HYBRID OPTIMISATION-SIMULATION APPROACH FOR THE DESIGN AND OPERATION OF AN URGENT CARE CENTRE

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ABSTRACT
This paper presents an optimisation-simulation approach for the design and operation of an Urgent Care facility. The Urgent Care Centre (UCC) could be an answer to decrease overcrowding in Emergency Departments, which is a common problem around the World. Despite Urgent Care Centres being widely used in Anglo-Saxon countries they are almost inexistent in the majority of Europe. A proper design of the UCC will increase its chances of doing well. This problem is focusing on the daily operation of unscheduled primary care needs that take place in an Urgent Care Centre. Unfortunately there are no tools for the design and operation of the UCC in the literature. The purpose of this work is to develop an optimization-simulation approach for the design and analysis of a new UCC facility that operates under certain uncertain conditions.

Keywords: simulation-optimisation under uncertainty, health-care system, rolling horizon technique.

1. INTRODUCTION
Urgent care Centres play a key role in Anglo-Saxon countries but they are inexistent in others parts of world such as European countries. Urgent Care Centres are a great option for minor illnesses and injuries that are urgent but not life-threatening. Those non-life-threatening injuries and illnesses put extra pressure on the ED (Emergency Department) in central Hospitals.
This extra pressure may create some problems, increasing the possibility of misdiagnoses which threaten patient's lives, and also increasing the patient's waiting time, which affect directly in the cost of the service, regardless of whether the cost will be paid by the government, patient or by an insurance company.
The overcrowding of European EDs has been increasing over recent years (Sánchez et al., 2013). Richardson (2006) studied that quantifies the effect in the dysfunction in EDs caused by the overcrowding associated with longer waiting times, delays in admission and even the increase of risk of infectious disease. The magnitude of the effect in 10 day mortality in an Australian hospital was about 13 deaths per year.
From the economic point of view this overcrowding in EDs could be beneficial for private hospitals. But from a holistic perspective this multifactorial problem resulted in increased waiting times, decreased patient satisfaction and had a deleterious domino effect on the entire hospital operation. In Europe unlike the US, healthcare is viewed as a utility for everyone. All European countries have a legal framework for healthcare delivery for the general population, and so the implementation of a solution like US could be seen as governmental policy (Jayaprakash et al., 2009).
Despite it not being possible to extrapolate these results to calculate the deaths that are caused in Europe because of overcrowded EDs, it is clear that it is necessary to look for solutions to decrease the pressure on the ED.
One possible solution that is highlighted by researchers and practitioners such as Derlet and Richards (2000) and Borkowski (2012) is the use of more Urgent Care Centres to relieve the pressure on EDs.
The Urgent Care Centres are focusing on the delivery of ambulatory care in a dedicated facility outside the traditional EDs.
When patient populations were seeking care for non-life-threatening conditions 60% of them felt that the ED was the best place for them to receive care for their medical problem, thereby creating an inefficient use of expensive resources (Burnett and Grover, 1996.) The authors hypothesise that being unfamiliar with alternative care options and negative opinions about the alternatives were some of the main reasons.
The projected attention time is a major decision factor for the choice of Urgent Care Centres, since if you are going to wait the same time patients prefer to go to the ED. For example Tallahassee Memorial Healthcare offers their patients a guarantee to be seen by a nurse practitioner, physician's assistant or a physician within 15 minutes or they will be compensated with two cinema tickets.
Despite the fact that the majority of Urgent Care Centres do not offer free tickets for patients that stay more than 15 minutes, they do not let patients leave without being seen (LWBS). The time that a patient is willing to wait before leaving varies according to the type of illness or condition.
The design of an Urgent Care Centre is a complex task where we have to minimize the cost of the proposed facility in terms of the number of exam and procedure rooms, and staffing while maintaining a reasonable figure for patients that leave without being seeing.
To the authors' knowledge there are no Urgent Care Centre design models in the literature, so we will bring some ideas from the hospital design and emergency care design

literature. Baesler et al., 2003 used simulation to estimate the capacity of the EDs. Li and Benton (2003) presented research for management and quality control in the design, and Gallivan et al., 2002 made a mathematical model study to calculate the length of stay of the patients to investigate the capacity needed.

These kinds of problems are purely stochastic since the arrival of the patients, the type of disease of the patients, the leave-time without being seen and the duration of the medical treatments is not deterministic. Tackling all the stochastic variables in a mathematical model causes the size of the model grows to an extent that it is impossible to solve with current optimization tools.

