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MEDINFO 2021: One World, One Health – Global Partnership for Digital Innovation
P. Otero et al. (Eds.)

doi:10.3233/SHTI220219

Impact of the Automation of Inpatient Bed Management to Reduce the Emergency Service Waiting Time

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Abstract

The patient waiting time to be transferred for hospitalization is the time that the patient waits between the decision to hospitalize and the actual admission to an inpatient hospital bed. One of the difficulties encountered in qualifying waiting time for inpatient bed is the inability of hospital information systems to measure it. Hospitals in France have a specialized bed allocation team. This team must manage the bed allocation problem between different hospital departments using phone communication to assign patients to the adapted service. This kind of communication represents a lengthy additional workload in which effectiveness is uncertain. This paper presents a new approach to automate bed management in downstream service. For that, we have implemented algorithms based on artificial intelligent integrated in an inpatient web platform using IoT-Beacons, which is implemented to improve and facilitate the exchange of availability information of downstream beds within the Lille university hospital center (LUHC).

Keywords:

Inpatient bed management, patient pathway optimization, artificial intelligent for healthcare

Introduction

Today, worldwide in emergency departments ED, an increase in mortality, a prolonged length of stay, a decrease in the quality of care associated with an overcrowding situation can be detected [1]. Causes are multiple: (A) the organization of the upstream-ED, currently in France, upstream management resources are limited to the various regulation systems like CRRA (the center of the receiving and regulation calls) or CTA (call processing center), which regulate a minority of inputs (patients). The vast majority of other patients arrive spontaneously without any means of regulation. The optimization of upstream by developing models for anticipating spontaneous incoming patient flow based on data analysis therefore becomes necessary, in order to adapt internal resources and communication with upstream services accordingly. (B) the organization of the ED (intra-emergency), the difficulty of optimizing and scheduling care tasks into an environment classified as complex because it is simultaneously inaccessible, non-deterministic, dynamic and continuous [2]. (C) The organization of the downstream-ED, particularly, the occupancy rate of the downstream service and the availability of hospital beds for non-programmed patients (patients with incidental finding) [3], [4] are directly associated with the overcrowding situation in the ED [5], [2]. Each stage (A, B and C) of the care process contributes with varying degrees to the overcrowding situation into the ED. Consequently, interventions to reduce and limit this situation must affect all stages of the patient's pathway: from upstream to downstream [3]. In this paper, we are interested in improving the downstream part into the adult emergency department (AED) of the Regional University Hospital Center (RUHC) of Lille (city of north of France). In fact, in downstream units, an empty bed does not necessarily mean an available bed. An available bed must be unoccupied, clean, disinfected, not reserved and well-equipped. Indeed, the crossing from an empty bed to an available one by a nurse requires on average 30 min. In this context, a bed management tool that ensures an optimal bed distribution and better controls the number of crowding patients in various departments is needed. Therefore, the review of the literature reveals that this problem is of present interest [6], [7]. Given the complexity of the healthcare system and patient flow dynamics, deterministic approaches cannot be deployed. Although, the application of analytics, machine learning and artificial intelligence (AI) have become one of the most valuable assets for health system and for numerous companies and institutions. These techniques are used as the main methodologies for extracting and identifying actionable insights among complexes and unstructured data. In this context, the adoption of the IoT paradigm in the healthcare area is increasingly used, several experts determine that it plays an important role in the improvement and innovation of the healthcare services [8]. These techniques allows the transformation of data into useful, significant and actionable insights to improve patient care, support decision making, provide high quality care, optimize the use of resources, reduce costs and even predict crisis situations (predictive analytics) hence determining the best action for current situation [4], [9], [10]. Therefore, the application of these techniques is of utmost importance in healthcare, where a single decision can mean the difference between life and death [4]. However, effective exploitation of these data requires perfect knowledge and mastery of advance technologies.

