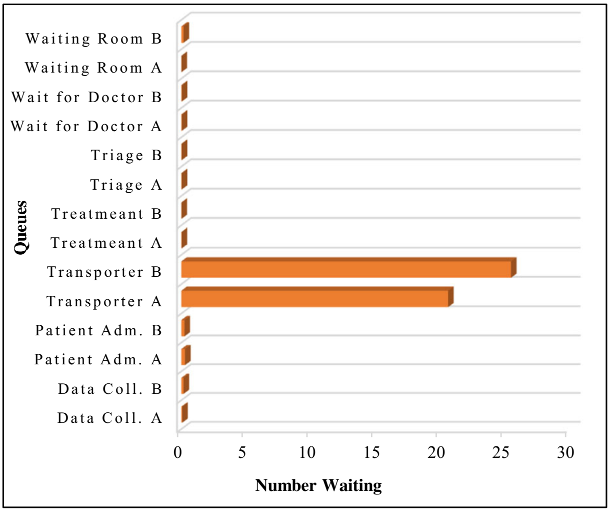

Fig. 3 Queues number waiting

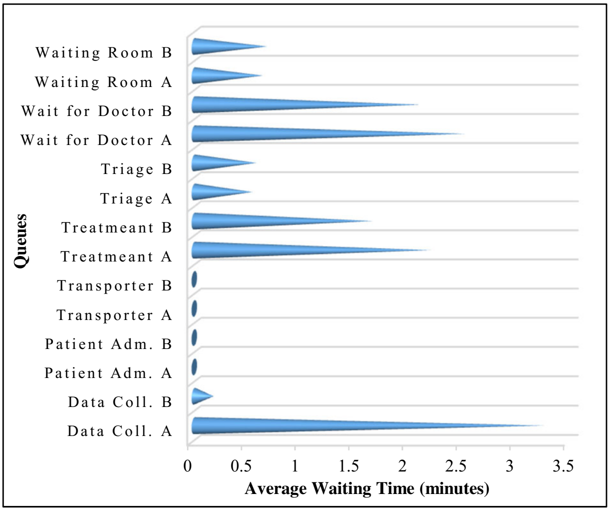

Fig. 4 Queues waiting time - 12 transporters

new transporter value gave an LoS is approximately 1.7 hours as per Fig. 8. This is below the lowest threshold and was approved by hospital management. Considering all the resource utilization rates, the workloads were accepted and fell between the hospital's high and low thresholds, as per Fig. 7, and maintained a minimal waiting time in the queues, as shown in Fig. 9. Note that the system number out is 134 of 137 arriving patients, as per Fig. 10. Therefore, performance V is acceptable and the MRA can be discontinued with a change in transporters only of one to nine in each ER. This represents a total increase of 16 transporters for the two emergency rooms: ER A and ER B.

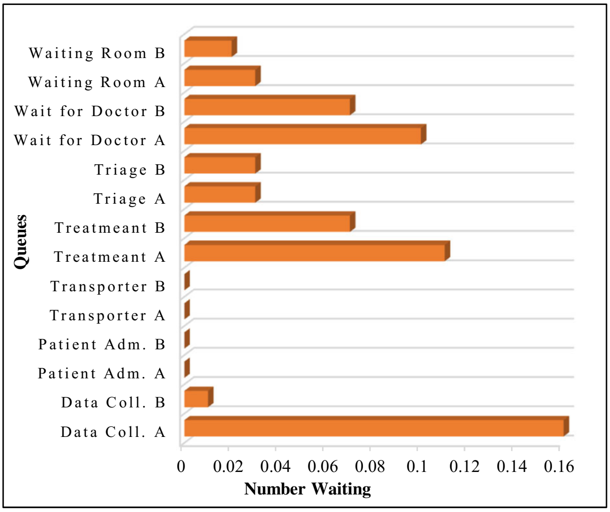

Fig. 5 Queues number waiting - 12 transporters

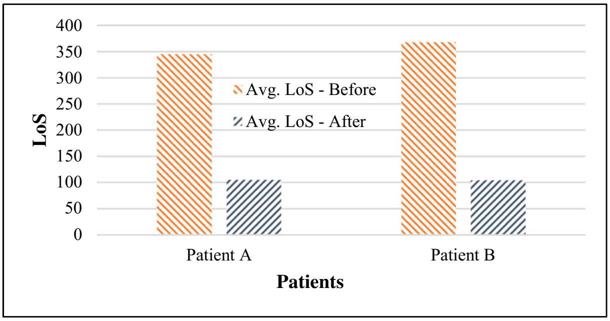

Fig. 6 Patient LoS

Thus, nine is the optimal number of transporters required to maintain the balance between the number of patients waiting in the bottleneck queue, the waiting time in the queues, resource utilization rates and system LoS, taking into consideration owner satisfaction through the high number of patients exiting the ED. The system is totally optimized without needing to optimize other types of resources.