Thus, discrete-event simulation emerges as an alternative solution technique for the decision makers to provide good-quality results with reasonable computational effort. The potential of discrete-event simulation for "as-is" analysis has been successfully demonstrated in Connelly and Bair (2004), to study average patient service times in EDs. Other studies have focused to analyse whether or not is able to handle a greater flow of incoming patients, as well as the related impact in their efficiency (Longo et al., 2014).

Despite the similarity in the design of health care facilities, especially between UCC and ED, is that UCC help fill a vital gap when you become sick or injured, but your regular doctor is not available and you cannot wait for an appointment. Then we can focus on the efficiency but we can allow certain number of patients to leave without being see, which is impossible in ED. Also UCC are different to regular medical centre because the main attention is not based on appointments. Moreover the majority of the approaches in the literature are more focus in the operation and not in the design of the facilities, using the simulation to make a daily solution.

In the last 10 years, many applications were developed using simulation techniques and also heuristic and metaheuristic approaches, to deal with the scheduling of patients in EDs. (see Azadeh et al., 2014). Many of these applications provide exact models, generally MILP models, which also represent the behaviour of the system with some simplifications. This kind of MILP models became easily unsolvable with the number of patient's treatments, that is why are commonly combined with decomposition or iterative algorithms to be solved in a reasonable CPU time.

Another important lack of exact models, in comparison with simulation approaches, relies on the stochastic behaviour of the system. For example, two-stage or multi-stage solution approaches can be developed for stochastic optimization using a scenario-based representation, but the number of scenarios to be considered should be reduced in order to deal with the problem in short CPU time.

In this paper we propose an optimisation-based simulation approach for the design and operation of an UCC. The proper interaction between an exact MILP and discrete-event simulation model allows us to solve this complex stochastic problem in a reasonable CPU time, obtaining important improvements at the design and operation costs of the UCC. In order to demonstrate the effectiveness of the solution approach, different scenarios were solved by considering a specific case study designed for this problem.

2. PROBLEM DESCRIPTION

The role of the Urgent Care Centres (UCC) in the health system is to attend to unscheduled primary care needs. This situation occurs when a patient cannot wait days or weeks for an appointment, or when they need treatment for injuries that require immediate Lab testing, X-ray or imaging to evaluate the severity of the injury. All the patients that cannot be attended to by the Urgent Care Centres should be forwarded to the Hospital. The UCCs mainly help the hospital ED by referring non-emergency patients to a more appropriate care setting.

The UCC works 7 days a week from 7 am to 9 pm. But they have to remain open until the last patients leave the centre. However, not all the staff need to remain but only those required finishing the patient's treatment. The staff required to operate the UCC are a Receptionist, Nurses, a General Physician, an Imaging Technician, Orthopaedic Physicians, Orthopaedic Technicians, and the Physician's Assistants.

The UCC is comprised of a registration area, waiting room, triage area and rooms that can be used for examinations and procedures (see Figure 1). For a matter of simplicity the UCC will attend to nine types of patients. The first type (mild sickness) does not require lab testing for treatment and could be attended to by a Physician's Assistant. The second one (standard sickness) requires lab testing and has to be seen by a Physician. The third type (orthopaedic injuries) requires setting and casting of the bone. The fourth type of patient is orthopaedic injury not requiring setting/casting. The fifth one is lacerations requiring stitches. The sixth type is minor cuts/bruises not requiring stitches. The next two types of patients are standard check-up/examinations such as physicals, flu shots, etc., and cardio problems such as mild strokes and irregular/rapid heartbeats. The ninth type is those requiring advanced emergency care who are immediately sent by ambulance to the emergency department.

Tables 1-9 summarize the flow for each of the nine patient types. Each treatment requires different professional staff and depending on the equipment needed the procedures could be done in a Procedure Room, not in an Exam Room.

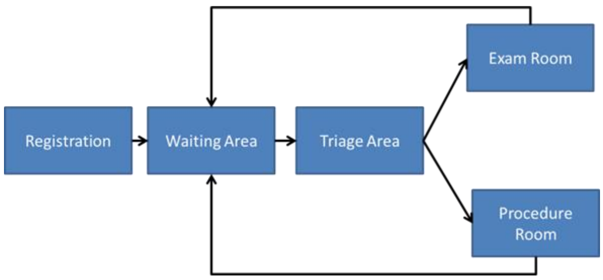

Figure 1: Flow process scheme of a UCC.