In this paper, we present a new approach to allocate beds/patients based on an automated bed management tool into the LUHC. This approach is based on two algorithms, the first algorithm is used to check the sufficiency of downstream bed (ASDB) in service i using genetic algorithm (GA) and the second one is used to automate beds availability information (ABAI) by exploiting real-time data coming from the IoT which represented by beacons (IoT-Beacons) installed at the downstream beds. These IoT-Beacons can also help track patient movement in hospital services. This approach has not only a positive impact to find an available bed automatically within a reasonable time but also decreases a workload for bed allocation teams.

Methods

The approach presented in this paper is implemented in the adult emergency department (AED) of the LUHC which is one of the greatest health campuses in Northern Europe. It operates 24/7 and receives approximately 12 patients per hour on average. The AED contains different structures: short and long circuit, short-term hospitalization unit and five zones (A, B, C, D and E). Zone E, also called transfer zone, receives patients who need to be transferred outside the AED (internal transfer or external transfer), to be hospitalized in specialize hospital services. Currently, the patient waiting time in this zone (E) has a strong impact on the AED overcrowding situation, i.e. the longer the patients waiting time in this zone, the longer the patients upstream waiting time (patient who continue their health care process into the AED before their passage on zone E). This observation shows the importance of establishing a solution allowing the efficient allocation of patients in the downstream service (specialize hospital services outside the AED, in which the patient will continue its health care tasks), in order to avoid overcrowding situation in the transfer zone (zone E), consequently in the whole AED. A workflow model represents the patient pathway in the AED, implemented using BPMN language and presented full details is now published in [11].

In this paper, we present a flexible approach to improve the AED management regarding its two main aspects: (a) verify in each service i if there are enough of material resources, especially in terms of the number of beds, and (b) automate beds availability information.

(a) Genetic algorithm GA to verify the sufficiency of the number of beds in service i

To check the sufficiency of the number of beds in each service i we present a queuing model that shape the flow of patients through the AED, and then we develop a GA to avoid both insufficiency and excess situations. The main aim of this algorithm is to control the number of beds in in each downstream service.

Parameters

$\omega_{i,d}$: the patient average length of stay per service i per day d;

σ_i: the average arrival flow in service i;

θ_i: the number of beds in service i;

ε_i: a cost per day d for an empty bed;

τ : a penalty cost per transferred patient.

In this paper, we refers to a M/PH/c queuing model to describe the theoretical model in which we denote: σ Poisson (Markov) arrivals patient flow, θ the state number (which is the number of beds that can be occupied), the occupancy of these θ beds distribution is phase-type, which is a special case of a continuous-time Markov process (when a patient cannot be accepted by the service i , he is lost by the system “absorbing state”).

A queue model is typically defined by two parameters: objective parameter which is that cannot be changed by the healthcare professional but change in some circumstances (epidemiology, demographics, etc) such as $\omega_{i,d}$ and σ_i. The other parameter is the subjective parameter that can be changed by the healthcare professionals in some circumstances. According to this model, it is possible to calculate the probability A_i that all beds are occupied (i.e. the fraction of patients cannot be accepted in the service, consequently these patients are the transferred patients) in each service i. This probability is based on Erlang loss formula (also known as the Erlang B formula),

$$A_i = \frac{\frac{(\sigma_i \omega_{i,d})^{\theta_i}}{\theta_i!}}{\sum_{k=0}^{\theta_i} \frac{(\sigma_i \omega_{i,d})^k}{k!}} \quad \text{(Erlang's loss formula)}$$

Based on the A_i, the fitness function f_i is calculated as follows:

$$f_i(\omega_{i,d}, \sigma_i, \theta_i, \varepsilon_d, \tau) = \tau\sigma_i A_i + \varepsilon_d \left\{\theta_i - \sigma_i \omega_{i,d}[1 - A_i]\right\} \quad (1)$$