The new allocation of resources is shown in Table 5, and the reward system will be calculated again after performing the optimization.

Now that the number of resources is optimized, a new reward system, $\mathfrak{R}_o$, is calculated using the equations of previous sections:

1. Resource satisfaction is calculated after simulating the model with the new resource allocation after the MRA has been applied; the value of each resource satisfaction factor f_{io} is presented in Table 6. Having calculated the satisfaction factors of all resources in the system, the total resource satisfaction can be determined by $F_{3o} = 44.75\ \%$.
2. After applying the MRA, the simulation results are used to calculate patient satisfaction. The average patient LoS in the system is 1.7 hours (102 min) as shown in Fig. 8), which reflects the actual LoS. Hospital management requires the LoS of an optimized system to be less than two hours (120 min), and this leads to $\mathbb{F}_{1o} = 94.75\ \%$. This means patient satisfaction became very high due to the system LoS decrease after the MRA is applied; from 65.17% to 94.75%, an increase of 45.39%.

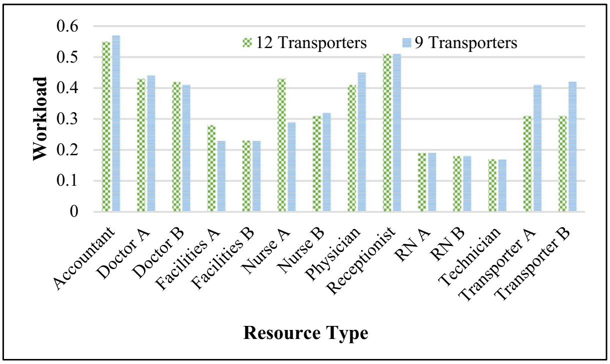

Fig. 7 Resource details - 12 and 9 transporters

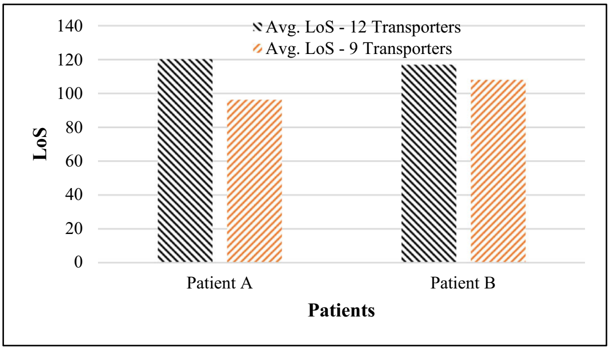

Fig. 8 Patient LoS - 12 and 9 transporters

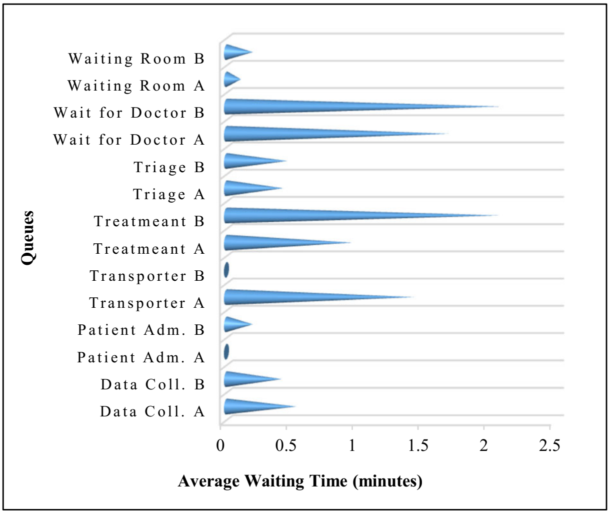

Fig. 9 Queues waiting time - 9 transporters

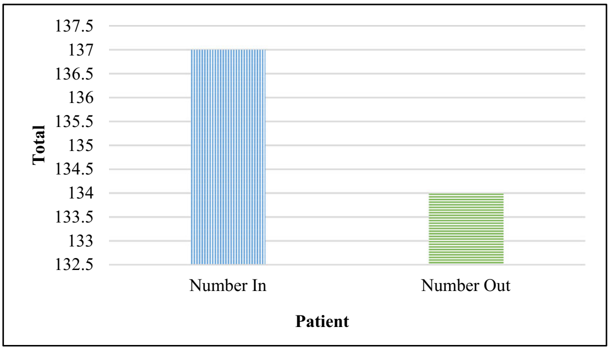

Fig. 10 Number of system out - 9 transporters

Table 5 MRA resource allocation for both ERs

Resource type	MRA resource allocation
Doctor	2
RN	2
Nurse	4
Transporter	18
Accountant	8
Receptionist	1
Physician	1
Technician	3
Facilities	10

3. To determine owner satisfaction $\mathbb{F}_{2o}$ after applying the MRA, new total expenses and revenues were calculated. Arena simulation results showed a system number out of 134 patients after optimization. This means the new revenue averages \$140,700 per month, and $\mathbb{F}_{2o}$ =53 %.