Table 1. Mild Sick

Step	Location	Resource	Processing Time
1	Registration	Receptionist	Triangular(1.5,3,7)
2	Triage Area	Nurse	Normal(2,.3)
3	Exam Room	Physician Assistant	Uniform(13,16)
4	Registration	Receptionist	Triangular(3,4,5)

Table 2. Sick

Step	Location	Resource	Processing Time
1	Registration	Receptionist	Triangular(1.5,3,7)
2	Triage Area	Nurse	Normal(2,.3)
3	Exam Room	Physician	Uniform(15,21)
4	Exam Room	Nurse	2
5	Registration	Receptionist	Triangular(3,4,5)

Table 3. Orthopaedic injury requiring Setting/Casting

Step	Location	Resource	Processing Time
1	Registration	Receptionist	Triangular(1.5,3,7)
2	Triage Area	Nurse	Normal (5,1)
3	Procedure Room	Imaging Technician	Uniform(10,16)
4	Procedure Room	Orthopaedic Physician	Triangular(9,10,15)
5	Procedure Room	Orthopaedic Technician	Triangular(10,15,20)
6	Registration	Receptionist	Triangular(3,4,5)

Table 4. Orthopaedic injury not requiring setting/casting

Step	Location	Resources	Processing Time
1	Registration	Receptionist	Triangular(1.5,3,7)
2	Triage Area	Nurse	Normal (5,1)
3	Procedure Room	Imaging Technician	Uniform(10,16)
4	Procedure Room	Orthopaedic Physician	Triangular(18,20,22)
5	Registration	Receptionist	Triangular(3,4,5)

Table 5. Lacerations requiring Stitches

Step	Location	Resource	Processing Time
1	Registration	Receptionist	Triangular(1.5,3,7)
2	Triage Area	Nurse	Normal (5,1)
3	Procedure Room	Physician Assistant	Normal(25,3)
4	Registration	Receptionist	Triangular(3,4,5)

Table 6. Minor cuts/bruises

Step	Location	Resource	Processing Time
1	Registration	Receptionist	Triangular(1.5,3,7)
2	Triage Area	Nurse	Normal (4,.5)
3	Exam Room	Physician Assistant	Normal(15,2)
4	Registration	Receptionist	Triangular(3,4,5)

Table 7. Standard Treatments

Step	Location	Resource	Processing Time
1	Registration	Receptionist	Triangular(1.5,3,7)
2	Exam Room	Physician Assistant	Normal(15,3)
3	Registration	Receptionist	Triangular(3,4,5)

Table 8. Cardio Problems

Step	Location	Resource	Processing Time
1	Registration	Receptionist	Triangular(1.5,3,7)
2	Triage Area	Nurse	Normal (5,1)
3	Procedure Room	Physician	Uniform(23,25)
4	Procedure Room		Uniform(45,60)
5	Registration Area	Receptionist	Triangular(3,4,5)

Table 9. Advanced Emergency Care

Step	Location	Resource	Processing Time
1	Registration	Receptionist	Triangular(1.5,3,7)
2	Triage Area	Nurse, Physician	Normal(5,1)
3	Triage Area	Ambulance	

Once the patients arrive they have to go to the registration area, and then all but those receiving standard check-ups are triaged by a nurse and in the event of an emergency a physician will attend. All the movement between the different areas will be performed by the Nurse.

The patients will leave without being seen (LWBS) after a time that will be measured between the period that the patient enters the registration and until they enter an Exam or Procedure room. In Table 10 the percentage by type of patient and the LWBS is displayed.

Table 11 shows the arrival rate of patients. Despite the arrival of new patients and closing at 9pm, it remains open until all the patients leave the facility. Then, it maybe makes sense to schedule staff to stay after the closing time. If a care–provider is required to stay overtime they will receive a 50% premium over the price.

Table 10. Patient type

Patient Type	Mix	LWBS
Mild Sickness	11	Uniform(15,35)
Standard Sickness	32	Uniform(25,40)
1st Injuries Ortho-setting/casting	7	Uniform(30,40)
2nd Injuries Ortho- Non setting/casting	5	Uniform(30,40)
3rd Injuries - Laceration	13	Uniform(25,35)
4th Injuries – Minor Cut Bruise	4	Uniform(30,40)
Standard Checkup/Exams	10	Uniform(10,20)
Cardio problems	10	Uniform(10,30)
Severe Non-Treatable	8	Uniform(5,10)

The overtime is calculated on an hourly basis.

In addition to these arrival patients, the system should be able to handle a mass accident causing 30 patients of type 3-6 in a 15 minute period, which could happen at any moment of the opening hours.