Let us consider that $\tau\sigma_i A_i$ is the cost of transferred patients and $\varepsilon_d\{\theta_i - \sigma_i \omega_{i,d}[1 - A_i]\}$ is the cost of beds not used. Minimising f_i that mean identify the optimum values of the parameters $(\omega_{i,d}, \sigma_i, \theta_i, \varepsilon_d, \tau)$ in order to estimate the optimal number of beds in each service i, In our case, we focus on finding the optimal values of $\omega_{i,d}, \sigma_i$ and θ_i while keeping a trade-off between ε_d and τ. The optimization method chosen in this case involves the use of GA, with real chromosome coding, to estimate the optimum values of the parameters, especially the optimal number of beds in each service i. The main idea is to apply the different steps of GA, by choosing an empirical search interval for each of the above parameters based on real database of the AED provided by the LUHC. The performance of our GA depends on its components such as initial populations (chromosomes), number of generations, selection method (tournament, roulette, a mix of both, etc.), crossover and mutation operators, probability, etc. The pseudo code of the ASDB based on a GA is shown in the algorithm 1.

Algorithm 1: The pseudo code of ASDB

Input $\omega_{i,d}$, σ_i, θ_i, ε_d, τ
Output The n good solution minimising f_i
Initialization :
1. Encode chromosome in the vector form ($\omega_{i,d}$, σ_i, θ_i, ε_d, τ);
2. Set of initial population n chromosome in which the parameters are randomly chosen from an empirically interval and for each chromosome i calculate its fitness function f_i.

while *(The termination criterion is not satisfied)* **do**
- **Step 1 :** Using the tournament selection operator. The better-scoring chromosome (equation 1) is selected for reproduction (until the new population is complete, one chromosome can appear several times in this population);
- **Step 2 :** Using the recombination probability: a pair of chromosomes are randomly selected, one of the parameters ($\omega_{i,d}$,σ_i,θ_i,ε_d,τ) of these chromosomes is randomly selected and exchanged between this pair of chromosomes. The two new descendants are added to the population;
- **Step 3 :** Using the mutation probability, one of the selected chromosome parameters ($\omega_{i,d}$,σ_i,θ_i,ε_d,τ) is randomly chosen to change its value. If the fitness of the mutant is good, it will be added to the population and then replaces the original in the population;
- **Step 4 :** Update the population with the selected n best individuals.

end
end

(b) Automate beds availability information

As mentioned in the literature, the occupancy rate of the downstream services and the availability of its beds for non-programmed patients have a highly impact on the ED overcrowding situation. In order to cope, an approach to automating downstream service bed availability information is needed. In this context, we have implemented an inpatient web platform using IoT-beacons (IWPB), which is implemented to improve and facilitate the exchange of availability information of downstream beds within the LUHC of Lille. This platform offers real-time access to various departments' data, which are equipped with Beacons. This data is presented in a clear and ergonomic way to emergency physicians (figure 1). Indeed, we have allotted a beacon for each bed, in the downstream service treated. Beacon technology is a current pervasive phenomenon that not only provides data transfer services, but also enables indoor positioning and navigation. In our approach, IoT-beacons ensure the procession and transmission of bed availability information in real time, thanks to the fact that constantly emits signals containing a unique identifier (UUID). To receive this information, an android application has been developed and installed on patient's smartphone. If the patient does not possess a smartphone (or he has an iOS smartphone), a borrowing smartphone with our application is possible from zone E. Upon patient arrival in zone E of the AED, an unique identifier is assigned to him, allowing to create the connection between IoT-Beacon, bed and patient when patient is assigned to a bed (figure 1). The application sends patients' position to our IWPB platform thanks to the Internet connection in its smartphone, thus ensuring the traceability of patient in real time. Figure 2 shows an example of patient assignment : Paul Gome is in bed A1-003. The IWPB manages the follow-up of patients who have already obtained availables beds in the corresponding service *i* thanks to the IoT-beacons. Furthermore, if a bed is empty, it does not necessarily mean that it is available because the patient who is assigned to this bed may has gone for a radiology, MRI, etc. Thanks to the android application installed on the patients' smartphones, the IoT-beacons will be able to know the position of patients in hospital in real time. In addition, this mobile application notifies the IWPB about the real availability of beds, since a patient UUID disconnected from the LUHC Internet system means that the bed that was occupied by that patient is empty.