In conclusion, the owner satisfaction went from 20% before optimization to 53% after applying the MRA, an increase of 54%. This is expected, as the bottleneck in the transporter queue was solved and more patients are now exiting the system, which increases revenue.

With all three satisfaction factors, $\mathbb{F}_{1o}$, $\mathbb{F}_{2o}$ and $\mathbb{F}_{3o}$ calculated, the reward system for normal flow after optimization is $\mathfrak{R} = 77.2$ %. This metric will satisfy hospital management, since they stipulated the thresholds of satisfaction to be a minimum of 70% for a satisfied reward system, and greater than 70% for a highly satisfied reward system. The increase in the reward system of 50.1% to 77.2% proves that the proposed reward system $\mathfrak{R}$, and the optimization algorithm MRA, are efficient and reliable after being applied to a real-life situation like the emergency department of a healthcare system.

Table 7 summarizes all the satisfaction factors and reward systems calculated for normal flow in the previous sections, as well as the satisfactory levels both before and after MRA. The table makes it clear that almost all satisfaction values increased and the reward system also increased, with the exception of $\mathbb{F}_3$ due to dependencies among the resources. It should be mentioned here that the resource satisfaction $\mathbb{F}_3$ is the factor that least affects the reward system, $\mathfrak{R}$, so slight changes can be disregarded. There are also limitations prescribed by hospital management, such as allowing additional resources for the bottleneck stages only. Since accountants, receptionists, physicians and technicians were not optimized, future

Table 6 Resource satisfaction factors after optimization

Resource type	Satisfaction factor (%)
Doctor	$f_{1o} = 40.25$
RN	$f_{2o} = 44.37$
Nurse	$f_{3o} = 48.06$
Transporter	$f_{4o} = 49.33$
Accountant	$f_{5o} = 42.25$
Receptionist	$f_{6o} = 44.5$
Physician	$f_{7o} = 29.78$
Technician	$f_{8o} = 59.5$

Table 7 Satisfaction factors and reward system

Factors	Before MRA(%)	After MRA(%)	Satisfactory level
$\mathbb{F}_1$	65.17	94.75	Extremely Satisfied
$\mathbb{F}_2$	20	53	Satisfied
$\mathbb{F}_3$	48.19	44.755	Satisfied
$\mathfrak{R}$	50.1	77.2	Satisfied

improvement can be realized by applying the MRA to these resources as well. Regardless, the reward system increased from 50.1% to 77.2%, proving the reliability and efficiency of the MRA and reward system $\mathfrak{R}$.

From a management perspective, the satisfactory levels are measured as follows:

- 0-20: Extremely Unsatisfied
- 21-40: Unsatisfied
- 41-80: Satisfied
- 81-95: Extremely Satisfied
- 96-100: Optimal

7 Conclusion and future work

Our cities are facing significant challenges regarding services and resources, and the smart city concept has emerged as the potential resolution for all issues by employing its capabilities and offering various services for citizens. As discussed in this paper, the use of multimedia technologies along with mobile edge and cloud computing is very efficient in enhancing medical services and especially resource allocation and medical information delivery. In this paper, we investigate and discuss the importance of healthcare systems in a smart city, and examine most of the prominent difficulties. Healthcare resource allocation is the most critical and annoying issue for patients, medical resources and owner. Motivated by the need to improve healthcare resource allocation in emergency departments, the paper introduces an effective utilization and delivery model. Through experimentation and simulation, we prove that the proposed algorithm can provide reliability, efficiency and optimal resource utilization from 50.1% to 77.2%. In the future, a new satisfaction factor $\mathbb{F}_4$ will be introduced to the reward system. $\mathbb{F}_4$ reflects corporate social responsibility (CSR) to help an organization accomplish a goal, and also serves as a guide to what a company offers to patients. The CSR policy is a self-regulatory mechanism whereby a business monitors and ensures active compliance with the spirit of the law, ethical standards and national and international norms [28].

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