Table 11. Arrival Time Period

Time Period	Patient Arrivals per Hour
7am – 9am	11
9am – 11am	6
11am – 2pm	10
2pm – 3pm	7
3pm – 6pm	11
6pm – 8pm	8
8pm – 9pm	4

Table 12 shows the shift patterns for all care-providers. Each shift pattern has 9 working hours and a 1 hour break. Overtime only considers the last 2 hours of the day.

Table 12. Shift Pattern

Shift Type	Working Periods
Early	7am – Noon, 1pm – 5pm
Late	Noon – 4pm, 5pm -10pm
Overtime	10pm – Midnight

The hourly cost for each care–provider and those who own and operate each operating room and procedure room is summarized in Table 13. Only the operational cost will be addressed. For example, since the cost of a Receptionist room for 3 or 4 people is almost the same, only the cost of the Receptionist will be taken into consideration. The care–providers have to be paid the entire shift even if they are only used for one minute.

Table 13. Resource Information

Resource Required	Cost per Hour
Receptionist	$13
Nurse	$35
Physician Assistant	$55
Orthopaedic Technician	$25
Imaging Technician	$21
Physician	$90
Orthopaedic Physician	$110
Exam Room – Operating Cost	$15
Procedure Room – Operating Cost	$30

All patients have a priority that is based on the patient type as shown in Table 14. A patient with a higher priority will be attended to before one with a lower priority even though the patient with the lower priority has arrived before. But once a patient treatment starts this will not be suspended if someone with a higher priority arrives because not all the procedures are life threatening.

Table 14. Patient's priority

Patient Type	Priority
Mild Sickness	5
Standard Sickness	4
1st Injuries Ortho-setting/casting	2
2nd Injuries Ortho- Non setting/casting	3
3rd Injuries - Laceration	2
4th Injuries – Minor Cut Bruise	3
Standard Checkup/Exams	5
Cardio problems	1
Severe Non-Treatable	1

The data used for the experimentation purposes was taken from an instance used at the Student Simulation Competition of Simio® LLC 2015.

3. MOTIVATION

Given a set of unscheduled patients, with specific features, like LWBS time and processing time, the main idea of this problem is to determine the number of Operation Rooms and Exam Rooms and also the number of Staff we will need to achieve a reasonable value of LWBS with a minimum operational cost. Despite that the ideal value for #LWBS(%) is zero, a percentage value lower or equal to 10% is considered acceptable.

4. DISCRETE-EVENT SIMULATION MODEL

A discrete-event simulation model was developed in Simio® to assess the main features of the problem presented above. Given a specific configuration of staff and rooms, this model is able to represent the daily operation of the UCC.

All the staff is modelled as resources that are required depending on the room and the patient type. The patients are simulated as entities that are created randomly arriving at the system according to Table 11, and once the entities are created the patient type in Table 11 is assigned. Then these patients go to the registration room to fulfil the paperwork and then proceed to the waiting area with the help of a nurse. Once in the waiting area they have to wait until a Triage / Procedure / Exam Room is available while a nurse must be available to go with them to the needed room. This logic is implemented in an Add-On process inside the Nurse, which only accepts the Transport Request if there is a room to take the patient. Once that the procedure is finished in the room the patients come back to the waiting area where they wait for the next procedure until the last assigned task, which is the Reception to make the check out.

The patients could only leave the UCC because:

1. The LWBS time has already passed.
2. They need to be transferred to the Hospital.
3. They have completed the treatment.

The operational cost will be grouped in 3:

1. Cost of the use of the rooms
2. Cost of the use of the staff in regular hours
3. Cost of overtime

4.1. Simulation model features

One of the features of the model is that the manager could allow the model to do the activities that require Exam Rooms in the Procedure Room. The use of the Procedure Room is higher but using it when it is idle could be more convenient than having another Exam Room.

Following the same idea, another important feature allows a more qualified care-provider to perform the task of a less qualified care-provider. For example, allowing the Physician to do the task of the Physician's assistant. Despite the use of the Physician being higher than the Physician's Assistant, using an idle Physician could be better than hiring another Physician's Assistant.

The model also allows imitating the behaviour of the system if a major accident occurs during the operation hour creating a peak of demand.

The simulation model features a dashboard (see Figure 2) that allows the user to see the most important information during the simulation. The control chart is divided into three parts: the first one refers to the operational cost, the second to the patients attended to and the ones that leave, and finally the use of resources.