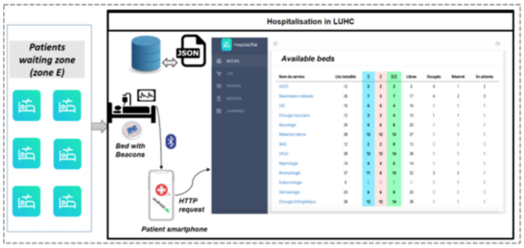


Figure 1. Architecture of IWPB platform

Figure 2. Example of a bed assignment display

This platform must be completed to take into account the management of the automation of downstream service bed allocation, and then present a complete decision support tool to emergency physicians. In this context, the ABAI is developed. It aims to schedule patients according to a predefined order of priority using list algorithm. The ABAI integrates the IoT-Beacons aspect and allows to create an automation bed allocation process. The originality of this algorithm is its capacity to adapt to dynamic hospital situations (overcrowding and normal situation). For example, in overcrowding situations the ABAI allows the assignment of patients to the inappropriate services in order to continue their care pathway, and then improve de AED situation. In the ABAI, every patient *p* has an individual score s_p that reflects its need to be assigned. The s_p is calculated using equation 2.

$$s_p = \alpha \frac{\text{CCMU}}{\text{AverageCCMU}} + \beta \frac{\text{LOS}_p}{\text{AverageLOS}} + \mu \frac{\text{CEN}_p}{\text{AverageCEN}} \quad (2)$$

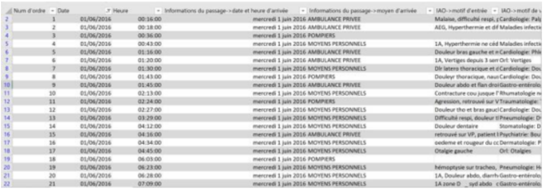
Where CCMU, LOS and CEN represent respectively the clinical classification of patient into emergency which represents the computerized triage scale in France, the length of stay and cycles expected number. This score s_p is considered as a dynamic rule and at each ABAI step the calculation of s_p can give us a new score for each patient, which is crucial for the progress of the ABAI. For that reason, a weighting given successively to these parameters α=0.4, β=0.2, μ=0.4, which are chosen by the LUHC physicians. The higher the score s_p, the higher patient's *p* priority of assignment. These scores are used in the list algorithm included in the ABAI to schedule patients waiting in Zone E.

Algorithm 2: The pseudo code of ABAI

```
Input
S_pat: the set of patients waiting in zone E for an available downstream bed;
Tab_A_Patient: a table containing an optimal number of beds required for the service's care activity
Tab_AV_b: a matrix (i, j), j = 1..x, x is the maximum number of services in the hospital and i = 1..y, y
  is the maximum number of beds in the service. This matrix consider that each bed has a unique
  IoT-beacons identifier (UUID) and it is updated in real time by our IWPB. Tab_AV_b[i, j] = 1 the bed i
  in service j is available otherwise Tab_AV_b[i, j] = 0;
Output S_pat = ∅ every patient of the set S_pat was attributed an available downstream bed to continue
  his care;
Begin
Ass_pat_wait = ∅;
Call ASDB // Among the ASDB results we have the optimal θ_i for each service i ;
We put these information in Tab_A_Patient : Tab_A_Patient[i] = θ that means θ beds are necessary for
  the service i, θ is the optimal number found by the ASDB 1
while (S_pat ≠ ∅) or (S_pat_wait ≠ ∅) do
    1. Calculate the maximum priority score S_p equation 2 using patients in S_pat and S_pat_wait;
    2. Using list algorithm to schedule patients waiting in zone E according to the dynamic rule S_p;
    3. Identify the service j corresponded to the assignement of patient p which has the maximum score
      S_p;
    4. Update (Tab_AV_b) with the information received by IoT-beacons and IWPB;
    Ass = false;
    Ass_wait = false;
    i = 1;
    while (not Ass) and (not Ass_wait) and (i =< Tab_A_Patient[j]) do
        if (Tab_AV_b [i, j] == 1) then
            assign patient p to the bed i in service j;
            if (patient p ∈ S_pat) then
                Ass = true;
                S_pat = S_pat \ {patient p};
            else if (patient p ∈ S_pat_wait) then
                Ass_wait = true;
                S_pat_wait = S_pat_wait \ {patient p};
            end
        else
            i = i + 1
        end
    end
    if (not Ass) then
        S_pat = S_pat \ {patient p};
        S_pat_wait = S_pat_wait ∪ {patient p};
    end
    if (i > Tab_A_Patient[j]) then
        No available bed found in service j we have an overcrowding situation, so we must find a bed in
          other service k;
        j = k;
    end
end
end
```