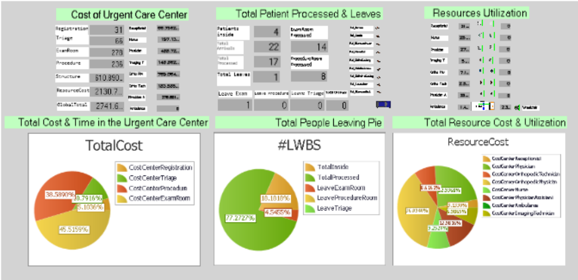

Figure 2: Model Dashboard

In order to facilitate the understanding of the results for healthcare managers a 3D visualization of the Urgent Care Centre was implemented. In Figure 3 we show a screen shot of the model after 570 minutes.

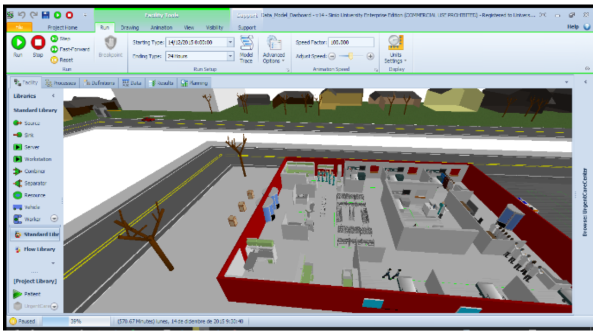

Figure 3: 3D model visualization

The simulation model presented here could be used to evaluate a particular configuration of staff and rooms by running multiples scenarios of uncertainty, but this model does not change the values or propose a different design. For this we use an optimization-based tool for helping us in the search of new configurations.

4.2. Optimisation-based simulation approach

In order to find a good configuration of staff and rooms, we generate and solve a set of 100 possible solutions using a well-known optimisation-based tool named OptQuest®. This tool allows us to test many solutions for many replication runs while varying control values, such as the number of staff and rooms in the system. Based on the information provided at each replication, the tool decides a new configuration of staff and rooms to be tested. After that, according to the results obtained for an initial number of replications, we can select a subset of promising scenarios, of staff and rooms, for in-depth analysis. Otherwise, we can let the tool decide the best promising scenario, using a Kim & Nelson procedure for selecting the best (see Kim and Nelson, 2001). In both cases, a maximum number of replications should be done to finally decide, based on the interval confidence, the best scenario of the system.

5. MATHEMATICAL FORMULATION

An MILP model was also proposed in this work. The main contribution of this model is the possibility to take into account discrete and continuous time characteristics of the problem without losing the global optimal solution. To do this, a general precedence and a STN constraints are combined is order to represent timing and sequencing decisions by Eqs.(1-8), units and resource assignment by Eqs.(9-10) and resource and units availability constraints are represented by Eqs.(18-23). Time-period assignment and sequencing constraints are proposed in Eqs.(11-17) to link both formulations. We consider intervals of 60 minutes (1 hour). Finally, the objective function is stated by Eqs.(24), representing the total cost of the system.

Sets

- I — *patients (i,ii)*
- L — *stages (l,ll)*
- J — *units (j,jj)*
- R — *resources (r,rr)*
- S — *shift (s,ss)*
- T — *time-period (t)*
- TS — *time at shift*
- IL — *tasks*
- ILJ — *units for task*
- ILR — *resource for task*

Parameters

- $tp_{i,l}$ — *treatment time for task (i,l)*
- rd_i — *ready time of patient i*
- $d^r_{r,t}$ — *availability of resource r in time t*
- h_t — *time limit of time period t*
- $c^j_{j,s}$ — *unit cost at work-shift s*
- $c^r_{r,s}$ — *resource cost at work-shift s*
- $LWBS_i$ — *leave time without been seen for i*
- M — *horizon time*
- N — *penalty cost per patient*

Binary Variables

- $x_{i,ii,l,ll}$ — *1 if task (ii,ll) precedes task (i,l)*
- $w_{i,l,j}$ — *1 task (i,l) is performed in unit j*
- $q_{i,l,r}$ — *1 task (i,l) is performed by resource r*
- $wp_{i,l,t}$ — *1 task (i,l) is processed in time t*
- $ws_{i,l,t}$ — *1 task (i,l) starts at time t*
- $wf_{i,l,t}$ — *1 task (i,l) finishes at time t*
- g_i — *1 if patient i violates LWBS constraint*
- f_j — *1 if unit j is available the whole day*

Positive Variables

- $Tf_{i,l}$ — *finishing time of task (i,l)*
- $Ts_{i,l}$ — *starting time of task (i,l)*
- $req_{r,t,s}$ — *resources r required at time t*
- $reqs_{r,s}$ — *resources r required at work-shift s*
- $rec_{j,t,s}$ — *units j required at time t*
- $recs_{j,s}$ — *units j required at work-shift s*

Free Variables

- TC — *total cost*

5.1. Timing Constraints

$$Tf_{i,l} \geq Ts_{i,l} + tp_{i,l} \qquad \forall i,l \in IL \qquad (1)$$

$$Ts_{i,l} \geq Tf_{i,l-1} \qquad \forall i,l \in IL \wedge l > 1 \qquad (2)$$

$$Ts_{i,l} - rd_i \leq LWBS_i + M^* g_i \qquad \forall i,l \in IL \qquad (3)$$

$$\sum_i g_i \leq 0.1^* |I| \qquad (4)$$

5.2. Task sequencing Constraints

$$Ts_{i,l} \geq Tf_{ii,ll} - M(1 - x_{i,ii,l,ll}) - M(2 - w_{i,l,j} - w_{ii,ll,j}) \qquad \forall i,l,j \in ILJ \qquad (5)$$

$$Ts_{ii,ll} \geq Tf_{i,l} - M(x_{i,ii,l,ll}) - M(2 - w_{i,l,j} - w_{ii,ll,j}) \qquad \forall i,l,j \in ILJ \qquad (6)$$

5.3. Resource sequencing Constraints

$$Ts_{i,l} \geq Tf_{ii,ll} - M(1 - x_{i,ii,l,ll}) - M(2 - q_{i,l,r} - q_{ii,ll,r}) \qquad \forall i,l,r \in ILR \qquad (7)$$

$$Ts_{ii,ll} \geq Tf_{i,l} - M(x_{i,ii,l,ll}) - M(2 - q_{i,l,r} - q_{ii,ll,r}) \qquad \forall i,l,r \in ILR \qquad (8)$$

5.4. Unit and Resource assignment Constraints

$$\sum_{j \in ILJ} w_{i,l,j} = 1 \qquad \forall i,l \in IL \qquad (9)$$

$$\sum_{r \in ILR} q_{i,l,r} = 1 \qquad \forall i,l \in IL \qquad (10)$$

5.5. Time-period assignment Constraints

$$\sum_t ws_{i,l,t} = 1 \qquad \forall i,l \in IL \qquad (11)$$

$$\sum_t ws_{i,l,t} = \sum_t wf_{i,l,t} \qquad \forall i,l \in IL \qquad (12)$$

$$\sum_{tt \leq t} ws_{i,l,tt} - \sum_{tt < t} wf_{i,l,tt} = wp_{i,l,t} \qquad \forall i,l,t \in IL \qquad (13)$$

5.6. Time-period sequencing Constraints

$$Ts_{i,l} \geq h_{t-1} - M^*(1 - ws_{i,l,t}) \qquad \forall i,l \in IL \qquad (14)$$

$$Ts_{i,l} \leq h_t - M^*(1 - ws_{i,l,t}) \qquad \forall i,l \in IL \qquad (15)$$

$$Tf_{i,l} \geq h_{t-1} - M^*(1 - wf_{i,l,t}) \qquad \forall i,l \in IL \qquad (16)$$

$$Tf_{i,l} \leq h_t - M^*(1 - wf_{i,l,t}) \qquad \forall i,l \in IL \qquad (17)$$

5.7. Resource availability Constraints

$$q_{i,l,r} + wp_{i,l,t} - 1 \leq \sum_{s \in TS} req_{r,t,s} \qquad \forall i,l,r,t \in ILR \qquad (18)$$

$$req_{r,t,s} \leq d^r{}_{r,t,s} \qquad \forall r,t,s \in TS \qquad (19)$$

5.8. Unit availability Constraints

$$\sum_{i,l \in ILJ} w_{i,l,j}{}^* tp_{i,l} \leq M^* f_j \qquad \forall j \qquad (20)$$

$$rec_{j,t,s} = f_j \qquad \forall j,t,s \in TS \qquad (21)$$

5.9. Resources and units per work-shift

$$recs_{j,s} \geq rec_{j,t,s} \qquad \forall j,t,s \in TS \qquad (22)$$

$$reqs_{r,s} \geq req_{r,t,s} \qquad \forall r,t,s \in TS \qquad (23)$$

5.10. Objective Function

$$TC = \sum_{j,s} (recs_{j,s} cj_{j,s}) + \sum_{r,s} (reqs_{r,s} cr_{r,s}) \qquad (24)$$

6. ROLLING HORIZON

During the last decades, many hybrid time formulations considering discrete-continuous representations have been developed to try to solve medium-term or industrial size problems with an acceptable computational time. Besides this, today there is no single representation that ensures an efficient solution for large-scale problems without any shortfall in the computational performance.
The MILP model of this work has been developed using the ideas of well-known Global Precedence and STN-based formulations. This model considers timing and assignment limitations and availability constraints. The statistics of the full-space MILP model are shown Table 15. This full-space model may become computational intractable due to the number of tasks to be performed in a single day. For example, for some cases, we could not provide a feasible solution after solving the full-space model for a couple of hours.