Results

To evaluate our approach, we start by testing the ASDB using a sample of real data of the LUHC collected over a period of four years, from June 2016 until June 2020 (figure 3).



	Num d'ordre	Date	Heure	Informations du passage->date et heure d'arrivée	Informations du passage->moyen d'arrivée	IAO->motif d'entrée	IAO->motif de v
2	1	01/06/2016	00:16:00	mercredi 1 juin 2016	AMBULANCE PRIVEE	Malaise, difficulté respi, (	Cardiologie: Pal
3	2	01/06/2016	00:18:00	mercredi 1 juin 2016	AMBULANCE PRIVEE	AEG, Hyperthermie et dif	Maladies infecti
4	3	01/06/2016	00:36:00	mercredi 1 juin 2016	POMPIERS		
5	4	01/06/2016	00:43:00	mercredi 1 juin 2016	MOYENS PERSONNELS	1A, Hyperthermie ne céd	Maladies infecti
6	5	01/06/2016	01:16:00	mercredi 1 juin 2016	AMBULANCE PRIVEE	Douleur bras gauche et n	Cardiologie: Phl
7	6	01/06/2016	01:20:00	mercredi 1 juin 2016	AMBULANCE PRIVEE	1A, Vertiges depuis 3 sem	Orl: Vertiges
8	7	01/06/2016	01:30:00	mercredi 1 juin 2016	MOYENS PERSONNELS	Dlr latero thoracique et d	Cardiologie: Dou
9	8	01/06/2016	01:43:00	mercredi 1 juin 2016	POMPIERS	Douleyr thoracique, naus	Cardiologie: Dou
10	9	01/06/2016	01:45:00	mercredi 1 juin 2016	AMBULANCE PRIVEE	Douleur abdo et flan droi	Gastro-entérolo
11	10	01/06/2016	02:13:00	mercredi 1 juin 2016	MOYENS PERSONNELS	Contracture cou jusque l'	Rhumatologie n
12	11	01/06/2016	02:24:00	mercredi 1 juin 2016	POMPIERS	Agression, retrouvé sur V	Traumatologie:
13	12	01/06/2016	02:27:00	mercredi 1 juin 2016	MOYENS PERSONNELS	Douleur tho et bras gaucl	Cardiologie: Dou
14	13	01/06/2016	03:29:00	mercredi 1 juin 2016	MOYENS PERSONNELS	Difficulté respi, douleur t	Pneumologie: D
15	14	01/06/2016	04:12:00	mercredi 1 juin 2016	MOYENS PERSONNELS	Douleur dentaire	Stomatologie: D
16	15	01/06/2016	04:16:00	mercredi 1 juin 2016	AMBULANCE PRIVEE	retrouvé sur VP, patient I	Psychiatrie: Bou
17	16	01/06/2016	04:34:00	mercredi 1 juin 2016	MOYENS PERSONNELS	oedeme et rougeur du cc	Dermatologie: F
18	17	01/06/2016	04:45:00	mercredi 1 juin 2016	MOYENS PERSONNELS	Otalgie gauche	Orl: Otalgies
19	18	01/06/2016	06:03:00	mercredi 1 juin 2016	POMPIERS		
20	19	01/06/2016	06:23:00	mercredi 1 juin 2016	MOYENS PERSONNELS	hémoptysie sur tracheo,	Pneumologie: H
21	20	01/06/2016	06:28:00	mercredi 1 juin 2016	MOYENS PERSONNELS	1A, Douleur abdo, diarrh	Gastro-entérolo
22	21	01/06/2016	07:09:00	mercredi 1 juin 2016	MOYENS PERSONNELS	1A zone D _ syd abdo c	Gastro-entérolo