Table 15. Statistics of the MILP model

MILP full-space model	Statistics
# Equations	1,322,341
# Continuous variables	91,560
# Discrete variables	87,822

So, in order to overcome this limitation, a dynamic decomposition approach based on the main concepts of rolling horizon technique has been proposed to solve each deterministic instance in a reasonable time by scheduling one patient at a time. For this, we consider a relative optimality gap of 5% and a time limit of 60 sec. per iteration.
After that we obtain 10 different solution configurations of the system. The interval confidence of Total Cost $IC_{(1-\alpha=95\%)}$=[9668,13977] and #LWBS $IC_{(1-\alpha=95\%)}$=[3,11] report the quality of the solutions found by the algorithm. The total time consumed by the algorithm for a single replication is about 1 hour, which is so CPU time consuming. This limitation is the main reasons why we do not consider solving a stochastic model using scenario-based approach and alternative solution approach, merging simulation and optimization, have been done for this particular problem.

7. SIMULATION & OPTIMISATION

Solutions obtained by both our simulation model and the MILP optimisation model have been validated using the same data for inter-arrival time, processing time and LWBS time. The results indicate that the MILP can achieve a better configuration of staff and rooms in the system with a reduced total cost. By the way, the MILP model becomes computational intractable for solving many uncertain instances.

In order to get the benefits of both methods, the results of the previous MILP were used in the upper level to find the initial bounds of the system configuration, after testing 10 specific replications (see Table 16). These bounds are used to restrict the values of the control variables in OptQuest®. Thus, this information is copied in OptQuest® which uses it to obtain a set of solutions. Each solution is run in the simulator by testing 50 replications of uncertain parameters. OptQuest® and Simio® run until a limited number of solutions (100 solutions) are reached (see Figure 4).

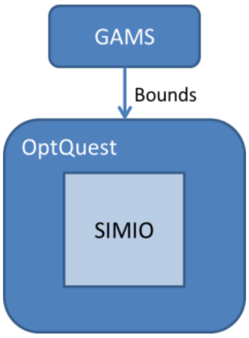

Figure 4: Hierarchical level of the solution approach

8. RESULTS

The experimentation was run under Windows 10 in a desktop PC with an Intel Core i7 processor with 16 GB of RAM. We used the GAMS® commercial software for the mathematical problem and Simio® for the simulation purpose.

Table 16. Solution bound of the MILP model

Resource	Lower bound	Upper bound
Registration rooms	3	3
Triage rooms	3	3
Exam rooms	2	3
Procedure rooms	2	3
Receptionist early shift	2	3
Receptionist late shift	2	3
Receptionist extra time	0	3
Nurses early shift	1	3
Nurses late shift	1	3
Nurses extra time	0	2
Physicians assistants early shift	2	5
Physicians assistants late shift	2	6
Physicians assistants extra Time	0	2
Orthopaedic technician early shift	0	2
Orthopaedic technician late shift	0	2
Orthopaedic technician extra Time	0	1
Imaging technician early shift	1	2
Imaging technician late shift	1	2
Imaging technician extra Time	0	1
Physicians early shift	1	3
Physicians late shift	1	3
Physicians extra Time	0	1
Orthopaedic physicians early shift	1	2
Orthopaedic physicians late shift	0	3
Orthopaedic physicians extra Time	0	1

Results in Table 17 are obtained from Simio® by using OptQuest®. As we explain before, we have used the results provided by the MILP to constrain the search.

Analyzing the results we can estimate an interval confidence for Avg. Total Cost $IC_{(1\text{-}\alpha=95\%)}$=[13330,16861] and Avg. #LWBS $IC_{(1\text{-}\alpha=95\%)}$=[2,11]. Despite we know that is not a fair comparison, the intervals confidences of the optimization and the simulation models are overlapped. According to this, we cannot infer that the statistical difference between both models is significant enough to decide which model is better. So, we can assume that the quality of the results obtained by the simulation model is good enough to suggest the use of this tool for further analysis.

Table 17. Best ten solutions found

Replications	Avg. Total Cost	Half Width	Avg. #LWBS(%)	Half Width
1	13021	30.15	8.14	1.15
2	15028	32.26	5.91	1.03
3	15040	28.19	8.26	0.86
4	15043	28.28	9.56	1.08
5	15054	24.65	8.63	0.95
6	15207	57.14	3.72	1.16
7	15324	70.16	4.40	2.26
8	15553	28.12	2.97	2.14
9	15726	75.16	8.32	1.65
10	15966	72.16	6.99	1.34

Figure 5 and Figure 6 resume the confidence interval of Avg. Total Cost and the Avg. #LWBS(%)found by OptQuest® by using our operation policy.

One advantage of using simulation relies in the possibility to evaluate other different operation policies without interfering with the real world and make some recommendations.

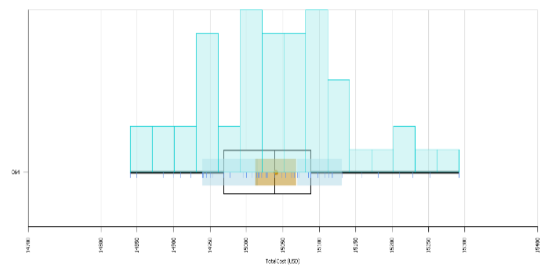

Figure 5: Avg. Total Cost confidence interval

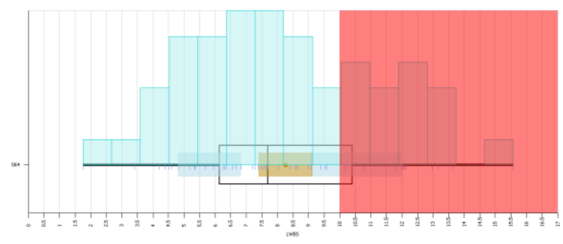

Figure 6: Avg. #LWBS confidence interval

The use of overtime is advisable since cancelling the overtime forces the UCC to have more workers to finish all the treatments before 9pm. Allowing the activities that require an exam room to be done in a procedure room when available gives a saving cost of around 5% but the saving is not so significant since both rooms have an hourly cost. The most interesting recommendation is to allow other care–provider types to tend patients. For example, allowing a Physician to perform the task of a Physician's Assistant has a saving effect of more than 15%, since we incur in a care–provider's cost even though he or she is idle almost all the day.

The other interesting recommendation is that being ready for a mass accident at any time of the day and maintaining the service level has an over-cost of more than 20% compared with the base model. This extra capacity is really costly for almost any health care system. To deal with the event of a massive accident, we need the patients to be split among different hospitals. And maybe if something like that happens all the low priority patients should be sent home so UCC can focus on the mass accident patients.

9. CONCLUDING REMARKS

The design and operation of a UCC represents a challenging problem for the Health-Care and PSE community today. This problem considers different sources of uncertainty, e.g. patient type, inter-arrival time, treatment duration and LWBS, where more than 100 patients per day have to be treated following certain conditions criteria.

These kinds of stochastic problems may be difficult to solve using traditional methods in a reasonable CPU time due to the nature of the stochasticity and also because of the huge number of tasks (>1000) to be assigned and sequenced in the system.

For example, if the design phase is performed using only simulation, the number of possibilities to consider become so high that it is impossible to try to solve them in a reasonable time. That is the case if we setup 0-10 resources for each type and we run the model for many hours without being sure how far from the optimal solution we are. Also, if we try to use only an MILP we could demonstrate the weakness in the computational performance.

One way to mitigate these limitations is by trying to use simple but, at the same time, robust solution procedures to find good solutions for the whole stochastic problem.

So, the integration of simulation and optimisation emerges as an efficient alternative to understand and solve these kinds of stochastic and combinatorial problems. Thus, using the MILP model to provide the best and worst bounds for the next step, and then run 50 simulations to test each scenario created, allows us to solve this complex and challenging problem within a reasonable computational performance.

The contribution of this paper is a simulation and optimisation tool for the Urgent Care Centre that to the authors' knowledge does not exist in the literature. The implementation of the UCC across Europe requires changes in the European healthcare policies. But as a first step the authors suggest running a trial close to the most overcrowded ED and measuring the effect of the UCC impact. The use of optimisation and simulation tools to achieve an appropriate design could increase the chances of success of the implementation.

In the next stage of the research we are looking for new ways to integrate the simulation optimisation, such as giving key information from the optimisation model that allows the simulation model to be more efficient.

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