Figure 3. Database of the AED of LUHC

Different versions of the ASDB were developed to determine the influence of each parameter on its performance. Figures 4 and 5 summarise successively the fitness and the execution time (in seconds) according to the number of generation in the ASDB for three different selection types (tournament, roulette and tournament-roulette). Knowing that the number of generation varies between 10 and 300 the result shows that tournament selection is always better for both solutions quality and execution time. Table 1 shows that thanks to the first algorithm the minimum patient redirected percentage is 1% can be reached with 100 beds, arrival rate around 40.18 patients per day and a LOS equal 25 days. In addition, it is important to note that, from the evolutionary experiment, it showed that our system is exceedingly flexible since the same patient redirected percentage of 5% can be reached either with 10 beds or 20 beds, but it depends on different arrival rates and LOS (10.02/8.05 vs. 15.03/30.03).

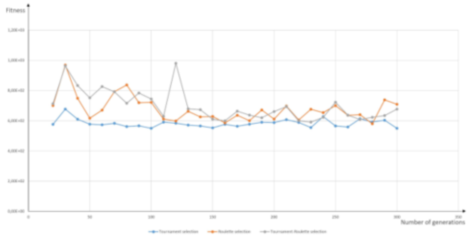


Figure 4. Comparison of solutions quality using different types of selection

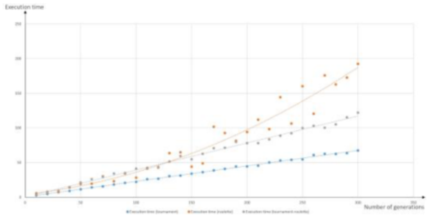


Figure 5. Comparison of the execution time using different types of selection

Table 1. the optimum values of the parameters (ASDB)

Service	θ_i [10-360]	σ_i [5-100] (Per day)	$\omega_{i,d}$ [5-100] (Per day)	ε_d (€)	τ (€)	Patient redirected (%)
Vascular surgery	60	10.68	25.11	30.97	1056.5	2
UHCD	20	15.03	30.03	21.13	1047.22	5
ZHTCD	10	10.02	8.05	20.60	1054.5	5
Resuscitation	100	40.18	25.27	40.41	2001.15	1
Endocrinology	80	30.03	13.04	66.33	2002.08	1.5

The particularity of the ABAI is its capacity to be executed in overcrowding situation or not. Therefore, in an overcrowding situation the ABAI allows the transfer of patients to downstream services different from the assigned downstream services (i.e. transfer for de-bottlenecking the AED situation, without endangering the safety of the patients). In order to evaluate our approach's level of performance, we applied our approach to find an available bed in two downstream services (Geriatric, Pneumology) of the LUHC for both normal and overcrowding situations. The choice of Geriatric and Pneumology downstream service was established because the patients transfer from zone E to these services is highly recurrent. The normal and overcrowding situation periods were deduced from the real data base, according to specific criteria such as : the influx of patients per hour, the average total waiting time and the total length of stays for patients in the AED. Table 2 shows the results obtained with our approach compared with those obtained in practice (according to the AED database used by the medical staff and the experience of doctors who are partners in this study). The results obtained with our approach, are issued via the IWPB. Indeed, the bed manager has a real time view on the availability of beds in the chosen downstream services (Geriatric, Pneumology). This is done thanks to the architecture of IWPB platform. Consequently, upon the arrival of patients in zone E, the bed manager can find a bed in one of these services in a shorter time compared to the actual practice. For example, the simulation period shows that, the application of our approach allowed us to decrease the average waiting time by approximately 40% and 35% in normal situations and by approximately 30% and in overcrowding situations respectively for the Geriatric and the Pneumology services. The difference in percentage gain in waiting time between the two services in the two situations (normal, overcrowding) shows firstly that our approach adapts according to the services, and secondly the importance of applying such an automatic downstream bed management tool that provides relevant information in real time to improve patient care in the hospital system.

Table 2. Patient average waiting time in Zone E with and without our approach

AED situation	Week	Downstream service	Patients (zone E)	Practice (hour)	Approach (hour)
Normal	23/04/2018-29/04/2018	Geriatric	13	2.051	1.230
	14/05/2018-20/05/2018		20	2.029	1.257
	11/06/2018-17/06/2018		12	2.1	1.26
	02/07/2018-08/07/2018		25	2.07	1.26
	23/04/2018-29/04/2018	Pneumology	20	2.52	1.63
	14/05/2018-20/05/2018		28	2.941	1.97
	11/06/2018-17/06/2018		25	2.1	1.36
	02/07/2018-08/07/2018		10	1.84	1.21
Overcrowding	19/11/2018-25/11/2018	Geriatric	26	2.58	1.806
	10/12/2018-16/12/2018		28	2.92	2.10
	07/01/2019-13/01/2019		30	2.62	1.83
	18/01/2019-24/01/2019		33	3.3	2.343
	19/11/2018-25/11/2018	Pneumology	30	2.71	1.89
	10/12/2018-16/12/2018		35	3.8	2.736
	07/01/2019-13/01/2019		30	3.01	2.16
	18/01/2019-24/01/2019		31	2.84	2.016

Discussion

In the AED of LUHC, we noticed that patients are often dissatisfied, because of excessive waiting times from their admission to their transfer into specialized services. This is mainly due to a poor organization in intra and inter AED. In fact, the issue of bed management is not only limited to the implementation of algorithms and tools for the automatic visualisation and information of available beds. This situation must affect all stages of the patient's pathway: from upstream to downstream. The proposed algorithms contribute to the implementation of a bed management decision system by indicating the best desired destination for the patient, as well as the possible second choice destinations compatible with a correct and patient secure care. Our approach can lead to a decrease in the length of stay, duration and number of overcrowding situation in the ED and can also improve financial management as shown in several recent works. Nevertheless, this approach includes financial limits concerning the equipment of the different downstream-ED by beacons within a large hospital such as the LUHC.

Conclusions

In this paper, we used an approach combining metaheuristic (GA) and IoT-beacons to improve the inpatient management and resource utilization. The aim is to provide healthcare professionals with a technology support tool to automate bed allocation process. It is significant to highlight that our approach is presented as a decision-support system that reduces the workload of bed managers. To test the performance of our approach, we have implemented it in some hospital departments of LUHC. The results show that the use of evolutionary algorithms with IoT-Beacons to optimize the inpatient management is beneficial and practical. The future work of this research can be two-fold. First, predict the LOS of inpatient for each care unit done using a learning algorithm such as Q-Learning algorithm. Second, we can also include a multi agent systems to ensure an efficient collaboration between the different hospital systems inter and intra regions.

Acknowledgements

This work is part of Inter and Intra Hospital Logistics (OIILH) project supported and financed by the National Research Agency and is performed in the AED of LUHC (Lille, France). Also we would like to thank the domain experts in LUHC for helping with field investigation and data collection (https://anr.fr/Project-ANR-18-CE19-0019).

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